Sensor-Based Organizational Design and Engineering

by

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Abstract

We propose a sensor-based organizational design and engineering approach that combines behavioral sensor data with other sources of information such as e-mail, surveys, and performance data in order to design interventions aimed at improving organizational outcomes. The proposed system combines sensor measurements, pattern recognition algorithms, simulation and optimization techniques, social network analysis, and feedback mechanisms that aim at continuously monitoring and improving individual and group performance. We describe the system's general specifications and discuss several studies that we conducted in different organizations using the sociometric badge experimental sensing platform. We have deployed such system under naturalistic settings in more than ten organizations up to this date. We show that it is possible to automatically capture group dynamics, and analyze the relationship between organizational behaviors and both subjective and objective outcomes (such as job satisfaction, quality of group interaction, stress, productivity, and group performance). We propose the use of static and dynamic simulation models of group behavior captured by sensors, in order to optimize group configurations that maximize individual and group outcomes, both in terms of job quality characteristics and organizational performance.

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The following people served as readers for this thesis:

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Chapter 1

Introduction

Recently, organizations have started mining data from e-mail, web pages, and other digital media for clues that will help them manage their knowledge-based systems in a more effective way. Studies of office interactions indicate that as much as 80 percent of work time is sometimes spent in spoken conversation (Allen 1997), and that critical pieces of information are transmitted by word of mouth in a serendipitous fashion (Pentland et al. 2004). Fortunately, the data infrastructure for mining real-world interactions is already in place. Most working professionals already carry electronic badges and mobile phones that can be enhanced with a few sensors and computational power.

This capability can be an extraordinary resource for capturing interaction patterns and modeling group behavior. The technology of *Reality Mining* allows one to cluster people on the basis of profiles generated from an aggregate of conversation, e-mail, location, and web data (Eagle & Pentland 2005). This clustering, in turn, enables one to identify collaboration or the lack thereof. For instance, if the members of two groups working on similar tasks never talk face-to-face, this suggests that they are not coordinating their efforts.

By leveraging recent advances in human behavior sensing, pattern recognition, and social network analysis, computational models that simulate the effects of organizational disruptions in existing social networks can be built. One could, for example, predict the organizational effects of merging two departments. Such data-driven models help transcend the traditional organizational chart, allowing organizations to form groups on the basis of communication behavior rather than hierarchy. In previous work, we have shown that active analysis of interactions within the workplace can radically improve the functioning of an organization. By aggregating this information, interpreting it in terms of work tasks, and modeling the dynamics of the interactions, a better understanding and management of complex organizations may be achieved.

In this thesis, we propose a sensor-based organizational design and engineering approach that combines sensor measurements, pattern recognition algorithms, simulation and optimization techniques, social network analysis, and feedback mechanisms that aim at continuously modeling and improving individual and group performance. We describe the specifications for a sensor-based organizational engineering system and discuss preliminary studies that we have conducted in several organizations using such platform to study communication patterns, task efficiency, productivity outcomes, and simulate optimal configurations of groups.

1.1 Research Question

How can behavioral sensor data be used to enhance organizational performance?

Organizational Data Mining (ODM) leverages data mining tools and techniques to enhance the decision-making process by transforming data into valuable and actionable knowledge to gain a competitive advantage (Nemati & Barko 2004). Advances in ODM technology have helped organizations optimize internal resource allocations while better understanding and responding to the needs of their customers. By applying ODM techniques and simulation algorithms to behavioral sensor data, we will show that it is possible to recognize social patterns, infer relationships, model organizational dynamics, and enhance organizational performance.

1.2 Motivation

Human sensing refers to the use of sensors to capture human behavioral signals including facial expressions, body gestures, nonlinguistic vocalizations, and vocal intonations (Pantic et al. 2007). Context sensing also plays an important role in understanding human behavior. Its goal is to characterize the situation in which specific behaviors are displayed. There is a large body of research in context sensing using wearable and environmental sensors (Gellersen et al. 2002, Harter et al. 1999, Jones & Brown 2002, Mantyjarvi et al. 2004, Van Laerhoven et al. 2002). The ultimate goal of human and context sensing is to automatically interpret the sensed behavioral signals to understand and describe the observed behaviors.

Our research group has developed several tools for analyzing voice patterns and quantifying social context in human interaction, as well as several socially aware platforms that objectively measure different aspects of social context, including non-linguistic social signals measured by a person's tone of voice, movements or gestures. We have found that nonlinguistic social signals are particularly powerful for analyzing and predicting human behavior, sometimes exceeding even expert human capabilities (Pentland 2005).

To the best of our knowledge, however, organizational studies have not yet incorporated data from social interactions in the workplace collected using electronic sensors. We propose the use of sensors capable of automatically identifying, quantifying and characterizing social interactions in order to incorporate this rich and untapped information (which was not possible to measure with such detail before) into formal organizational models. Our proposed approach augments traditional methods of gathering social interaction data such as surveys or ethnographic studies and incorporates behavioral sensor data into current Organizational Design and Engineering (ODE) practices.

1.3 Main Hypothesis

By combining behavioral sensor data with other information such as text documents, e-mail, surveys, and performance data; and using data mining and simulation techniques, it is possible to model human social behavior and enhance organizational performance.

In order to test this hypothesis, we developed a sensor-based organizational engineering system that uses wearable and environmental sensors to automatically quantify certain aspects of human social behavior such as non-linguistic social signals (contained in speech and body movement), face-to-face interaction, proximity and displacement.

1.4 Research Approach

Our goal is to design organizational interventions aimed at enhancing individual and group performance by applying a number of statistical analysis and simulation techniques to behavioral sensor data. With this in mind, we have devised a sensor-based organizational design and engineering approach to study the relationship between social signaling behavior, face-to-face communication patterns and social network characteristics, with organizational performance metrics such as task efficiency, productivity and job satisfaction. We have deployed our experimental research platform under naturalistic settings. Our approach is based upon the following propositions:

Proposition 1. Social signaling behavior and face-to-face interaction networks can be automatically captured using electronic sensors.

Proposition 2. Social signaling behavior is correlated with a variety of organizationally relevant outcomes such as performance and job satisfaction.

Proposition 3. Face-to-face interaction network characteristics are predictive of individual and group performance.

This approach to measure human behavior has several advantages over existing methods such as direct observation by humans, the use of pervasive cameras to videotape social interactions, or the use of surveys. Direct observation of humans by humans is expensive and limited to a few people per observer, and observers do not always agree. Deploying pervasive cameras is extremely expensive and their range of measurement is constrained to a particular place. The use of surveys is often subjective, inaccurate, and time consuming. In contrast, it would be a great advantage to be able to automatically capture the behavior of hundreds of people at the same time with unobtrusive sensors. The use of pervasive sensors allows us to study human behavior with unprecedented levels of detail. By capturing individual behaviors such as the amount of face-to-face interaction, speaking patterns, and non-linguistic social signals; and aggregating them at the group level, we show that it is possible to assess group performance and design organizational interventions aimed at improving organizational performance.

We present the results from several case studies where we have instrumented several participants with sociometric badges capable of measuring social signals (i.e. non-verbal cues extracted from speech and body movement), face-to-face interaction, and physical proximity. Each of the case studies are different in nature due to the difficulty in obtaining access to organizational performance data and digital communication records, as well as the complexity involved in deploying an experimental research platform under naturalistic settings in real organizations. The data that were made available to us by each organization were also slightly different in nature, therefore each case study addresses one or more hypotheses (specified in the corresponding sections) that support the abovementioned research propositions.

1.5 Outline

We begin chapter 2 with a brief review of organizational design and engineering theory. Next, we describe our proposed sensor-based organizational design and engineering approach in chapter 3. In chapter 4, we present an overview of the technologies and methodologies for sensing human behavior. In chapter 5, we describe the modeling and simulation techniques that were used to analyze the behavioral sensor data and optimize organizational performance. In chapter 6 we describe several case studies and discuss experimental results. Finally, we conclude and discuss further implications of the proposed approach in chapter 7.

Chapter 2

Organizational Research Background

2.1 Organizational Design

The basic goal of organizational research is to study what kinds of organizational designs or structures are most effective in different situations, as well as to identify variables that enable researchers to make consistent and valid predictions of such organizational structures (Tushman & Nadler 1978).

Organizational behavior is the systematic study of the actions and attributes that people exhibit within organizations. It seeks to replace intuitive explanations with systematic study, that is, the use of scientific evidence gathered under controlled conditions and measured and interpreted in a rigorous manner to attribute cause and effect (Robbins 2005). Analists of this field attempt to help managers understand people better so that productivity improvements, customer satisfaction, and a better competitive position can be achieved through better management practices (Gibson et al. 2009).

A recent approach that brings together organization and information systems research and that focuses on building and deploying computer-based tools for organizational design was proposed by Magalhães & Rito Silva (2009). They address the need to bring together the engineering and the design of organizations and define Organizational Design and Engineering (ODE) as "the application of social science and computer science research and practice to the study and implementation of new organizational designs, including the integrated structuring, modeling, development and deployment of artifacts and people". They draw a parallel with the agile software development process and suggest a combination of short observation stage, where the relevant parts of the organization's design are observed, followed by a rapid intervention design and deployment stage. This process would go on continuously as a sequence of short observation steps, followed by short intervention steps. This approach can be applied in sensor-based organizational design systems.

To understand how individual behavior affects performance, it is necessary to take into consideration several variables that directly influence individual behavior, such as abilities and skills, personality, perception, attitudes, values, and experience among others (Bowditch & Buono 2005). Behavior is also affected by a number of environmental variables such as the organizational structure, policies and rules, resources, and job design. While the individual variables are most likely fixed and do not change much over time, the environmental variables can be continuously manipulated in order to modify individual behavior and promote a desired outcome.

2.2 Organizational Engineering

Research in organizational theory and organizational behavior has contributed to the creation of a new field known as organizational engineering, whose focus is:

> "...to increase the efficiency, productivity, communication, and coordination of groups of people. These may include teams, departments, divisions, committees and many other forms of goal directed organizations. Focusing on how relationships and information are structured allows groups to be engineered to produce superior results on a consistent basis" (Organizational-Engineering-Institute 2007).

Tourish & Hargie (2009) argue that modern research on organizational communication must turn its efforts to exploring the in-situ, moment-to-moment, everyday communication practices of organization members. This means extending communication research beyond self-report techniques that rarely capture the full complexities of observed behavior in real-world organizations.

There exist several relatively disconnected perspectives within the field of organizational engineering (Castro Melo Godinho de Matos 2007): (i) Business Engineering is concerned with automation, elimination of bureaucracy, simplification of work flows, refinement of information infrastructure, and elimination of unnecessary work (Martin 1995); (ii) Enterprise Architecture is concerned with the role that information technology plays in organizations and with the adaptation that most enterprises have to face in order to remain competitive in the process of change (Winter & Fisher 2007); (iii) Language Action Perspective sees communication as a form of action and considers that people act through language (Dietz 2002, Reijswound & Lind 1998, Winograd 1986); and (iv) Computational Organization Theory studies organizations as computational entities (Carley 1995).

The work of Carley (2002) at Carnegie Melon University is particularly relevant to the design of organizational engineering systems. She has proposed that the same techniques used to engineer a product to meet some set of specifications can be applied to organizations and that it should be possible to design an organization, group, or team, so that it is "optimal" given some set of criteria (Carley & Kamneva 2004). Her research group has focused on several computational simulation tools for organizational design: (i) agent-based models that simulate the behaviors of the actors who make up a social system, and where the behavior of the social system is not modeled directly, rather the systems behavior emerges from the interaction of its agents; (ii) systems dynamics models that focus on modeling the behavior of the system as a whole; and (iii) cellular automata models for studying local interactions (Harrison et al. 2007). We believe this approach could be complemented with sensor data from social interactions in order to initialize simulation parameters and solve optimization problems.

2.3 Organizational Intervention Theory

Cummings & Worley (2009) define Organizational Development as "a process that applies a broad range of behavioral-science knowledge and practices to help organizations build their capacity to change and to achieve greater effectiveness, including increased financial performance, customer satisfaction, and organization member engagement". Organizational interventions are change processes that imply an intentional entry into an ongoing system of relationships (Rothwell et al. 2010). There are many possible ways to engineer organizational interventions, therefore we will only describe some background theory related to the proposed interventions that are presented in chapter 6.

2.3.1 Physical Environment

Proximity among people within an organization is known to exert considerable influence on face-to-face communication, coordination, balance of members' contribution, mutual support, effort, and cohesion (Hoegl & Proserpio 2004). The seminal work of Allen (1971) uses a dyadic measure of physical distance in terms of feet or meters that refers to pairs of physical locations that do not vary in reciprocal distance over time. Monge et al. (1985) define organizational proximity as "the extent to which people in an organization share the same physical locations at the same time providing an opportunity or psychological obligation to engage in face-to-face communication". They observed daily variations in organizational proximity as well as day-to-day regularities by asking employees from a software systems firm to indicate, in 15-minute intervals, where they spent their time during all five days of a typical work week. Their research suggests that the expected level of organizational proximity at any point in time and the patterns across time is a function of the nature of the physical facilities, the nature of the work, and the reporting relations. Several organizational interventions that rely on the modification of the physical environment to promote face-to-face interaction in the workplace (e.g. office layout redesign and office renovation) have been studied (Heubach et al. 1995, Shpuza 2006, Zagenczyk et al. 2007).

2.3.2 Feedback Intervention Theory

According to Alder (2007), performance feedback has been a topic of interest to organizational behavior and organizational-psychology researchers for over a century due to the fact that feedback affects numerous organizationally-relevant outcomes such as employees' job motivation, satisfaction, absenteeism and turnover. Kluger & DeNisi (1998) proposed the first comprehensive theory of feedback. Their Feedback Intervention Theory (FIT) states that behavior is regulated by comparisons to standards or goals and that feedback interventions affect behavior by changing individuals' locus of attention. Alder (2007) examined the effect of Computer Performance Monitoring (CPM)-based feedback on individual's task performance and found that allowing participants to control the amount and frequency of feedback they received enhanced their desire to respond to their feedback with improved performance.

Coaching can help individual learning and development. Individual feedback may help to understand the effects of one's own behavior on others. Individual feedback can take many forms, such as personal feedback, norm-based assessments, surveys, 360° feedback, and tests (Boonstra 2004). Recent research on real-time feedback interventions has shown that it is possible to modify group's behavior by displaying information about group interaction dynamics in real time (DiMicco et al. 2004, Kim & Pentland 2009). Laboratory study results show that sociometric feedback helps groups achieve higher interactivity levels and better communication (Kim et al. 2008). In a recent study, Kim et al. (2010) found that when given feedback on their communication patterns, individuals became more cooperative, increasing the overall performance of the group. These results suggest that real-time sociometric feedback can indeed change group dynamics and enhance group performance.

2.3.3 Continuous Change

There are two different kinds of organizational change: "episodic change", which is discontinuous and intermittent; and "continuous change", which is ongoing, evolving and incremental (Weick & Quinn 2004). The distinctive quality of continuous change is the idea that small continuous adjustments, created simultaneously across units, can cumulate and create substantial change.

One focal point of organizational development is organizational culture change (Rothwell et al. 2010). Intervention methods based on culture are mainly in the form of large-scale training and communication programs. According to Boonstra (2004), the first step in cultural change is to assess the organizational culture by using survey feedback or by bringing groups together to identify values and underlying assumptions. The next step is to identify cultural assumptions that aid to or prevent from getting to shared goals. After a reflective diagnosis, an action plan is developed to determine what steps might be appropriate. Finally, the execution of the action plan is monitored by members of the organization with the help of a facilitator. Culture change is a continuous change process.

2.4 Organizational Performance

Organizational performance cannot be measured using a single method or metric. There are many different ways of interpreting, defining and assessing organizational performance, as well as a wide range of stake-holders involved. Richard et al. (2008) make a distinction between "organizational performance" and "organizational effectiveness":

> **Organizational performance** encompasses three specific areas of firm outcomes: (1) financial performance (profits, return on assets, return on investment, etc.); (2) market performance (sales, market share, etc.); and (3) shareholder return (total shareholder return, economic value added, etc.).
>
> **Organizational effectiveness** is broader and captures organizational performance plus the plethora of internal performance outcomes normally associated with more efficient or effective operations and other external measures that relate to considerations that are broader than those simply associated with economic valuation.

In this thesis we use both subjective and objective measures of individual and group performance related to both organizational performance and organizational effectiveness. Business firms are usually compared in terms of profits, sales, market share, productivity, debt ratios, and stock prices. Hospitals use cost of recovery time, mortality rates, and occupancy rates. Universities use research productivity, faculty prestige, test scores of students, and rankings by popular magazines (March & Sutton 1997). Chapter 3 describes our proposed approach, and we argue that it can be applied to multiple performance measures as it will be shown in chapter 6.

Chapter 3

Proposed Sensor-Based Organizational Design and Engineering Approach

3.1 Proposed System

We have developed a set of tools and methods to automatically capture, measure, and analyze human behavior in organizational settings in order to improve performance and optimize organizational structures and decisions, e.g. office layout, team formation, and organizational structure (Olguín-Olguín, Waber, Kim, Mohan, Ara & Pentland 2009). Our goal is to be able to map behavioral patterns to quantifiable outcomes and provide employees and managers with feedback that allows them to adjust their behavior in order to optimize a desired outcome. Our proposed approach includes the following steps:

1. Capturing the interactions and social behavior of employees, managers and customers using wearable and/or environmental sensors. Other sources of information that can be incorporated into the system are any form of digital records (e.g. e-mail, chat, phone logs).

2. Performing data mining and pattern recognition to extract meaningful information from these data.

3. Combining the extracted information with performance data (e.g. sales, tasks, timing) and finding relationships between objective measurements and performance outcomes.

4. Behavior modeling and simulation.

5. Organizational intervention design.

6. Intervention implementation by means of generating feedback in the form of graphs, interactive visualizations, reports, or real-time audio-visual feedback for employees, managers and/or customers.

7. Continuous measurement and performance assessment.

A sensor-based system for organizational design consists of environmental and wearable sensors, computers, and software that continuously and automatically measure individual and collective patterns of behavior, identifies organizational structures, quantifies group dynamics, and provides feedback to its users. The purpose of such system is to improve productivity, efficiency, and/or communication patterns within an organization. The proposed system is composed of one or more wearable sensing devices functioning in a wireless sensor network, one or more radio base stations, a computer system, and several data processing algorithms. The system may include some of the following:

- Environmental sensors that monitor the current conditions of the workplace (temperature, light, movement, activity, sound, video, etc.).

- Wearable sensors that employees carry around and that measure human behavior (social interaction, activities, location, etc.). These can be mobile devices such as cell phones, PDAs, or electronic badges that collect data, communicate with a database (via Ethernet or wirelessly) to retrieve information, and provide feedback to their users.

- Software that automatically identifies relevant keywords in documents, web pages, e-mail, and instant messaging communication.

- A database that stores all the information collected by the environmental, wearable and software sensors (who-knows-what, who-knows-who, and where-is-who).

- Simulation and data mining algorithms.
- Feedback and visualization mechanisms.

3.2 Environmental Sensors

In addition to the wearable sensors, base stations can be placed in fixed locations inside a building in order to track the location of interaction events as well as subjects. A central computer can be used for data collection. Data from the wearable sensors is transferred wirelessly to the base stations and then uploaded to a server. The base stations may contain environmental sensors (temperature, light, sound, movement, activity, etc.) that capture the current conditions in an office environment, such as the number of people walking by, ambient noise, temperature and lighting conditions.

3.3 Wearable Sensors

Wearable sensing devices may include electronic badges, mobile phones, wrist-mounted devices, head-mounted devices, and electronic textiles, among others. These wearable devices could function as self-contained monitoring devices or communicate with each other and with fixed radio base stations in a wireless sensor network. The wearable sensing devices should have a small form factor, be comfortable to wear over long periods of time, and have a long battery life. A behavioral wearable sensor should be able to:

- Recognize common daily human activities (such as sitting, standing, walking, and running) in real time.
- Extract speech features in real time to capture non-linguistic social signals such as interest and excitement, and unconscious back-and-forth interjections, while ignoring the words in order to assuage privacy concerns.
- Communicate with base stations over radio and measure the radio signal strength (to estimate proximity and location).

- Perform indoor user localization by measuring received signal strength and implementing triangulation algorithms.

- Capture face-to-face interactions.

The wearable sensing device may include one or more of the following modules:

Table 3.1: Sensors and measurements for wearable sensing device.

Module	**Sensors**	**Measurements**
Audio	Electret or MEMS-type microphone.	Speech detection and segmentation, speaking time, speech features (e.g. energy, pitch, speaking rate, etc.), non-linguistic signals (e.g. activity, consistency, mirroring, influence).
Motion	Accelerometers, inclinometers, gyroscopes, piezoelectric vibration sensors.	Body movement detection, body energy level, body postures and physical activities.
Face-to-face interaction	Infrared transceivers, CMOS cameras.	Time spent in face-to-face interactions.
Proximity	Ultrasonic sensors, sonar, radio transceivers (e.g. ZigBee, WiFi, Bluetooth).	Proximity to other people and base stations (from radio signal strength).
Location	Radio transceivers (e.g. ZigBee, WiFi, Bluetooth).	Triangulation (using radio signal strength).
Input interface	Buttons, keyboard, touchscreen, haptic interface	
Output interface	Speaker, LCD, light emitting diodes.	
Memory	Flash, RAM, SD card interface.	
Processor	Micro-controller / DSP.	
Power	Battery and power management circuitry.	

3.4 Database

A database containing individual attributes (values, attitudes, self-concept, abilities, personality, job satisfaction, etc.); sociometric data captured from sensors (speaking state, speaking style, motion state, location, face-to-face interaction, proximity, etc.); group attributes (team assignment, communication frequency, social network features derived from the sociometric data); and performance data (projects or tasks, completion time, success/failure, resources, follow-ups, etc.) from each person in an organization must be maintained in order to manage the vast amounts of information generated by the system. Database software includes: MySQL, Microsoft SQL Server, Oracle, and IBM DB2. Analysis software includes: Matlab, Microsoft Visual Studio, UCINET, among others.

3.5 Feedback and Visualization Software

By aggregating information from sensor data, interpreting it, and modeling the dynamics of human interactions, one can create sensor-based feedback systems that help better understand and manage complex organizations. Performance dashboards are becoming increasingly popular, but how to structure this feedback, particularly when it comes from sensor data, is an unanswered question. Feedback on group dynamics has been proven to help with the performance of small group collaboration (Kim & Pentland 2009). Kim et al. (2009) have proposed a system to detect group dynamics and provide feedback according to a group's goals. By synchronizing multiple wearers' sociometric data, it is possible get information such as turn-taking, influence, body movement mimicry, and similarities in behavior. This information is then visualized in order to provide real-time feedback on group dynamics.

3.6 Organizational Re-engineering Process

Once the system has been put in place and sociometric data has been collected, the following steps would constitute an organizational re-engineering cycle:

1. Access personal attributes, sociometric data, and performance data.

2. Apply data mining and data processing algorithms.

3. Find relationship between desired/undesired performance outcomes and sociometric data.

4. Find relationship between personal attributes and sociometric data.

5. Set individual and group performance goals.

6. Design and perform an organizational intervention.

7. Provide users with feedback in order to induce behavioral changes and achieve the desired goals.

8. Deploy the data collection system again. If the performance goals have not been reached, predict future performance outcomes based on the sociometric data, and start organizational re-engineering cycle again.

We envision short cycles of measurement-feedback-intervention-measurement until significant improvements have been reached. The first measurement phase may last a few weeks or up to a few months. The feedback phase can happen in real time (while sociometric data is being collected), or after the first measurement phase. Interventions have to be implemented soon after the feedback phase and the second measurement phase has to be carried out a few weeks after the intervention has been put into practice. The second measurement phase is confirmatory step and the entire cycle can be repeated again.

Chapter 4

Sensing Human Behavior and Social Interactions

To date, research on human interactions has relied mainly on one-time, self-reported data on relationships. New technologies, such as video surveillance, e-mail, and mobile phones, offer an uninterrupted stream of interaction data over extended periods of time, providing information about both the structure and content of relationships. This has given rise to the emerging field of "Computational Social Science" that leverages the capacity to collect and analyze data with an unprecedented breadth and scale (Lazer et al. 2009). Vast amounts of data are created everyday from the use of personal electronic devices such as mobile phones and RFID cards. This calls for the use of pattern recognition and data mining techniques to uncover hidden structures of human behavior and social interactions.

In this section we present an overview of the state of the art in individual behavior recognition from sensor data including motor activities and social signaling behavior. We then move on to discuss the latest developments in group behavior recognition, such as face-to-face interaction, conversation detection and conversation dynamics. We also present a brief overview of pattern recognition methods in social network analysis for the automatic identification of groups and the study of social network evolution.

4.1 Individual Behavior

We are interested in recognizing human behavior from sensor data at the individual and group levels, as well as combining pattern recognition methods with dynamic social network analysis, with the goal of creating a general framework for modeling group dynamics.

At the individual level, several researchers have applied pattern recognition methods to sensor data that capture different aspects of human behavior such as primitive motor activities, e.g. standing, walking, running, etc. (Kern & Schiele 2003, Lee & Mase 2002, Mantyjarvi et al. 2001, Van Laerhoven & Cakmakci 2000); as well as complex or high-level activities, e.g. working on computer, having a phone conversation, etc. (Bao & Intille 2004); and body posture, facial expressions, hand gestures, and displacement patterns (e.g. location tracking).

Another aspect of individual behavior is the unconscious or "honest" signaling displayed during social interactions. According to Pentland (2008), these honest signals can be measured by analyzing the timing, energy, and variability of speech and body movement patterns. He describes four different types of honest signals in humans: influence (the extent to which one person causes the other person's pattern of speaking to match their own pattern), mimicry (the reflexive copying of one person by another during a conversation), activity (speaking time and energy), and consistency (low variability in the speech signal). The pattern of signaling behavior and social roles largely determines the pattern of communication within an organization. Consequently, the dynamics of group interaction can be inferred from the pattern of communication. For instance, dominant, high-influence individuals cause the pattern of communication to flow through them, making them more central in the organization.

Dong et al. (n.d.) use an "influence model" to represent the group discussion dynamics as interacting stochastic processes, in which each participant is represented by a single process. Their method identifies the different functional roles that the participants take at each time in a group discussion and evaluates the discussion efficiency within the framework of the stochastic process.

4.2 Group Behavior

At the group level, we are interested in automatically identifying face-to-face interactions, conversations, and conversation dynamics. Studies have shown that hand-coded analyses of communication in teams can predict performance (Foltz & Martin 2009). These studies have looked at the frequency, patterns and content of communication. For instance, an analysis of the communication patterns of air-crews in flight simulation experiments revealed significant differences between successful and unsuccessful crews (Bowers et al. 1998). In some cases, high-performing teams communicate with higher overall frequency than low-performing teams, but in other cases, this finding has not been supported.

According to Foltz & Martin (2009), to develop a human performance model, one needs to find out if, and the degree to which, a relationship between communication and performance exists. Computational models must accurately measure features in communication that relate to measures of team performance. To create such model, recent advances in the fields of computational cognitive models (e.g. latent semantic analysis, or LSA, social network analysis, and pattern recognition techniques (e.g. clustering, classification, generalization) can be leveraged.

More recently, there has been increasing interest on modeling more complex patterns of behavior over extended periods of time. Oliver et al. (2004) proposed the use of Layered Hidden Markov Models (LHMMs) to classify different office activities (e.g. phone conversation, face-to-face conversation, distant conversation, presentation, etc.). In their model, there is a hierarchy with multiple HMMs, each corresponding to a certain concept (for example, audio signals). These HMMs take as observations either the features computed from the raw signals or the inferential results from the previous level. In LHMMs, each layer of the architecture is connected to the next layer via its inferential results.

Gatica-Perez (2006) discusses some work on automatic analysis of face-to-face multiparty conversations from multi-sensory data that has appeared in the literature spread over several communities, including signal processing, computer vision, multi-modal processing, machine learning, human-computer interaction, and ubiquitous computing. The author proposes a categorization of conversational group activities on the basis of temporal scale and group size. The proposed categories are: addressing (e.g., who speaks to whom at every time), turn-taking patterns (e.g. floor control, discussions, monologues), and group trends (e.g. interest levels, dominance, and influence). Gatica-Perez (2009) later extended his review to more than a hundred different works addressing the computational modeling of interaction management, internal states, personality traits, and social relationships in small group conversations. His review focuses on small groups, non-verbal behavior, computational models, and face-to-face conversations.

4.3 Social Signaling

As argued before, honest signals are unconscious indicators displayed during social interactions. People display combinations of honest signals when they assume different social roles such as: exploring, listening, teaming, and leading. For instance, the social role of exploring combines low consistency and high activity. The role of active listening displays low consistency and low activity. The teaming role requires a combination of high influence, high mimicry, and high consistency. When adopting the role of leading there is high levels of influence, high activity, and high consistency. The pattern of signaling behavior and social roles largely determines the pattern of communication within an organization. Consequently, the dynamics of group interaction can be inferred from the pattern of communication.

In this section we describe the social signals that we implemented and used in the case studies discussed in chapter 6.

4.3.1 Physical Activity

A 3-axis accelerometer signal should be sampled at $f_s \geq 30$ Hz in order to capture the range of human movement since 99% of the acceleration power during daily human activities is contained below 15 Hz (Mathie et al. 2004). The acceleration signal vector magnitude ($|\vec{a}'_i|$) provides a measure of the degree of movement intensity that includes the effect of signal variations in the three axes of acceleration (Karantonis et al. 2006). $|\vec{a}'_i|$ is calculated on the normalized i^{th} acceleration sample as follows:

$$|\vec{a}'_i| = \sqrt{a'^2_{x_i} + a'^2_{y_i} + a'^2_{z_i}} \tag{4.1}$$

The mean accelerometer signal magnitude is indicative of an individual's "physical activity level" and is calculated as follows:

$$F^1(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} |\vec{a}'_i| \tag{4.2}$$

where $T = 60$ seconds, f_s is the accelerometer sampling frequency, and k is the k^{th} minute.

The standard deviation of the accelerometer signal magnitude is calculated as follows:

$$F^2(k) = \sqrt{\frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} [|\vec{a}'_i| - F^1(k)]^2} \tag{4.3}$$

This feature is indicative of an individual's "consistency of body movement" $(1 - F^2(k))$. The signal power or energy per minute is calculated as follows:

$$F^3(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} |\vec{a}'_i|^2 \tag{4.4}$$

4.3.2 Speech Activity

The speech signal must be sampled at $f_s \geq 8000$ Hz since the voice frequency band ranges from 300 to 3400 Hz approximately. The voiced speech of a typical adult male has a fundamental frequency between 85 and 155 Hz, and that of a typical adult female between 165 and 255 Hz. (Baken 1987). Several speech enhancement and speech recognition front-end systems based on band-pass filter banks have been shown to be effective in detecting speech (Ellis et al. 2002, Mouchtaris et al. 2005). A band-pass filter bank that divides the speech frequency spectrum $[85, 4000]$ Hz into four (or more) frequency bands (e.g. f_1 from 85 to 222 Hz, f_2 from 222 to 583 Hz, f_3 from 583 to 1527 Hz, and f_4 from 1527 to 4000 Hz) can be used to detect speech.

We can compute the speech volume modulation from the output of filter 1, since that is where the majority of the speaking energy resides:

$$v(i) = |(f_1(i) + f_1(i-1)) - (f_1(i-2) + f_1(i-3))| \tag{4.5}$$

Feature $F^4(k)$ (mean volume modulation per minute, or "speech activity") is then obtained as:

$$F^4(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} v(i) \tag{4.6}$$

The standard deviation of volume modulation per minute is calculated as:

$$F^5(k) = \sqrt{\frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} [v(i) - F^4(k)]^2} \tag{4.7}$$

"Speech consistency" can then be calculated as $1 - F^5(k)$. The amount of speaking time per minute is simply calculated by counting the number of samples in one minute where the volume modulation is $v(i) > 0$:

$$F^6(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} v(i)h(i) \tag{4.8}$$

where $h(i)$ is the step function:

$$h(i) = \begin{cases} 1 & \text{if } v(i) > 0 \text{ (speaking)} \\ 0 & \text{if } v(i) = 0 \text{ (not speaking)} \end{cases}$$

An experimental threshold value for each of the band-pass filters can be determined in order to detect voiced and unvoiced speech. These threshold values can be coded using a bit mask and the amount of voiced speech per minute can be obtained as:

$$F^7(k) = \frac{1}{f_s T} \sum_{i=1+f_s T(k-1)}^{f_s T k} v(i)b(i) \tag{4.9}$$

4.3.3 Face-to-face (f2f) Interaction

Infrared (IR) transmissions can be used as a proxy for the detection of face-to-face interaction between people (Choudhury & Pentland 2003). In order for one person to be detected through IR, two IR transceivers must have a direct line of sight and the receiving sensor must be within the transmitter's IR signal cone of height h and radius $r \leq h \tan \theta$.

We define the amount of face-to-face interaction $F^8(k)$ as the total number of IR detections per minute divided by the IR transmission rate (TR_{ir}). Feature $F^9(k)$ is simply the number of different IDs detected every minute.

4.3.4 Proximity

The Radio Signal Strength Indicator (RSSI) is a measure of the signal strength between transmitting and receiving devices. An average threshold can be determined experimentally in order to detect when two people are in close proximity to each other by collecting RSSI measurements over an extended period of time under different environmental conditions. The time spent in close proximity to another person $F^{10}(k)$ is calculated by dividing the number of radio packets with RSSI > RSSI$_{th}$ by the radio transmission rate (TR_{radio}).

4.3.5 Social Network

Social network attributes can be calculated using the number of IR and radio detections as the link strength between two actors. We have used conventional social network analysis as described by Wasserman & Faust (2005). In particular, we have used individual and group degree and betweenness centrality as well as contribution index (Gloor et al. 2003). Betweenness centrality is a measure of power and influence within a group. Degree centrality measures the number of direct interaction partners. Contribution index measures how much of a sender or a receiver within a group somebody is.

4.4 Sociometric Badges

4.4.1 Previous Work

The first electronic ID badge was developed at Xerox PARC as a solution to the problem of efficient location and coordination of staff in large organizations (Want et al. 1992). The electronic tag was designed as an *Active Badge* that emitted a unique code every 15 seconds. These signals were then picked up by other infrared sensors placed around a building. The size of the badge was roughly 55 x 55 x 7 mm and weighted 40 g. The design of this first badge was very simple: it consisted of a commercial remote controller encoder, an infrared emitter driver, a timing circuit, and a test button.

More complex badge platforms have been developed after the *Active Badge*. In 1996, the *Thinking Tags* (Borovoy et al. 1996) were the first computationally augmented name tags that were capable of displaying how much two people at a conference or meeting had in common, simply by lighting LEDs of different colors depending on how many questions the participants had previously answered the same. Two years later they evolved into the so-called *Meme Tags* (Borovoy et al. 1998), allowing conference participants to electronically share brief ideas or opinions through a large LCD screen. This system further evolved into the *nTAG System*, a commercial system to improve, measure, and automate meetings and events (*Ntag Interactive* n.d.).

The *Wearable Sensor Badge* developed at Philips Research Labs in 1999 (Farringdon et al. 1999) was capable of detecting simple pre-ambulatory activities using an accelerometer. The *iBadge* (Park et al. 2002) was designed to be worn by children to capture interactions with teachers and common classroom objects. The *UbER Badge* developed at the MIT Media Laboratory in 2006 was a research platform for facilitating interaction in large professional or social events (Laibowitz et al. 2006). These badges were equipped with a large LED display, wireless infrared and radio frequency networking, and a host of other sensors used to develop features and algorithms aimed at classifying and predicting individual and group behavior (Paradiso et al. 2010). It measures 110 x 120 x 20 mm and weighs 170 grams.

A PDA-based system that allowed users to automatically collect pictures into a continually growing and adapting multimedia diary was developed at the MIT Media Laboratory (Blum et al. 2006). It used patterns in sensor readings from a camera, microphone, and accelerometers to classify the user's activities and automatically collect multimedia clips when the user was in an interesting situation. Microsoft Research developed *SenseCam*, a sensor augmented wearable still camera designed to compile a digital record of the user's day, by recording a series of images and capturing a log of sensor data without user intervention (Hodges 2006). It was built around a PIC micro-controller and contained several sensors such as a VGA camera module, a 3-axis digital accelerometer, a temperature sensor, a passive IR sensor, audio recording, and a standard SD card. It has been used in several memory recall research projects since then.

The *Mobile Sensing Platform* (MSP) 2.0, developed at Intel Research in 2008, is a wearable device specifically designed for embedded activity recognition and context aware applications (Choudhury 2008). It is based on Intel's iMote2 board containing one XScale processor and one ATMega128 micro-controller, measures 60 x 60 x 50 mm, and weighs 115 g. It was designed to be worn with a belt clip. This device includes several sensors such as an electret microphone, a light sensor, a 3-axis digital accelerometer, a digital barometer, and a digital temperature sensor, among others. One featured application was for on-body sensing, real-time activity inference, and a mobile ambient display to encourage individuals to be physically active.

The first sociometric sensor developed at the MIT Media Laboratory was called the *SocioMeter*. It was a wearable sensor package designed to measure face-to-face interactions between people with an IR transceiver, a microphone, and two accelerometers (Choudhury 2004). These early prototypes were used in a group study involving 25 participants wearing the badges for two weeks. The low-level sensor data were used to learn and model the structure and dynamics of the social network (e.g. who was talking to whom and how someone's turn-taking patterns influenced the other person's interaction style) (Choudhury 2004). However, due to its size and weight, users reported feeling somewhat uncomfortable while wearing it.

In order to test our proposed system, we developed the *Sociometric Badges*, wearable electronic sensors capable of detecting face-to-face interactions, conversations, body movement, and proximity to others (Olguín-Olguín 2007). The sociometric badges are capable of extracting speech features without recording the content of conversations (in order to preserve privacy), and of wirelessly transferring data to a central server. We have used them in several organizations to capture face-to-face communication patterns and study the relationship between collective behavior and performance outcomes, such as productivity and job satisfaction (Olguín-Olguín, Gloor & Pentland 2009, Olguín-Olguín, Waber, Kim, Mohan, Ara & Pentland 2009, Wu et al. 2008).

The design of the sociometric badges was motivated by the fact that a large number of organizations already require employees to wear RFID name tags that identify them and grant them access to several locations and resources. These traditional RFID name tags are usually worn around the neck or clipped to the users clothing. With the rapid miniaturization of electronics, it is now possible to augment RFID badges with more sensors and computational power that allow measuring human behavior without requiring any additional effort on the user's side. By capturing individual and collective patterns of human behavior with sociometric badges and correlating these behaviors with individual and group performance, it is possible to identify successful vs. unsuccessful teams, high performing teams, and predict group outcomes. The added value for the users is the feedback that they can receive about their daily behaviors and interactions with others, and how these behaviors affect their individual and group performance.

The following is a list of some of the social signals that have been implemented for the sociometric badges:

1. Body movement activity. Minute-by-minute body energy (motion sensor).
2. Consistency of body movement. Negatively proportional to the minute-by-minute variation in body energy (motion sensor).
3. Speech activity. Minute-by-minute speech energy (microphone).
4. Consistency of speech. Negatively proportional to the minute-by-minute variation in speech energy (microphone).
5. Speaking time. Minute-by-minute percentage of speaking time (microphone).

6. Other speech features such as mirroring and turn-taking patterns (microphone).
7. Face-to-face (f2f) time. Minute-by-minute number of infrared detections divided by the maximum transmission rate (infrared sensor).
8. Proximity time. Minute-by-minute number of radio detections divided by the maximum transmission rate and minute-by-minute average radio signal strength (radio transceiver).
9. Degree. Number of different participants with whom there was face-to-face interaction, normalized by the maximum number of participants (calculated from the f2f network).
10. Centrality. It indicates to what extent an actor has a central position in the organization (calculated from the f2f network).
11. Cohesion. It is a measure of how well connected an actor's acquaintances are connected to each other.

We have manufactured several hundred sociometric badges and used them in organizations to automatically measure individual and collective patterns of behavior, and help organizations maximize their groups' performance through specialized software that analyses behavioral patterns and generates automatic feedback reports and dynamic visualizations. It is possible to design organizational interventions based on these measurements and feedback mechanisms. In the following section we discuss four different case studies and several proposed organizational interventions.

Based on the first version of the badges and with some major hardware and firmware improvements, a second version of the badges was designed (Olguín-Olguín 2007). More than 600 prototypes were built and used under naturalistic and laboratory settings in several research projects that we will briefly describe next:

- **Face-to-face communication vs. e-mail.** We instrumented a group of 22 employees of a marketing division in a German bank for 20 working days (Olguín-Olguín, Waber, Kim, Mohan, Ara & Pentland 2009). Face-to-face communication patterns were compared with e-mail exchange patterns. Based on our findings we suggested as a possible intervention to modify the employees' team configuration and seating arrangement in order to minimize the physical distance among members of each team, as well as the distance between teams that interacted the most. This would ideally promote more face-to-face interaction and reduce the amount of e-mail, resulting in less communication overload.

- **Task performance.** Sociometric badges were deployed for 20 working days at a Chicago-area data server configuration firm that consisted of 28 employees (Waber et al. 2008). The analysis examined employee behavior at the task level rather than at the individual level. Results indicate that there are behavioral clusters that exhibit completion times and number of follow-ups that vary according to physical activity levels and speaking time. It was also found that in the face-to-face network, network cohesion is positively correlated with higher worker productivity (Wu et al. 2008).

- **Nurse behavior.** We instrumented a group of 67 nurses working in the Post-Anesthesia Care Unit (PACU) of a Boston area hospital with sociometric badges (Olguín-Olguín, Gloor & Pentland 2009). Each nurse wore a sociometric badge for 27 days. Reducing the patient's length of stay (LOS) within the PACU would help lower costs. We found that the nurses' social signaling behavior and face-to-face interaction patterns captured with the badges were predictive of patients' LOS, having a direct effect on cost savings.

- **Bank sales.** A sociometric badge study was carried out in three branches of a bank in the Czech Republic (Olguín-Olguín & Pentland 2010*b*). 52 employees and 6 managers participated in the study and wore the badges for 20 working days. We studied the relationship between several behavioral features captured by the sociometric badges, and employee self-perceptions (from surveys) and productivity data. Several features from the face-to-face social network that were captured by the badges were predictive of sales performance in the three branches.

- **Call center.** We deployed our system at a bank's call center, where a group of 80 employees and managers used sociometric badges for 30 days (Kim et al. 2009). Preliminary results indicate that cohesion in the face-to-face social network captured by the badges is negatively correlated with the average phone call handle time. Our suggested intervention was to change the way employee's breaks are currently scheduled so that more people working in the same team can take a break at the same time. This would allow members of the teams to form more cohesive ties over time.

- **Team performance.** We used sociometric badges during the Entrepreneurship Development Program (EDP) at MIT in January of 2009 to capture the participants' social interactions and predict team performance (Olguín-Olguín & Pentland 2010*a*). 109 participants used a sociometric badge during the first day of the program. There were 17 different teams and three of them were judged as winners in an elevator pitch contest. We used logistic regression and bootstrapping to predict the winning teams from the badge features averaged across members of each team with 90% accuracy.

- **Real-time feedback.** The badges have also been used in conjunction with mobile phones to create a real time group feedback system for meetings (Kim et al. 2008). This system, called "Meeting Mediator", attempts to bridge the communication gap in distributed groups by detecting and reincorporating lost social signals. More than 120 4-person teams have been studied in-lab so far. Results from these studies show that the system effectively reduces the dynamical difference between co-located and distributed collaboration as well as the behavioral difference between dominant and non-dominant people.

- **One-on-one interaction.** Ten cohabiting couples shopping for furniture were studied with sociometric badges to test if the interaction patterns among shoppers convey their interest level and predict the probability of purchase (Kim & Pentland 2009). Sensible differences in customer behavior depending on their interest level were observed. When couples were interested in an item they discussed it for a longer period of time and had a more balanced speaking style.

- **Collective intelligence.** In a recent study with more than 600 participants working in groups, evidence of a general collective intelligence factor that explains a group's performance on a wide variety of tasks was found (Williams-Woolley et al. 2010).

Sociometric badges were used in a subset of these participants and the collective intelligence factor was found to be correlated with the equality in distribution of conversational turn-taking.

- **Personality traits.** Personality tests have been applied to the participants in some of the studies described above. It has been found that several personality traits (e.g. extroversion, neuroticism, openness, and agreeability) can be estimated from the sociometric badge measurements (Olguín-Olguín, Gloor & Pentland 2009), (Gloor et al. 2010).

- **Software programming teams.** There is a pilot study currently going on in three industrial software development teams in two multinational software companies in Finland (Niinimaki et al. 2009). Sociometric badges are being used to capture face-to-face interaction patterns, in addition to collecting electronic communication logs across different media. The goal of the study is to establish data collection and analysis methods to empirically evaluate and verify the claims made by agile software development practices.

Due to the encouraging results obtained in the studies carried out with the previous version of the badges, and the increasing interest of researchers from several research communities in using the badges for multiple applications, we decided to design and build a third generation that would make it easier for others to collect and analyze their own sociometric data.

4.4.2 Lessons Learned

Having deployed and used the sociometric badges 2.0 in a variety of settings and applications has allowed us to learn from their shortcomings and common deployment mistakes.

- **Real-time clock.** One of the first hardware limitations that we encountered with the sociometric badge 2.0 was the lack of a real-time clock. Without it, data synchronization was quite challenging and required the use of one or several "global" base stations (badges placed in fixed locations and turned on at a precise date and time).

Each badge kept track of its own global time in micro-controller clock-ticks that could be later on converted into the total amount of elapsed time since the badge was turned on. However, each time the badge was turned off the clock-tick counter was reset to zero and therefore several algorithms had to be implemented in order to synchronize each badge's data and obtain real time-stamps. A real-time clock is essential for large data collection studies.

- **Storage.** Another limitation was the 1 GB storage limit of the microSD cards (due to compatibility issues with the micro-controller). This capacity was enough to store minute-by-minute features for a few months or even a year but it was a limitation in case the raw data (audio, accelerometer, etc.) had to be stored. We usually solved this problem by replacing the microSD cards once they were full. Being able to use higher capacity microSD cards would be highly beneficial.

- **Lack of operating system and file system.** The lack of an embedded operating system running on the badges made it more difficult to deploy new applications and modify the data collection settings. The lack of a file system also made it difficult to store data in known file formats. A parsing script had to be run off-line in order to create separate text files.

- **Programming connector.** The only way the badges could be programmed was using a custom-made JTAG connector that required a careful assembly process and could not be purchased or made by others. This made it almost impossible for other researchers to compile and run their own code in the badges. Furthermore, the JTAG connector was not easily accessible through the plastic enclosure and the badges had to be opened each time they had to be re-programmed. This made re-programming the badges with new firmware a very time-consuming process.

- **USB compatibility.** The USB data transfer protocol and drivers only worked with Linux or Mac systems but not with Windows. Several libraries and scripts had to be compiled and installed before users could easily download data from the badges.

- **Enclosure.** The plastic enclosure was very sturdy but not water resistant. This limits it's usability in certain case scenarios. A waterproof enclosure might be eventually required.

- **Battery life.** No power saving modes were implemented in the second version of the badges, therefore the microprocessor and peripherals were continuously running when the badge was turned on. This limited the battery life to approximately 12 hours of continuous data collection. A larger battery or backup battery had to be used when 24-hour data collection was necessary. Implementing several power saving modes and automatically detecting when a person is wearing a badge would greatly improve the battery life.

- **Common deployment mistakes.** Some users forgot to re-charge their badges at the end of the day. This would cause the battery to get completely depleted (since there was no under-voltage protection) and some of the batteries had to be replaced after some use. Adding a battery charge indicator and a protection circuit would solve this problem. Another common mistake was forgetting to turn the badges on at the beginning of each day (which would cause no data to be collected at all), or forgetting to turn the badges off at the end of the day (resulting in large amounts of useless data).

4.4.3 System Requirements

Based on our previous experience using sociometric badges we defined the following measurement requirements, which in turn led to the hardware architecture described in section 4.4.4.

Sensors and Measurements

Face-to-face interaction detection. One or more infrared transceivers or directional sensors are required in order to detect when two users wearing a badge are facing each other. An IrDA compliant transceiver with an extended low power range was selected because of its low-profile size, power consumption, transmission range (typ. 1 m) and direct interface.

Audio capture and speech processing. One or more electret- or MEMS-type microphone(s) are required for capturing speech. A digital MEMs microphone and audio codec were selected for audio capture and playback. MEMs microphones are the latest low-power technology used in mobile phones. The badge also has digital signal processing (DSP) capabilities in order to implement digital filters and speech processing algorithms that automatically extract social signals contained in speech.

Motion capture and body movement processing. One or more motion sensor(s) including accelerometers, inclinometers, gyroscopes, piezoelectric vibration sensors, are required for capturing motion. The badge is capable of measuring body movement energy and activity levels (i.e. standing still, walking, running, etc.). An ultra-low power digital 3-axis accelerometer capable of measuring ± 16 g was selected.

Proximity and location detection. One or more wireless radio transceivers such as Bluetooth, ZigBee or any other radio frequency transceiver operating in the ISM (Industrial, Scientific, and Medical) and SRD (Short Radio Device) frequency bands are required for sending/receiving information to other badges, base stations, mobile phones or computers. Radio signal strength indicator (RSSI) measurements can be used to estimate proximity and location. An ultra-compact, low-power, high-sensitivity 2.4 GHz Bluetooth module designed for wireless sensing, control and data acquisition applications was selected because it eliminate the need for costly and time-consuming development.

Data transfer and storage. One or more storage media (on-board flash memory, removable memory cards such as SD or microSD, etc.) are required for storing data. On-board SRAM and NAND flash memory were selected for storing and running the firmware. A microSD card is used for storing the raw and pre-processed data since it is the smallest and highest capacity available memory option. USB and wireless data transfer are possible as well.

Micro-processor. A micro-processor with DSP capability, capable of running Linux, enough peripherals for all required sensors, and low-power consumption is needed. The AT91SAM9G20 micro-processor was chosen based on the integration of an ARM926EJ-S processor with fast ROM and RAM memories and a wide range of peripherals. It embeds an Ethernet MAC, one USB Device Port, and a USB Host controller. It also integrates several standard peripherals, such as the USART, SPI, TWI, Timer Counters, Synchronous Serial Controller, ADC and MultiMedia Card Interface.

Power. The total power consumption for the badge running at full speed has been estimated at < 100 mA. The thinnest available lithium-polymer rechargeable battery with a 2600 mAh capacity was selected for 24 hours of continuous data collection. It can be re-charged over USB or AC adapter. A battery charger, voltage regulator, and power management module will also be included.

4.4.4 Hardware Architecture

The sociometric badge 3.0 hardware was designed with energy and space requirements in mind. The printed circuit board (PCB) measures 90 x 55 x 7 mm. This size was determined by the size of standard lithium-polymer batteries (85 x 55 mm at various thicknesses depending on battery capacity) and the number of components on the PCB. The main capabilities of the third generation of sociometric badges are:

- **CPU:** Atmel AT91SAM9G20 ARM Thumb processor with DSP instruction extensions and CPU frequency of 400 MHz.
- **Memory:**
  - One 64-KB internal ROM.
  - Two 16-KB internal SRAM.
  - 8-bit or 16-bit bus 64 MB SDRAM (up to 128 MB).
  - 32-bit bus 512 MB NAND Flash Memory (up to 1 GB).
  - Removable microSD HC memory card (up to 32 GB).
- **Sensors:**
  - Digital MEMs microphone (to capture non-linguistic social signals) and audio codec (to record and play back audio through headphones).
  - Digital 3-axis accelerometer (to capture body movement social signals).
  - ZigBee module (wireless data transfer and proximity detection).

  - IrDA transceiver (face-to-face interaction detection).
  - CMOS image sensor interface (footprint for future implementation).

- **USB Interfaces:**
  - microUSB 2.0 full speed (12 Mbits per second) device port for data transfer and badge programming.
  - microUSB 2.0 full speed (12 Mbits per second) host port for external USB WiFi module (base stations), and battery charging.

- **Miscellaneous:**
  - 2 LEDs + 1 LED (charging status indicator).
  - 1 tri-directional scan/select push button.
  - Real time clock with rechargeable manganesum lithium battery.
  - Rechargeable lithium polymer battery (option 1: 3-mm thick 1600 mAh capacity, option 2: 5-mm thick 2600 mAh capacity).
  - Maximum badge enclosure dimensions: 94 x 59 x 11 mm with battery option 1, or 94 x 59 x 13 mm with battery option 2.
  - Total current consumption (running at full speed): $<$ 100 mA. Battery option 2 will provide at least 24 hours of continuous use.

Figure 4-1 shows the block diagram for the hardware architecture. Figure 4-2 shows the front and back views of the badge's printed circuit board. Figure 4-3 shows the evolution of the sociometric badges.

4.4.5 Firmware and Software Architectures

The firmware stack for the third generation of sociometric badges is based on embedded Linux. The firmware stack consists of a bootstrap, device firmware uploaders, a boot loader and the Linux kernel. The bootstrap is responsible for configuring the low-level settings of the hardware platform for the use of other components. Device firmware uploaders will be used to upload firmware code to sensor modules requiring custom firmware. The boot

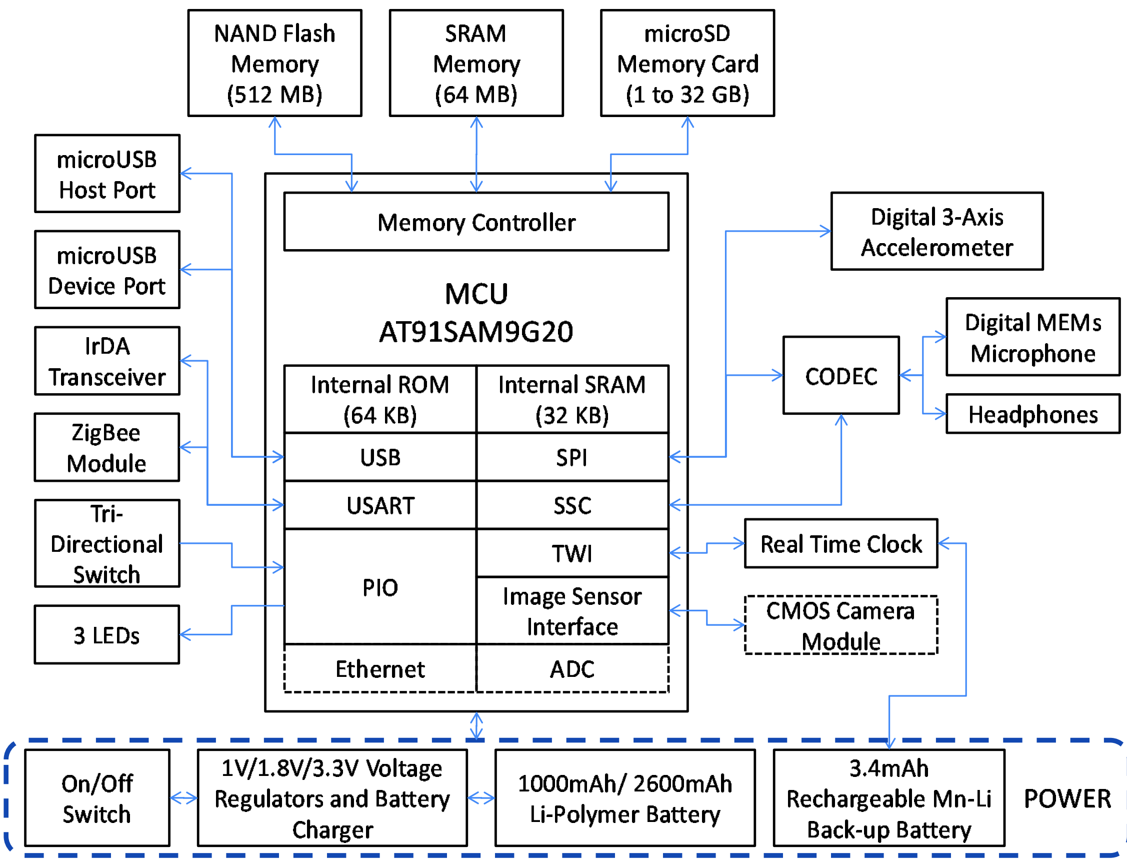
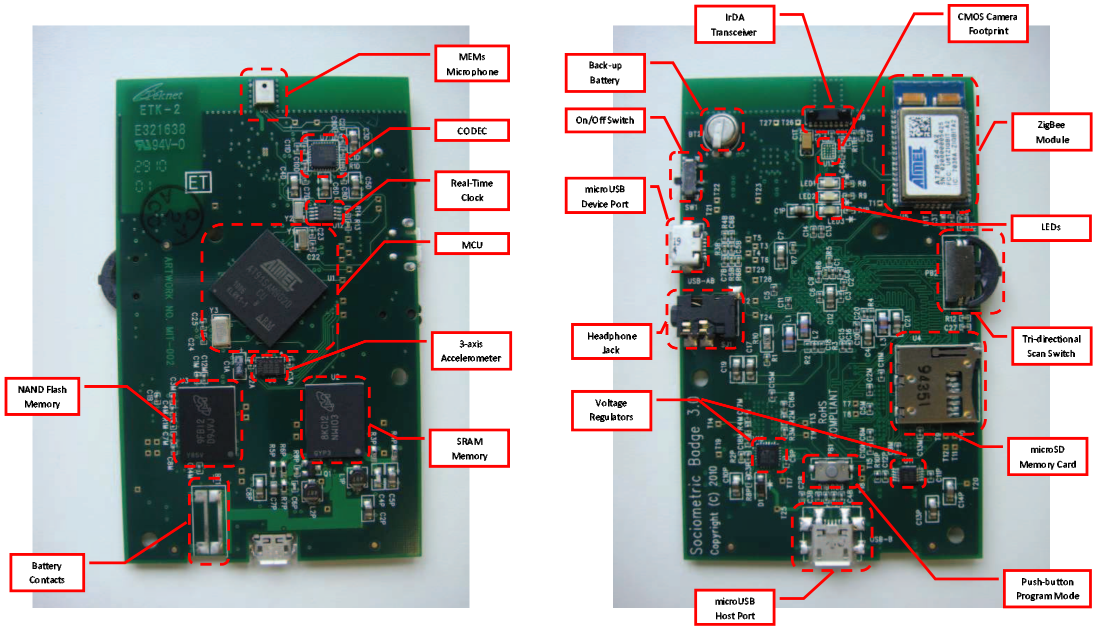


Figure 4-1: Hardware architecture block diagram



(a) Back view

(b) Front view

Figure 4-2: Sociometric badge printed circuit board

loader will load, configure and start up the Linux kernel. The Linux kernel will then set up the actual device drivers and interfaces, as well as start up the main application for the system. The software will be composed of a main application and a varying number of standalone modules. The main application is responsible for managing the overall system configuration, starting up and monitoring the status of other modules in the system, and maintaining a directory of communication interfaces provided by each module in the system.

(a) Version 1.0

(b) Version 2.0

(c) Version 3.0

Figure 4-3: Sociometric badge evolution

Table 4.1: Sociometric badge comparison

Capabilities	Badges 1.0	Badges 2.0	Badges 3.0
Processor	20 Mhz PIC16F877	55 MHz AT91SAM7S256	400 MHz AT91SAM9G20
Operating System	C-code	C-code	Linux
Memory	256 MB	Up to 1 GB microSD	Up to 32 GB microSD
f2f detection module	4 IR transmitters (1.8-m range)	IrDA transceiver (1-m range)	IrDA transceiver (1-m range)
Speech module	Electret microphone	MEMs analog microphone and 4 analog band pass filters	MEMs digital microphone and codec
Body movement module	2-axis analog accel	3-axis analog accel	3-axis digital accel
Proximity module	433 MHz FM radio	Bluetooth and 2.4 GHz	Bluetooth module
Battery life	4 AAA batteries	10 hours (1000 mAh li-ion)	24 hours (2600 mAh li-pol)
Data transfer	Compact flash card	USB, Bluetooth, 2.4 GHz	USB, microSD, ZigBee, WiFi
Dimensions	130 x 90 x 24 mm	82 x 50 x 20 mm	94 x 59 x 11 mm
Weight	150 g	110 g	80 g
Subjects studied	23	> 500	-

Chapter 5

Social Network Simulation and Optimization

5.1 Social Network Analysis

A social network is formed by a set of actors (or nodes) and the relations (or ties) between these actors. Actors may be individuals, groups, organizations, or entire communities, and relations may span across or within levels of analysis. Relational variables are defined and measured at the dyadic level and can include a wide variety of social and physical ties, each of which may have a number of different basic properties (Wasserman & Faust 1994).

Social network analysis is a collection of techniques for identifying, describing, and explaining various kinds of structures among individuals, groups, and organizations:

> "It is a set of tools used to help account for the relationships or interactions of individuals who interact within a given social context. Specially, network methods can be used to describe the often complex web of ties between people in a group. These relations can be examined at many different levels, revealing information about the network as a whole as well as about individual actors within the network" (Slaughter et al. 2009).

Social networks, in which people build relationships with others through some common interest, can be visualized as a large graph with people as nodes and connections as links between the nodes. Social network analysis examines the structure of the graph and extracts meaningful organizational data out of the graph (Krebs n.d.). Complete network data is difficult to collect. Four primary data collection techniques are the use of questionnaires, interviews, observations, and archives. In (Olguín-Olguín & Pentland 2008) we propose the use of electronic data collection methods that use wearable sensors to capture face-to-face interactions.

Pattern recognition methods have also been applied to social network analysis. Clustering techniques have been used to identify communities and study their evolution over time (Mishra et al. 2007). An important property found in many networks is community structure, in which network nodes are joined together in tightly knit groups, between which there are only looser connections. Girvan & Newman (2002) proposed a method for detecting such communities, built around the idea of using centrality indices to find community boundaries. Palla et al. (2007) developed a new algorithm based on clique percolation that allows to investigate the time dependence of overlapping communities on a large scale and to uncover basic relationships characterizing community evolution.

Some of the most recent analytical developments are exponential random graph models (Robins et al. 2007), which allow modeling complex patterns of dependencies at different levels of analysis. These models allow for simple inquiries, such as whether there are homophily effects in networks; or more complex research questions like whether the tendency toward various hierarchy-related structures differ across groups that use different strategies to complete a team task (Slaughter et al. 2009). Recent developments in modeling longitudinal social networks (Snijders 2001, Snijders et al. 2006, Snijders et al. 2010) would allow the use of fine-grained social interaction data in organizational design systems.

5.2 Social Network Properties

There are many different measures that describe the structural properties of social networks. The first level of analysis is usually the individual. At this level, measures are mainly used to describe the positions of individual actors in the social structure, such as the degree to which they are embedded or share similar roles with others in the network. The second level of analysis is the dyad. At this level, there are measures that describe ties that exist between pairs of individuals, for example, whether or not social relationships are reciprocated or how important certain ties are for connecting the network. Examples of common structural features of interest are: individual location or importance (centrality), roles, homophily, reciprocity, multiplexity, type and degree of hierarchy, clustering, size and diameter of the network, and density, among others (Slaughter et al. 2009).

The extent to which individuals are embedded in a social structure is one of the most basic relational properties of individuals in a network. The most common way of defining this is through measures of centrality. Centrality indices provide a way of quantifying the extent to which a given individual is connected to the rest of the network and is often interpreted as a measure of structural importance. For directed relations, centrality indices focus on the actors as senders of relational ties (Slaughter et al. 2009). There are many centrality and prestige measures in the literature, we summarize the most commonly encountered measures next:

5.2.1 Degree Centrality and Prestige

Degree centrality (or the number of ties an individual has) is one of the most simple and frequently used measures of structural importance. Slaughter et al. (2009) argue that:

> "for non-directional relations, degree centrality provides an index of the number of direct network partners for each individual in the network. For directional relations, ties can be partitioned into incoming or outgoing ties, representing indegree and outdegree respectively. Indegree has been referred to as an index of prestige and is sometimes interpreted as the popularity of a given actor. Outdegree is less frequently used than indegree centrality but may still provide an important measure of individual activity".

Wasserman & Faust (1994) define $C_D(n_i)$ as an actor-level degree centrality index:

$$C_D(n_i) = d(n_i) = \sum_j x_{ij} = \sum_j x_{ji} \tag{5.1}$$

One problem with this measure is that it depends on the group size g. The degree centrality of a node is then standardized as $C_D(n_i) = d(n_i)/(g-1)$, so that it ranges from 0 to 1 and indicates how well a node is connected in terms of direct connections.

5.2.2 Closeness Centrality and Proximity Prestige

Closeness centrality is defined as an index of actors' average distances to others in the network, and is another common measure of centrality. Slaughter et al. (2009) point out that:

> "in many settings, the distance between actors may represent important features of communication or interaction. For example, actors who are very far away from others in the communication network will tend to be the last to receive information. Thus, actors for whom it requires very few hops through the network to reach all other actors will have a high closeness centrality. Closeness centrality is sometimes interpreted as a measure of access to information or other resources. For directional relations, closeness centrality focuses on the distance from a given actor to others in the network, whereas proximity prestige represents the closeness of other network members to a given actor" .

This closeness-based measure can be calculated as the inverse of the average distance between node i and any other node j:

$$C_C(n_i) = \frac{n-1}{\sum_{j=1}^{n} l(n_i, n_j)}, \tag{5.2}$$

where $l(n_i, n_j)$ is the number of links in the shortest path (geodesic) between nodes i and j. A richer way of measuring centrality based on closeness is to consider a decay parameter δ, where $0 < \delta < 1$ and then consider the proximity between a given node and every other node weighted by the decay (Jackson 2008). In particular, the decay centrality of a node is defined as:

$$\sum_{j \neq i} \delta^{l(n_i, n_j)}, \tag{5.3}$$

where $l(n_i, n_j)$ is set to infinity if i and j are not path-connected. As δ approaches 0, then decay centrality gives infinitely more weight to closer nodes than farther ones and it becomes proportional to degree centrality.

5.2.3 Betweenness Centrality

A measure of centrality that is based on how well situated a node is in terms of the paths that it lies on, was first proposed by Freeman (1978). He introduced a set of measures that define centrality in terms of the degree to which a point falls on the shortest path between others and therefore has a potential for control of communication. Slaughter et al. (2009) write about this third type of centrality that frequently appears in the literature:

> "for information or work to move from one individual to another, it must often pass through a number of intermediaries or facilitators. In many settings, being the intermediary (or broker) is said to provide a measure of control or power. Betweenness centrality provides an index of the extent to which a given individual falls along the shortest paths (or geodesics) connecting pairs of other actors".

The betweenness centrality of a node is calculated as:

$$C_B(n_i) = \frac{\sum_{j<k} g_{jk}(n_i)/g_{jk}}{(n-1)(n-2)/2}, \tag{5.4}$$

where $g_{jk}(n_i)$ denotes the number of geodesics (shortest paths) between j and k that i lies on, and g_{jk} is the total number of geodesics between j and k. This index is standardized by $(n-1)(n-2)/2$ (the number of pairs of actors not including n_i).

5.2.4 Status or Rank Prestige

A fourth major indicator of centrality is known as status or rank prestige. In words of Slaughter et al. (2009):

> "although most types of centrality and prestige are based on an individual's position in the network, rank prestige also takes into account the position of

individuals to which a given actor is tied. For example, in some situations, characteristics such as status or prestige may be a function of characteristics of the actors to whom an individual is tied. Having a relationship to a prestigious actor may itself improve an actor's prestige".

The Kats prestige of a node i is the sum of the prestige of its neighbors divided by their respective degrees (Jackson 2008). It is also a measure of centrality. Node i gains prestige from having a neighbor j who has high prestige. However, this measure is corrected by how many neighbors j has, so that if j has more relationships then i obtains less prestige from being connected to j. The Kats prestige of a node is calculated as:

$$P_K(n_i) = \sum_{j \neq i} n_{ij} \frac{P_K(n_j)}{d(n_j)} \tag{5.5}$$

5.2.5 Eigenvector Centrality

This measure was proposed by Bonacich (1987) and does not normalize the network of relations in order to avoid reduction to degree centrality. Let $C_E(A)$ denote the eigenvector centrality associated with a network A (where A is the adjacency matrix). The centrality of a node is proportional to the sum of the centrality of its neighbors $\lambda C_E(A) = AC_E(A)$, where λ is a proportionality factor. Thus $C_E(A)$ is an eigenvector of A, and λ is its corresponding eigenvalue. The j^{th} component of the related eigenvector then gives the centrality score of the j^{th} node in the network. The definition of eigenvector centrality also works for weighted and/or directed networks (Jackson 2008).

5.3 Social Network Simulation

Simulation of social networks in the social sciences is a relatively recent development. Social network simulation research is useful in testing current theory and exploring new possibilities where real-life experimentation is impossible (Stocker et al. 2001). Even though simulation modeling is a powerful methodology for advancing theory and research on complex behaviors and systems, it has been embraced more slowly in management than in social science (Harrison et al. 2007). Simulation models of social networks can be used for both explanatory and predictive purposes. Such models can be based on cellular automata (CA), agent-based models (ABMs), exponential random graph models (ERGMs), actor-based longitudinal models, among others. In this section we describe some of the basic methods used for social network simulation.

5.3.1 Agent-based Models

Agent-based modeling (ABM) involves simulation of large numbers of autonomous agents that interact with each other and with a simulated environment, as well as the observation of emergent patterns from their interactions (Smith & Conrey 2007). In most models related to social psychology, an agent is a simplified abstract version of a human being and has a number of important characteristics, among them: being a self contained individual, existing in and interacting with an environment, being embodied (as a robot or as a purely software-simulated entity, being active, having limited information, having its own internal goals, having bounded rationality, and being capable of adaptation.

Sycara & Lewis (2008) characterize current knowledge of teamwork and factors that need to be included in a comprehensive simulation of team behavior. They review several agent-based models (ABM) of teamwork describing work involving both teamwork approaches to the design of multi-agent systems and agent-based representations of human behavior. Out of 29 models reviewed, 20 include communication as a necessary behavior. According to the authors, teamwork has typically been characterized by an Input-Process-Output (IPO) model consisting of inputs (such as team composition or personalities of the team members), a process in which the inputs are combined to determine team behavior, and output defined in terms of team performance or team effectiveness. There are several individual and group attributes that are a desirable part of a team simulation. Individual differences may include general mental ability of team members, personality traits, task knowledge and skills. Fundamental group attributes include cohesiveness (or the degree to which team members identify with the team and the team goals), organizational climate, team efficacy (or the team's belief in its abilities to perform a task), and team potency (or the team's confidence in its general abilities). Because of the difficulty in validation, ABM has been used primarily as a confirmatory method to demonstrate the feasibility of producing an observed result from a hypothesized mechanism.

There are two key issues in team formation: team member selection and task assignment. Both issues are tightly connected and shall be addressed if the ultimate goal is to optimize team performance (Sycara & Lewis 2008). Team assignment can be either static (neither the team members nor their tasks will change once the team has been formed) or dynamic (new team members may join and some existing members may leave, or their tasks may also change over time). Static team assignment can be solved as a typical assignment problem studied in Operations Research, in which a mathematical program determines the optimal assignment of the agents to a given set of tasks to either maximize the total payoff, or minimize the total cost (Kuhn 1955). Similarly, generalized assignment problems (GAP) can be used to minimize the cost of assigning the tasks. Dynamic programming (DP) can be used when there are multiple periods in which decisions need to be made on task and agent assignment, and the goal is to optimize the aggregated performance over time.

Using graph based models, Stocker et al. (2001) simulate individual influence and the communication of ideas in a population. Simulations of Dunbar's hypothesis that natural group size in apes and humans arises from the transition from grooming behavior to language or gossip (Dunbar 2003), indicate that transmission rate and neighborhood size accompany critical transitions. They demonstrate that critical levels of connectivity are required to achieve consensus in models that simulate individual influence.

5.3.2 NK Models

Even though the NK model was initially conceived by Kauffman (1993) for understanding biological systems, it has been extensively applied in many other domains including computational organization theory. An organization is conceptualized as a system of activities. It makes decisions concerning N activities where each activity can take on two states, 0 or 1, so that, referring back to the general model, $A = \{0, 1\}^N$. A particular configuration of activity is then described by a binary vector of length N. The distance between two such vectors, $x = (x_1, \ldots, x_N)$ and $y = (y_1, \ldots, y_N)$, is captured by the Hamming distance. As part of the NK model, the mapping v from the activity vector to the level of performance is a primitive. v is set to depend on the performance contributions that these activities make individually, where the contribution of each activity depends on the interactions among a subset of activities. The degree of interdependence among activities is captured by a parameter K which is the number of other activities that directly affect the contribution of a given activity. Many organizational models using the NK framework choose the interaction pattern so as to explore how different architectures influence performance (Chang 2006).

Using NK models, Fang et al. (2010) argue that an organization divided into semi-isolated groups may help reach a balance between exploration and exploitation in organizational learning. They simulated such organization by varying the interaction patterns between individuals to explore how the degree of subgroup isolation and intergroup connectivity influences organizational learning, and found that moderate levels of cross-group linking led to the highest equilibrium performance. To study how interpersonal network structure affects organizational learning, they varied the form of subgroup structure by randomly re-wiring some of the existing links in the structure with probability β. The bigger the value of β, the greater the percentage of random cross-group links.

Carrol & Burton (2001) introduce NK models as theoretical frameworks that offer an explanation for group performance. They seek to develop a better understanding of the relationship of group structure and the level of interdependency between individuals on group performance under various task complexities. They find that structures that are highly connected (actors communicating with all others) perform much worse than those with a lower level of connection. Further experiments varying both the number of actors and the degree of interdependence between them find evidence of the "edge of chaos". The authors suggest that there is an optimal range of interconnectedness between actors or tasks that explains the variation in performance. An interesting result is that this optimal level of interdependence is fairly low, regardless of the size of the group. Similarly, Lazer & Friedman (2007) used an NK model to simulate how the communication pattern among actors engaged in a broad class of human collective behaviors conceived as parallel problem solving, affected their collective performance.

5.3.3 Exponential Random Graph Models (ERGMs)

Some of the most recent analytical developments are in the form of exponential random graph models (ERGMs), which allow for modeling of complex patterns of dependencies at different levels of analysis. Exponential random graph models define the probability of an observed network as a function of different structural characteristics such as density, reciprocity, or cliquing (Robins et al. 2007).

ERGMs, also referred as p^* models, are a generalization of Markov graphs and were originally described by Wasserman & Faust (1994). The probability distribution of a network is given by

$$Pr\{Y = y\} = \exp\left[\theta^{\intercal} u(y) - \psi(\theta)\right] \tag{5.6}$$

where $u(y)$ is a vector of network statistics, and $\psi(\theta)$ is a normalizing constant.

Monte Carlo Markov Chain (MCMC) likelihood estimation is the preferred estimation procedure and it is based on refining approximate parameter estimates by comparing the observed graphs against a distribution of random graphs generated by a stochastic simulation using the approximate parameter values. If the parameter estimates never stabilize (converge), the model is likely to be degenerate (Robins et al. 2007).

5.3.4 Longitudinal Social Network Models

A recent development in social network analysis is the stochastic actor-based model for network dynamics developed by Snijders et al. (2010). This model can represent a wide variety of influences on network change, and allow to estimate parameters expressing such influences, and test corresponding hypotheses. It assumes that the network evolves as a stochastic process driven by the actors. The probabilities of tie changes are in part endogenously determined, i.e., as a function of the current network structure itself, and in part exogenously, as a function of characteristics of the nodes ("actor covariates") and of characteristics of pairs of nodes ('dyadic covariates"). Stochastic actor-based models can be used to analyze longitudinal data on social networks jointly with changing attributes of the actors (Snijders et al. 2010). The basic assumptions (some of which are limitations) of the model are:

1. The time parameter is continuous. The process unfolds in time steps of varying length, which could be arbitrarily small. The parameter estimation procedure, however, assumes that the network is observed only at two or more discrete points in time.

2. The changing network is the outcome of a Markov process.

3. Actors control their outgoing ties.

4. At any given moment one actor may get the opportunity to change one outgoing tie.

5. Tie change rates may depend on the network positions of the actors (e.g. centrality) and on actor covariates (e.g. age, sex, etc.).

6. The change determination process, modeling the precise tie changes made when an actor has the opportunity to make a change, may depend on the network positions, as well as covariates.

In the end, the actor-based model can be regarded as an agent-based simulation model used for statistical inference and has been applied to multiple datasets. Van de Bunt & Groenewegen (2007) applied this model to longitudinal data about collaborative agreements within the genomics industry, and studied how firms choose collaborative partners given their present network configuration, their goals, and characteristics to get a strategic network position. Burk et al. (2007) used this model and provided an empirical example investigating the co-evolution of friendship networks and delinquent behaviors in a longitudinal sample of adolescents with the goal of simultaneously assessing selection and influence processes. According to Van de Bunt & Groenewegen (2007), some drawbacks of this model are the fact that it is currently restricted to binary network data; the model still lacks easy-to-understand and easy-to-use procedures to calculate or approximate goodness-of-fit tests; and actors can only change their network choices with respect to one kind of network. Regardless of these drawbacks, this model seems quite promising in the study and simulation of longitudinal network data. Other promising methods for longitudinal social network analysis include discrete temporal models (Hanneke et al. 2010), dyadic event models (Brandes et al. 2009), and hidden temporal exponential random graph models (htERGMs) (Guo et al. 2007).

5.4 Social Network Optimization

The idea of optimizing a social network based on its properties and their relationship to performance comes from the organizational literature. For example, Gabbai et al. (2003) explored performance, cost, and structure trade-offs from social network simulations. They observed the emergence of organization classes and identified optimal organizational structures that met specified constraints and tasks. They used several network properties such as centrality, degree hierarchy, specialization, heterogeneity, and several performance metrics. Using a Pareto curve to appreciate the relationship between degree hierarchy and performance, an optimal point along that curve was determined.

The study of complex systems has recently gained momentum in management science, as simulation and optimization tools, originally developed in biology and physics, have been applied to organizational, social, and technological settings (Rivkin & Siggelkow 2007). As an example, Rivkin & Siggelkow (2007) studied how much exploration was necessary to discover a good network configuration. They embedded social network patterns such as centralization, small-world connections, power-law distributions, hierarchy, and preferential attachment into an NK simulation model and found that by holding fixed the total number of interactions among decisions, a shift in the pattern of interaction could alter the number of local optima by more than an order of magnitude.

5.5 Proposed Simulation and Optimization Methodology

Given several observed network snapshots or panels, we can calculate network features using static or dynamic network models (e.g. centrality, degree, clustering, rate of change, etc.). In chapter 6 we will show that network properties are related to performance metrics (e.g. productivity, job satisfaction, stress, among others). By using multiple polynomial regression to estimate the network's performance, and applying the bootstrap method and the response surface methodology described in sections 5.5.1 and 5.5.2 respectively, it is possible to find an operational region that optimizes multiple performance metrics. This simulation and optimization methodology facilitates the design of organizational interventions that promote an optimal network configuration. Chapter 6 presents the experimental results after applying this methodology to several case studies.

5.5.1 Bootstrapping Regression Models

There are two general applications of multiple regression: explanation and prediction. When multiple regression is used for explanatory purposes, one seeks to explore relationships between multiple variables in a sample to shed light on a phenomenon, with the goal of generalizing this new understanding to a population. When multiple regression is used for prediction, one is using a sample to create a regression equation that would optimally predict a particular phenomenon within a particular population (Osborne 2000). In general, multiple regression can be an effective tool for creating prediction equations, provided that certain assumptions are met, particularly: adequate measurement, large enough samples, and care is taken to evaluate the regression equations for generalizability (Osborne 2000).

There are usually two approaches for bootstrapping regression models. When the regressors are fixed, the bootstrap uses re-sampling of the error term. If the regressors are random, the bootstrap uses re-sampling of the observation sets. We follow the bootstrap methodology described by Sahinler & Topuz (2007):

1. Let the $(k+1) \times 1$ vector $w_i = (y_i, x'_{ji})'$ denote the values associated with the i^{th} observation.

2. Draw an n sized bootstrap sample $(w_1^{(b)}, w_2^{(b)}, \ldots, w_n^{(b)})$ with replacement from the observations, giving $1/n$ probability to each w_i value, and labeling the elements of each vector $w_i^{(b)} = (y_i^{(b)}, x_{ji}^{(b)})'$, where $j = 1, 2, \ldots, k$, and $i = 1, 2, \ldots, n$.

3. Form the vector $Y_i^{(b)} = (y_1^{(b)}, y_2^{(b)}, \ldots, y_n^{(b)})'$ and the matrix $X_{ji}^{(b)} = (x_{j1}^{(b)}, x_{j2}^{(b)}, \ldots, x_{jn}^{(b)})'$.

4. Calculate the ordinary least squares (OLS) coefficients from the bootstrap sample: $\hat{\beta}^{b1} = (X^{(b)\prime} X^{(b)})^{-1} X^{(b)\prime} Y^{(b)}$.

5. Repeat steps 2,3, and 4 for $r = 1, 2, \ldots, B$, where B is the number of iterations.

6. Obtain the probability distribution $F(\hat{\beta}^{(b)})$ for the bootstrap estimates and use it to estimate the regression coefficients, variances, and confidence intervals. The bootstrap estimate of the regression coefficients is the mean of the distribution $F(\hat{\beta}^{(b)})$.

Thus, the bootstrapped regression equation is:

$$\hat{Y} = X\overline{\hat{\beta}^{(b)}} + \epsilon. \tag{5.7}$$

5.5.2 Response Surface Methodology

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes. As described by Myers et al. (2009), the most important applications of RSM are in the industrial world, where several input variables potentially influence some performance measure or quality characteristic of the product or process. This performance measure or quality characteristic is called the response, and the input variables are usually called independent variables. Once the factors or variables that are likely to be important in a response surface study are determined, an experiment is designed to investigate these factors. The objective of a first screening experiment is to reduce the list of candidate variables to a relative few. Once the important variables are identified, the objective is to establish whether the current levels or settings of the independent variables result in a value of the response that is near the optimum. If the current settings are not consistent with optimum performance, then a set of adjustments to the process variables that will move the process toward the optimum has to be determined. The second phase of a response surface study begin when the process is near the optimum. At this point, a model that will accurately approximate the true response within a relatively small region around the optimum (usually a second-order model) will be used. Once an appropriate model has been found, a sequential experimental process is performed within a region of the independent variable space called "operational region", to determine the optimum conditions for the process.

Most multiple-response optimization methods concentrate on the estimation of a single set of optimal parameters. In order to find an optimal operational region for the set of network parameters that maximize/minimize multiple responses (i.e. organizational performance and job quality characteristics) at the same time, we propose to use a new methodology derived from that described by Jiang et al. (2009) which includes the following steps:

1. Design an experiment for data collection. An experimental design is used to deter-

mine an optimal operational region. Factorial designs are widely used in experiments involving several factors where it is necessary to investigate the joint effects of the factors on a response variable (main effects and interactions). The central composite design (CCD) is one of the most important designs for fitting second-order response surface models (Myers et al. 2009).

2. Fit a regression model. A high R^2 regression model is required in order to avoid large variance in the estimated regression coefficients. A quadratic model is required for optimization purposes.

3. Obtain multiple sets of simulated regression coefficients for the multiple responses. This can be done using the Monte Carlo simulation technique or the bootstrap method. If there are r quality characteristics, the r regression models are obtained as follows:

$$\begin{aligned}
\hat{y_1} = \quad & \beta_{0,1} + \beta_{1,1}x_1 + \beta_{2,1}x_2 + \ldots \beta_{i,1}x_i + \beta_{11,1}x_1^2 + \ldots \\
& \beta_{ii,1}x_i^2 + \beta_{12,1}x_1x_2 + \ldots \beta_{ij,1}x_ix_j \\
\hat{y_2} = \quad & \beta_{0,2} + \beta_{1,2}x_1 + \beta_{2,2}x_2 + \ldots \beta_{i,2}x_i + \beta_{11,2}x_1^2 + \ldots \\
& \beta_{ii,2}x_i^2 + \beta_{12,2}x_1x_2 + \ldots \beta_{ij,2}x_ix_j \\
\vdots & \\
\hat{y_r} = \quad & \beta_{0,r} + \beta_{1,r}x_1 + \beta_{2,r}x_2 + \ldots \beta_{i,r}x_i + \beta_{11,r}x_1^2 + \ldots \\
& \beta_{ii,r}x_i^2 + \beta_{12,r}x_1x_2 + \ldots \beta_{ij,r}x_ix_j
\end{aligned} \tag{5.8}$$

4. Obtain one set of operational regions. A desirability function and the trust region approach can be applied to generate a set of optimal operational conditions. According to the single-side or double-side natures of a quality characteristic y_i, it can be transformed into a desirability function d_i. The overall desirability index D can then be obtained to combine multiple d_i using the geometric average:

$$D = \sqrt[k]{d_1 \times d_2 \cdots \times d_k} \tag{5.9}$$

The set of X with the maximum D value is the optimal operational condition set that satisfies the multiple-quality characteristics. The set of one-sided desirability functions proposed by Derringer & Suich (1980) are:

$$d_i = \begin{cases} 0 & \hat{y}_i \leq y_i^{min} \\ \left[\frac{\hat{y}_i - y_i^{min}}{y_i^{max} - y_i^{min}}\right]^r & y_i^{min} < \hat{y}_i < y_i^{max} \\ 1 & \hat{y}_i \geq y_i^{max} \end{cases} \tag{5.10}$$

and the set of double-sided desirability functions are:

$$d_i = \begin{cases} \left[\frac{\hat{y}_i - y_i^{min}}{c_i - y_i^{min}}\right]^s & y_i^{min} \leq \hat{y}_i \leq c_i \\ \left[\frac{\hat{y}_i - y_i^{max}}{c_i - y_i^{max}}\right]^t & c_i < \hat{y}_i \leq y_i^{max} \\ 0 & \hat{y}_i < y_i^{min} \text{ or } \hat{y}_i > y_i^{max} \end{cases} \tag{5.11}$$

where y_i^{min} is the minimum acceptable value for the i^{th} quality characteristic and y_i^{max} is the maximum acceptable value for the i^{th} quality characteristic. The r, s, and t parameters are set based on the selected desirability function. In order to solve this constrained non-linear optimization problem, the trust region approach is used.

5. Determine the optimal operational region. By repeating steps 3 and 4 b times, b sets of operational conditions can be obtained. With b sets of such relations, the upper and lower limits of each quality characteristic determine the overall best operational condition.

Chapter 6

Experimental Results

6.1 Case Study 1: Retail Bank

6.1.1 Introduction

An old question in organizational and management research is how to obtain the best performance from individuals in an organization. A small number of psychological characteristics have robust, though oftentimes small, predictive validity at the individual level, such as general intelligence (Hunter & Schmidt 1996), job satisfaction (Judge et al. 2001), personality traits (Barrick & Mount 1994, Mount & Barrick 1998), and stress (Jamal 1984), among others. However, the degree to which team dynamics and team structure contribute to performance is more difficult to measure, model, and test.

The study of social networks has grown very rapidly in the last three decades. Even though it is not a formal theory in sociology, it is a strategy for investigating social structures that can be applied to many fields (Otte & Rousseau 2002). Traditional social theory considers the behavior of individual actors and groups (where individuals usually have similar attributes). In social network analysis (SNA) the relationships between actors are the main focus of attention, while individual attributes are secondary. In reality, individuals within groups react in different ways and socialize at different frequencies within an organization. This research acknowledges such differences and focuses on their effects on performance.

One of the basic elements of cooperation in groups is face-to-face interaction. Individuals promote each other's success by helping and encouraging each other's efforts. It is well known that accountability to peers, the ability to influence each other's reasoning, social modeling, social support, and interpersonal rewards, all increase as the face-to-face interactions among the group members increase (Johnson & Johnson 1999). Nevertheless, too much face-to-face interaction might lead to information overload and have negative effects on individual performance (Eppler & Mengis 2004).

This study is an attempt to uncover some of the important social dynamic mechanisms driving an individual's performance by looking at individual centrality and face-to-face interaction strength in the context of distributed knowledge (i.e. transactive memory systems) and information overload theory. We explore the effect of individual centrality and face-to-face interaction strength on individual sales performance in three branches of a bank in the Czech Republic. We used sociometric badges, to quantify the amount of face-to-face interaction of 52 employees and 6 managers for a period of 20 working days.

6.1.2 Background

Face-to-face Interaction Tie Strength

Granovetter's (1973) theory of "the strength of weak ties" argues that job search is embedded in social relations which he defined as strong or weak ties. Tie strength is a function of time, intimacy, emotional intensity (mutual confiding), and reciprocity. Strong ties are often characterized as friends and family; weak ties are acquaintances. Granovetter found that the weak ties were more often the source of helpful job information than strong ties (Brass 2011).

Similarly, Tushman & Nadler (1997) found that strong ties (or "embedded ties") were characterized by higher levels of trust, richer transfers of information and greater problem solving capabilities. On the other hand, these stronger ties require more time and energy to maintain. Consequently, building strong ties to lots of people might be inefficient. Rather, having weak ties to a limited set of actors may be a better strategy. People with whom one has weak ties are likely to have few ties among themselves and, therefore, are likely to provide diverse non-redundant information (Kilduff & Brass 2010).

It appears that in the context of the workplace, the advantage of weak ties would be greater for the efficient transfer of information than the benefits of strong ties. That is, this body of research leads us to predict that in some cases, less face-to-face interaction time could enhance the effective and efficient transfer of information, necessary for good team performance, while stronger ties might have a negative impact on performance.

Information Overload

The term "information overload" is often used to convey the simple notion of receiving too much information. Researchers across various disciplines have found that the performance of an individual correlates positively with the amount of information he or she receives up to a certain point. If further information is provided beyond this point, the performance of the individual will rapidly decline and information overload will be the result (Eppler & Mengis 2004). This is usually represented with an inverted U-curve relationship. Research indicates that too much face-to-face communication also leads to information overload (Sparrowe et al. 2001)

According to Hunter & Schmidt (1996), strategies of sales force specialization imply that too much information can reduce sales performance, yet theoretical and practical guidance regarding when information becomes detrimental to sales performance is sparse. The author presents results that offer preliminary evidence that a self-report measure of information overload can offer guidance to sales managers in identifying when information becomes detrimental to sales force performance.

Centrality and Performance

We outline some studies that demonstrate that greater centrality across a variety of task domains can either enhance or impair performance depending on the nature of the tasks and networks. For example, Yang & Tang (2003) investigated the effects of social network centrality on students performance in online education. They used data from a 40-student course and tested how individual degree centrality affected individual performance in friendship, advise, and adversarial networks. They found a significant positive relationship between centrality in the advice network and academic performance (scores in classroom participation but not on final exam scores); and a negative relationship between centrality in the adversarial network and all academic indicators.

Ahuja et al. (2003) studied the effects of functional role, status, communication, and individual centrality, on individual performance of virtual R&D groups. They found that centrality mediated the effects of functional role, status, and communication on individual performance. They also showed that centrality was a stronger direct predictor of performance than the individual characteristics considered in the study. The authors used degree centrality to quantify the degree of involvement of a person in the group and found that central individuals were higher performers.

Greve et al. (2010) investigated how social capital (measured by degree centrality) contributes to individual productivity in organizations. They measured performance as the number of projects completed and used online questionnaires and interviews to map the social networks of the participants in three organizations. They found that social capital was the most important factor to determine productivity, with degree centrality having a curvilinear relationship, using a third degree polynomial fit.

Some implications of this final research are that social metrics should not be assumed to be linear, although higher degree polynomial models are not an obvious mechanism to explain social phenomena.

Distributed Knowledge and Transactive Memory Systems

Transactive memory "refers to knowledge of information distribution within a team (i.e., knowledge of who knows what)" (Kozlowski & Ilgen 2006). Due to the increasing implausibility of knowing everything relevant to one's job tasks, and the difficulty of having all the skills and competencies required to carry out those tasks, resourcing others' skills and knowledge is becoming increasingly important in the dynamic modern workplace, especially outside of repetitive jobs. To maintain transactive memory, individuals within a team must update each other on members' new areas of expertise, facilitating the efficient tracking of information as it is required.

When the memory system is both compatible and distributed (i.e., individual team members are experts in different areas of knowledge and skill), advantages are likely to be conferred in more than one way. First, the cognitive efficiency with which individuals within a team can source relevant information is likely to be greater, resulting in fewer unnecessary interactions between individuals. Second, times to complete tasks that use distributed knowledge will be shorter because information is transmitted more efficiently among members of the team. Third, with distributed knowledge, transactive memory allows high specialization and reduced risk of information overload (i.e., greater collective capacity).

Transactive memory is likely to involve the accurate encoding of others' knowledge and skill bases, as well as the accurate retrieval of information. With sufficient transactive memory, greater interactions are likely to bring about better performance because those interactions will more likely be efficiently targeting the right source for specific information.

Yuan et al. (2010) are among the first to study the relationship between social network properties and transactive memory-related processes. They argue that basic transactive memory processes (i.e. individual directory development and expertise exchange) are more likely to occur under high shared task interdependence and strong communication ties. They studied 218 people in 18 teams and computed individual expertise exchange by asking participants to record whether they had allocated information to or retrieved information from each team member. Individual communication tie strength was measured by asking respondents to report how frequently they had communicated with each member of the team. They found that expertise exchange was influenced not only by the strength of individual communication ties with others, but also the overall strength of communication ties within a team.

In an earlier publication, Yuan et al. (2007) argue that the most important factor influencing the development of individual expertise directories is neither tie strength, nor structural holes, but rather network "reachability", defined as having connections to many different people in the network through both strong and weak ties, and both bridging and non-bridging links. Network reachability can facilitate the development of individual knowledge directories by (a) allowing people to have multiple sources to cross-validate the accuracy of the information, and (b) allowing people to reach the other actors in the network via a minimum number of steps.

Rulke & Galaskiewicz (2000) hypothesized that groups that have knowledge broadly distributed across group members (i.e. groups with lower centrality) will outperform groups that have unique knowledge concentrated in different group members (groups consisting with higher centrality). Similarly, groups that have narrowly distributed knowledge will perform as well as groups that have broadly distributed knowledge if group structures are more decentralized.

Based on these theories (transactive memory and information overload), we make the assumption that better transactive memory in a system is characterized by individuals with lower centrality (i.e. less information channels going through them, and rather, more direct communication with the right person). Groups with low centrality and greater face-to-face interaction will have better performance, whereas greater face-to-face interaction in groups with high centrality will lead to communication overload and be detrimental to performance.

6.1.3 Hypotheses

We studied the relationship between several behavioral features captured by the sociometric badges, employee self-perceptions (from surveys) and productivity data. In this study we focused on two of the four social signals described by Pentland (2008): activity and consistency of speech and body movement. The activity level signals interest, and consistency signals mental focus and determination. We also studied the relationship between several social network features (degree, centrality, and cohesion) and subjective (survey) and objective data.

Transactive memory is used to describe team processes and invokes the idea that having good communication channels and knowledge of where the expertise sits in a team facilitates better performance. Underlying these premises is the notion of distributed knowledge. Distributed knowledge occurs when individual team members are experts in different areas of knowledge and skill, saving every individual from having to master all aspects of a family of tasks. However, distributed knowledge can only function effectively if individuals know how and where to obtain any knowledge or skill gaps that they do not possess. This theory would predict that higher face-to-face interaction strength with the right individuals (those who have the right knowledge) is conducive to higher performance.

On the other hand, information-overload theory provides robust and reliable data showing that tasks that require a person to manipulate too many pieces of information can impair a their ability to use that information effectively. For example, too many one-on-one or group interactions are likely to present too many inputs into an individual's cognitive system impairing performance in the workplace. As a consequence, this theory would predict that higher face-to-face interaction strength is conducive to lower performance.

Even though there are only a limited number of network studies addressing the relationship between network measures and job satisfaction, results suggest there may be an optimal degree of centrality in a social network that is neither too little, nor too great, and that the degree of network centrality mediates individual variables such as job satisfaction (Brass, 2009). We propose to reconcile the tension between the two theories (transactive memory and information overload) by suggesting that the relationship between face-to-face interaction strength and performance is non-linear, but changing with the distribution of individual centrality in the network.

Hypothesis H1-1

Centrality in the f2f interaction network moderates the effect of tie strength on performance.

Hypothesis H1-1a

For low-centrality networks, greater f2f tie strength has a positive effect on performance, because greater f2f tie strength increases the efficiency of distributed cognition and transactive memory.

Hypothesis H1-1b

For high-centrality networks, in which information tends to be relayed through central agents, greater f2f tie strength is inefficient and has a negative effect on performance, because of increased overloading of central individuals.

Hypothesis H1-2

It is possible to find a network configuration within an optimal range of network properties (e.g. centrality and tie strength) that maximize performance and optimize other job characteristics (such as job satisfaction and stress) at the same time.

6.1.4 Experimental Setting

Participants. We carried out a study in three branches of a bank in the Czech Republic. 52 employees and 6 managers participated in the study and used sociometric badges for 20 working days. In total, we collected 4800 hours of sensor data. Branch 1 was of small physical size (5 participants working in the same floor); branch 2 was of large physical size (31 participants distributed across two floors); and branch 3 was of medium size (16 participants in the same floor). Each participant was part of one of 6 teams: management team, three retail teams, and two small and medium enterprise (SME) teams. 53% percent of the participants were female and 47% male. The average age was 37.8 years (std = 9.9 years) and the average tenure was 8.6 years (std = 7.4 years)

Each of the teams was characterized by individuals with (i) a variety of positions from the front-line to senior management, and (ii) a variety of clients, e.g. personal retail bankers serving individuals, small-to-medium enterprises (SME), and (iii) specializing in a variety of products such as investment portfolios and credit accounts. While participation in the study was encouraged, no employee refused to participate. In return for participation, participants were promised a presentation of team-level feedback with respect to social networking patterns, as well as identity-protected individual-level feedback regarding their individual position within the social network. To protect identities, sealed envelopes were given to individuals containing their individual level data, coded by a randomly assigned employee number so that names were never attached to personal data.

6.1.5 Measures

Daily surveys including items such as job satisfaction, stress, optimism, trust, and risk-taking were administered every day of the study. Each question could be answered on a 1-7 scale and the answers to the daily surveys were averaged across days in order to obtain a single measure for each participant.

Productivity data including information about the total number of meetings with clients, number of phone calls with clients, and number of sales were made available to us. We focused on the total number of individual sales that occurred during the 20-day study period.

Face to face interaction (f2f) was automatically measured using sociometric badges. Each badge broadcasts its unique ID through an infrared transceiver located on its front side every two seconds. Whenever two people wearing badges are facing each other (within a distance of one meter and a 30-degree cone) their IDs are exchanged through the infrared transceiver, recorded in local memory, and time-stamped. From the infrared face-to-face detections we created an adjacency matrix representing the frequency of face-to-face communication. Several social network features can be calculated from this f2f adjacency matrix. We calculated the amount of face-to-face interaction during the study by adding the values in each column (representing the total number of times each badge detected all other badges) and normalizing it by the total number of hours each person was wearing a sociometric badge to control for the fact that individuals wore the badges for varying amounts of time (e.g., part-time versus full-time). The average amount of face-to-face interaction was 18.71 f2f interactions per hour (standard deviation, std = 10.80).

We calculated the normalized degree by binarizing and symmetrizing the f2f adjacency matrix, counting the number of different people that each person interacted with, and normalizing this value by the maximum number of people wearing a badge in each branch. The average normalized degree was 0.33 (std = 0.22).

The average face-to-face **tie strength** was calculated by dividing the amount of f2f interaction by number of different people that each person interacted with (i.e. un-normalized degree). The average individual tie strength was 4.21 interactions per hour per interacting partner (std=5.59).

We calculated Freeman's **betweenness centrality** from the f2f adjacency matrix using UCINET 6.0. This metric indicates the extent to which an actor has a central position in the organization's face-to-face network. For the remainder of this chapter we will refer to betweenness centrality just as "centrality". The average centrality of the network was 6.42 (std = 5.60).

In our regression analysis, we controlled for age (in years), sex (0 male, 1 female), tenure (years working for the bank) and team (0 retail, 1 SME or small-medium enterprise).

6.1.6 Analysis

In the following subsection we present the results from a correlation analysis, an analysis of variance (ANOVA), and a moderation analysis (to measure interacting effects of centrality and face to face tie strength on sales performance). We also used social network analysis to calculate several features on the face-to-face social network. We followed the moderated regression procedure proposed by Peters and Champoux (1979) since it is an analytical procedure that avoids an arbitrary division of the data at the median or some other point such as upper and lower quartiles, and makes a more complete use of the data.

6.1.7 Findings

A one-way analysis of variance revealed significant differences ($p < 0.05$) among the three branches. Branch 2 (large physical size) was significantly different from the other two branches in that it had the highest ratings of optimism, trust, acceptance, and limitlessness. Along with this difference in attitude was a difference in behavior, with their badge measurements showing a significantly lower consistency of body movement, lower degree, and lower centrality compared to the other two branches. There were no significant differences in the average number of sales across the three branches. These different group dynamics were correlated with very different attitudes about their job and their outlook on the future. All three branches had very similar overall average performance despite having very different group dynamics. From a social network perspective, branches 1 and 3 were organized around dominance and influence, whereas branch 2 was organized around teaming behavior. This difference in social dynamics has its largest effect on the attitude and expectations of the employees, which in turn determine organizational resilience, employee turn-over, and similar bottom-line issues.

Even though the average number of sales was not significantly different across the three branches, it is clear that employees in branches 1 and 3 have different f2f communication patterns and job attitudes from employees in branch 2. Therefore, we grouped employees in branches 1 (small size) and 3 (medium size) and created an ordinary least squares (OLS) regression model to estimate the individual number of monthly sales using the f2f social network features as predictors and controlling for team (0 for retail, 1 for SME), sex (0 for

Table 6.1: Significant differences across the three branches in terms of job attitudes and f2f social network features (ANOVA), $N = 41$ employees.

Variable	**Branch 1**	**Branch 2**	**Branch 3**	**F-value**	**p-value**
Optimism	$\mu_o = 4.28$	$\mu_o = 5.48$	$\mu_o = 5.10$	$F = 4.42$	$p < 0.05$
Trust	$\mu_t = 3.38$	$\mu_t = 4.67$	$\mu_t = 3.85$	$F = 4.59$	$p < 0.05$
Acceptance	$\mu_a = 4.29$	$\mu_a = 5.27$	$\mu_a = 4.45$	$F = 3.82$	$p < 0.05$
Limitlessness	$\mu_l = 3.94$	$\mu_l = 4.95$	$\mu_l = 4.30$	$F = 3.47$	$p < 0.05$
Degree (x_8)	$x_8 = 0.63$	$x_8 = 0.16$	$x_8 = 0.38$	$F = 45.09$	$p < 0.00001$
Centrality (x_9)	$x_9 = 13.9$	$x_9 = 2.24$	$x_9 = 7.56$	$F = 26.45$	$p < 0.00001$

male, 1 for female), age, and tenure. Table 6.2 shows the regression model obtained for employees in branches 1 and 3:

Table 6.2: Model 1. Prediction of monthly sales for branches 1 and 3 using monthly f2f social network features as predictor variables ($R^2 = 0.68$, adjusted $R^2 = 0.46$, $F = 3.12$, $* = p < 0.05$, $N = 21$ employees).

Predictors	**Coefficient**
Intercept	$\beta_0 = 109.00$
Team (0 retail, 1 SME)	$\beta_t = -13.36$
Sex (0 male, 1 female)	$\beta_s = 3.56$
Age	$\beta_a = -0.66$
Tenure	$\beta_n = 0.31$
f2f time x_6	$\beta_6 = -1.30$
Degree x_8 (*)	$\beta_8 = 115.13$
Centrality x_9 (*)	$\beta_9 = -3.33$

In this model, the most significant predictors are degree and centrality. Having a higher number of f2f interacting co-workers (x_8), and lower centrality (x_9) predicted higher sales. The control variables were not significant, which indicates that team, age, sex, and tenure do not have an effect on the number of sales. Adjusting for the number of covariates, this model explains 46% of the variation in sales. Even though the average sales performance is similar to that of branch 2, these behaviors occurred in an environment of lower optimism, trust, acceptance, and limitlessness.

Table 6.3 shows the linear regression model obtained for the individual number of monthly sales for employees in branch 2 using the same predictor variables:

This model explains 57% of the variation in sales when controlling for team, sex, age, and tenure. The most significant predictor was the amount of f2f interaction time with co-workers. Having a higher amount of time spent in f2f interaction with co-workers (x_6),

Table 6.3: Model 2. Prediction of monthly sales for branch 2 using monthly f2f social network features as predictor variables ($R^2 = 0.72$, adjusted $R^2 = 0.57$, $F = 4.61$, $* = p < 0.01$, $N = 23$ employees).

Predictors	**Coefficient**
Intercept	$\beta_0 = 59.32$
Team (0 retail, 1 SME)	$\beta_t = -4.94$
Sex (0 male, 1 female)	$\beta_s = -21.26$
Age	$\beta_a = -0.76$
Tenure	$\beta_n = 0.77$
f2f time x_6 (*)	$\beta_6 = 0.85$
Degree x_8	$\beta_8 = 25.58$
Centrality x_9	$\beta_9 = -0.69$

higher number of f2f interacting co-workers (x_8), and lower centrality (x_9) predicted higher sales. Even though the average sales performance was similar to that of branches 1 and 3, employees' self-perceptions were higher in terms of optimism, trust, acceptance, and limitlessness.

Whereas f2f interaction time x_6 is not significant in model 1, it is significant and has a positive sign in model 2. This means that while the time employees in branches 1 and 3 spent interacting f2f with co-workers is not associated with the number of sales, it was observed that the more time employees spent interacting f2f with other co-workers in branch 2, the higher the number of sales. While one should take these results with caution, given the sample size and the specification of the model, similar social network characteristics are related to performance. In general, higher degree (or number of f2f interacting partners) and lower centrality were predictive of higher sales across the three branches. These results provide support for our third research proposition: Social signaling behavior and f2f network characteristics are predictive of individual and group performance.

Next, we decided to explore the moderating effect of centrality and tie strength on the average number of sales across branches. Table 6.4 shows the linear regression coefficients for three different models in which the dependent variable is the individual monthly number of sales.

Model 3 shows the effect of using the control variables only. The only significant coefficient is the binary variable controlling for team, indicating that members of SME teams in this study usually obtained a lower number of sales. Using this variable only, we can explain 23% of the variance in the monthly number of sales. Model 4 uses tie strength and centrality as predictor variables in addition to the control variables; however these predictor variables are not statistically significant by themselves.

An interesting finding comes from model 5, which adds the interaction term (tie strength $\times$ centrality) as a predictor variable. Adding this term causes the regression coefficients for the three predictor variables to become significant and increase the percentage of explained variance to 48% ($p < 0.0001$).

Table 6.4: Regression models for the individual number of monthly sales ($N = 41$)

Variable	**Model 3**			**Model 4**			**Model 5**		
	β	t-value	p-value	β	t-value	p-value	β	t-value	p-value
Intercept	27.72			27.72			a=27.72		
Team	-11.52	-3.28	0.002	-10.82	-2.73	0.0098	-8.32	-2.56	0.015
Sex	-3.43	-0.98	0.34	-3.85	-1.02	0.31	-0.91	-0.29	0.77
Age	-1.21	-0.28	0.78	-1.04	-0.23	0.82	-2.25	-0.61	0.55
Tenure	1.38	0.32	0.75	1.86	0.41	0.68	0.28	0.08	0.94
Tie strength (x)				-1.01	-0.28	0.78	b=28.57	3.97	0.0003
Centrality (z)				1.46	0.39	0.7	c=37.34	4.39	0.0001
Centrality * Tie strength (xz)							d=-43.77	-4.51	0.0001
R^2		0.3			0.31			0.56	
adjusted R^2		**0.23**			**0.19**			**0.48**	
F		4.16			2.69			6.44	
p		0.007			0.03			0.00007	
RMSE		20.67			21.16			17.07	

In addition, we introduce a second variable (z) believed to moderate the influence of the original predictor (x) on the criterion variable (y). The moderated regression model can be expressed as:

$$\hat{y} = a + bx + cz + d(xz) \tag{6.1}$$

This model can be restated as:

$$\hat{y} = (a + cz) + (b + dz)x \tag{6.2}$$

Substituting the linear regression coefficients from table 3 on equation 6.2 we obtain:

$$\hat{y} = (27.72 + 37.34z) + (28.57 - 43.77z)x \tag{6.3}$$

We can find the critical value of z for which the moderating effect of centrality changes from positive to negative by:

$$\begin{aligned} z_{\text{critical}} &= b/|d| \\ z_{\text{critical}} &= 28.57/43.77 = 0.6527 \end{aligned} \tag{6.4}$$

From equation 6.3 it is straightforward to see that for values $z < 0.6527$ (low centrality), the effect of f2f tie strength on sales will be positive, while for values $z > 0.6527$ (high centrality), the effect of f2f tie strength on sales will be negative. This means that high f2f interaction tie strength is associated with better performance in low centrality networks (where information is more evenly distributed).

6.1.8 Social Network Optimization

To demonstrate the social network simulation and optimization methodology proposed in section 5.5 we will attempt to find the optimal operational region for tie strength (x_1) and centrality (x_2) that maximize performance (y_1) and minimize individual stress ratings (y_2). Table 6.5 shows the quality characteristics (performance and stress) and their optimal specifications. Note that we have specified a 10% increase in the average number of sales (currently 32.32) as the performance target value, and a 10% decrease in stress ratings (currently 3.63) as the target value for stress. The minimum acceptable value is the current average, and the maximum acceptable value is twice the optimal change from the current value. This allows to constrain the search space for an optimal operational region.

Table 6.5: Optimal quality characteristics

Quality characteristics	**Specification**	**Target value**
Performance (y_1)	$32.32 \leq y_1 \leq 38.79$	$y_1^{target} = 35.56$
Stress (y_2)	$2.91 \leq y_2 \leq 3.63$	$y_2^{target} = 3.27$

Step 1: Experimental design

The central composite design is generally used to design an experiment that measures the response variables at specific values of the predictors. However in the proposed methodology it is not possible to fine-tune the network properties (predictors) in everyday organizational settings in order to measure the responses (e.g. performance). On the other hand, it is possible to observe the network properties and associated responses under naturalistic settings and code these values so that they fall within a specific range. We chose to normalize the predictor values within the range $[-1, 1]$ in order to constrain the search space.

Step 2: Regression model

A quadratic regression model is fit using the predictor variables and response variables and a unique set of regression coefficients is obtained. The desirability function d_i is calculated for every set of operational conditions $X^{(b)}$.

Step 3: Bootstrap

In order to obtain multiple sets of simulated regression coefficients for the multiple responses, the bootstrap method is used. At each iteration, a unique set of operational conditions is obtained with its corresponding desirability functions. The maximum D with its corresponding operational condition can then be selected.

The bootstrapped regression coefficients are:

$$\begin{aligned} \hat{y_1} = &\quad 35.91 - 55.87x_1 - 14.89x_2 - 57.49x_1x_2 - 3.86x_1^2 - 28.35x_2^2 \\ \hat{y_2} = &\quad 3.31 - 1.22x_1 + 1.94x_2 - 2.38x_1x_2 + 2.07x_1^2 + 1.96x_2^2 \end{aligned} \tag{6.5}$$

Step 4: Optimal operational region

The desirability functions d_1 and d_2 for every set of operational condition during the bootstrap method are calculated. At each iteration b, the trust-region method was used to solve the non-linear programming equation:

$$\text{Maximize } D(b) = \sqrt[2]{d_1(b) \times d_2(b)}, \tag{6.6}$$

where

Table 6.6: Optimal operational regions (OOR) from simulation

Variable	**OOR (coded units)**	**OOR(original units)**
Tie strength (x_1)	$[-0.65, -0.07]$	$[5.55, 15.84]$
Centrality (x_2)	$[-0.81, 0.11]$	$[2.90, 15.82]$
D value	$[0.58, 1]$	
Performance (y_1)		$[32.36, 38.20]$
Stress level(y_2)		$[3.05, 3.60]$

$$d_1(b) = \begin{cases} \left[\frac{\hat{y}_1 - 32.32}{35.56 - 32.32}\right] & 32.32 \le \hat{y}_1 \le 35.56 \\ \left[\frac{\hat{y}_1 - 38.79}{35.56 - 38.79}\right] & 35.56 < \hat{y}_1 \le 38.79 \\ 0 & \hat{y}_1 < 32.32 \text{ or } \hat{y}_1 > 38.79 \end{cases} \tag{6.7}$$

$$d_2(b) = \begin{cases} \left[\frac{\hat{y}_2 - 2.91}{3.27 - 2.91}\right] & 2.91 \le \hat{y}_2 \le 3.27 \\ \left[\frac{\hat{y}_2 - 3.63}{3.27 - 3.63}\right] & 3.27 < \hat{y}_2 \le 3.63 \\ 0 & \hat{y}_2 < 2.91 \text{ or } \hat{y}_2 > 3.63 \end{cases} \tag{6.8}$$

subject to the following constraints:

$$\begin{aligned} 0 < d_1(b), d_2(b) < 1, \\ -1 < x_j(b) < 1, j = 1, 2 \end{aligned} \tag{6.9}$$

in order to find the optimal set of operational conditions for the network properties.

Step 5: Upper and lower limits

Table 6.6 shows the results that were obtained after 1000 iterations of the bootstrap method. Figure 6-1 shows a contour plot for response variable y_1 (performance), while figure 6-2 shows the contour plot for response variable y_2 (stress level). A dotted rectangle shows the optimal operational region (OOR) that maximizes performance (assuming a 10% increase from the current average value) and minimizes stress levels (10% decrease from the current average value) at the same time. Contour plots provide one of the most visually useful ways to interpret the response surface system. The contour plot is merely a two-dimensional graph that shows contours of constant response with the axis system being a specific set of design variables, while the other design variables are held constant.

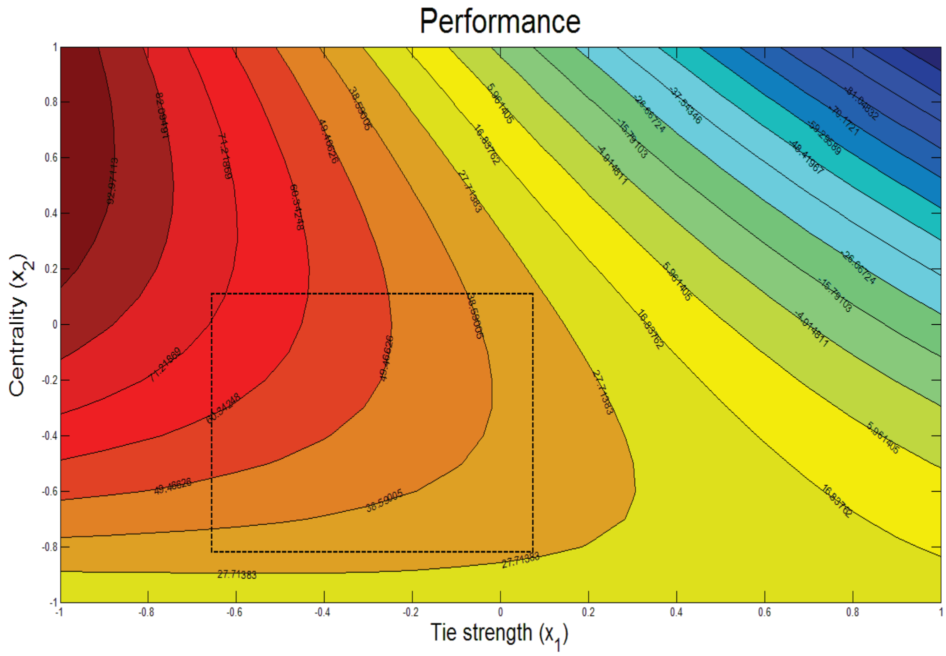


Figure 6-1: Contour plot displaying areas filled with constant colors between isolines for response variable y_1 (performance)

6.1.9 Discussion

In this study we found that greater centrality can produce inefficient f2f communication networks, both because of overloading of the central individuals, and because of loss of information due to messages that are not directly delivered. Lower centrality reduces overload and indirect information paths, but may require greater reliance on transactive memory and knowing who knows what. This result supports our hypothesis H0.

Consequently, the relationship between face-to-face time and sales depends on the configuration of the f2f network (we find support for H1-1a and H1-1b). The more one communicates with others the better, but only if those interactions with others are with the right people (i.e. not through unnecessary agents in the network). Observe in figure 6-1 that when centrality is high, higher tie strength (more face to face interactions) will be a hindrance to performance because of overloading of the central individual. On the other hand, when centrality is low, higher tie strength is more likely to increase performance because it allows individuals to more accurately know who knows what. Indeed, marrying individual

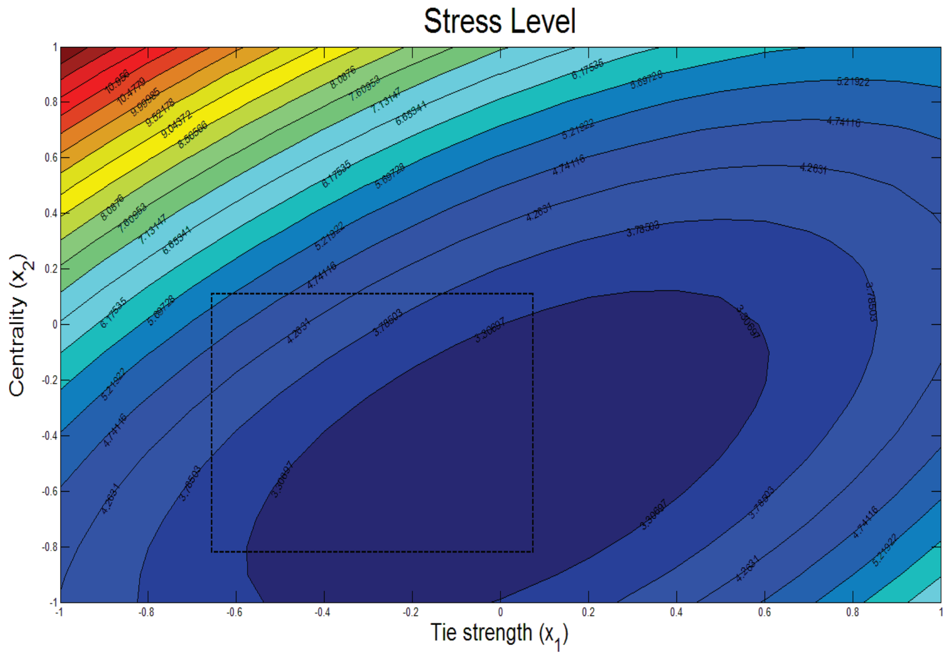


Figure 6-2: Contour plot displaying areas filled with constant colors between isolines for response variable y_2 (stress level)

and team characteristics is likely to be a cornerstone in the quest to explain variability in performance across organizations and industries, with obvious advantages for individuals and teams, human resource management, and organizational design.

An optimal operational region for the two network properties of interest (centrality and tie strength) that achieves a 10% increase in performance (average number of sales) and a 10% decrease in stress ratings was found, as hypothesized in H1-2. This optimal region depicted in figures 6-1 and 6-2 as a dotted rectangle suggests that the best performance could be achieved by promoting lower centrality and lower tie strength in this particular organizational setting. This region would also achieve lower stress ratings, as shown in figure 6-2. Using a similar approach, a different set of network operational conditions can be obtained that optimizes more than two quality characteristics (e.g. maximize performance, maximize job satisfaction, and minimize stress).

6.1.10 Proposed Organizational Intervention

A longer time-frame study would probably have revealed significant differences in performance across the three branches, with branch 2 having a higher performance and being more resilient over the long term. One possible intervention to increase the overall level of satisfaction would be to promote a teaming culture similar to that of branch 2 in the other two branches by implementing a training program that would try to reproduce the work environment, communication patterns and interaction behaviors that occur in the branch where the best job attitudes were observed.

6.2 Case Study 2: Hospital Post-Anesthesia Care Unit

6.2.1 Introduction

Reducing patients' length of stay (LOS) within Post-Anesthesia Care Units (PACU) can control or even lower costs. The length of time a patient remains in the PACU is medically attributed to the anesthetic drugs used during the operation and additional side effects that may occur, such as nausea and vomiting (Zollinger & Saywell 1999). Previous studies demonstrate that as many as 20% of patients experience delayed discharge from the PACU and over half of the delays may be personnel-related or due to personnel shortages and inefficiencies (Meyer 2006).

We instrumented a group of 67 nurses working in the Post Anesthesia Care Unit (PACU) of a Boston area hospital with sociometric badges. Using the data collected with these sensors we were able to identify different personality traits and estimate the overall group's perception of workload, difficulty to obtain information, quality of group interaction, productivity and stress, as well as the average patient length of stay and daily number of patient transfer delays.

6.2.2 Background

Personality

Over time researchers have tried to describe and measure personality traits (individual tendencies to react emotionally or behaviorally in a specific way) using various tests. The most popular model is the "Big Five" model that describes five personality traits (Tosi et al. 2000):

- (N) Neuroticism. Being highly emotional, tense, insecure, suffering from depression, and easily upset, suspicious and having low self confidence.
- (E) Extroversion. Tendency to be sociable, liking to be with others, energetic and forceful.
- (O) Openness. Being imaginative, curious, cultured, broad minded, having broad interests and tending to be self-sufficient.
- (A) Agreeableness. Tendency to be more tolerant, trusting, generous, warm, kind, good-natured, and less likely to be aggressive, rude and thoughtless.
- (C) Conscientiousness. Being responsible, dependable, persistent, punctual, hard working, and oriented toward work.

Group Behavior

The study of groups has been a focus across the social and behavioral sciences for over 50 years. Poole et al. (2004) have described nine different interdisciplinary perspectives on small groups. We are particularly interested in two of these nine perspectives: the *social-evolutionary perspective*, which posits that group structure and interaction reflect evolutionary forces that have shaped human social behaviors over thousands of years, and the *social network perspective*, which considers groups as interlinked structures embedded in larger social networks. The social-evolutionary perspective treats groups as aggregates of individuals and views group behavior as the product of individual behaviors that scale up to the group level, whereas the social network perspective uses members attributes and social network properties as inputs and treats performance, efficiency, cohesiveness, attitude, and belief convergence as the model outputs.

6.2.3 Hypotheses

Hypothesis H2-1

Personality traits manifest themselves in the way individuals speak, move, and interact with others. Therefore it is possible to identify personality traits from individual behavioral sensor data.

Hypothesis H2-2

Aggregate individual behaviors described in terms of physical activity, speech activity, face-to-face interaction, physical proximity, and social network attributes are predictive of group performance.

Hypothesis H2-3

It is possible to find an optimal range of individual and group properties (e.g. physical activity level and face-to-face interaction time) that optimize several job quality characteristics (e.g. performance, job satisfaction, stress, etc.) at the same time.

6.2.4 Experimental Setting

The hospital has 50 Operation Rooms (OR). After surgery is completed, patients are taken to the PACU, where they are kept under supervision until they recover from anesthesia. Thereafter they are admitted to the floor units where they convalesce before being discharged. Patients without assigned beds on the floors are kept in the PACU until vacancies on the floors can be found. The PACU is a critical intermediary step in the surgical patient throughput system and it consistently experiences delays of various kinds. These delays cause hold ups in the OR resulting in schedule disruptions, overtime work and productivity losses. This translates into loss of revenue for the hospital since the health-care system reimburses a fixed sum for a particular surgical procedure irrespective of the patient's length of stay in the hospital (Samarth 2007).

We placed base stations next to each bed and phone in the PACU in order to detect when the nurses were in close proximity to a bed or a phone and track their location and displacement patterns. There were 37 beds in the PACU, with only 30 being used during the study and 12 phones distributed around the room for patient scheduling.

The sociometric badges and base stations broadcasted their ID every 5 seconds using a 2.4 GHz transceiver and each time another badge or base station received a radio packet it logged the sender's ID and the radio signal strength. This allowed us to track the location of the nurses and detect when they were in close proximity to other nurses, beds or phones. The sociometric badges also transmitted their ID every 2 seconds using an infrared (IR) transceiver.

Participants

The sample was composed of 67 nurses who worked in the PACU of a Boston-area hospital. Each nurse wore a sociometric badge during 27 days. In total we collected 3,906 hours of data. The mean number of hours each participant wore a badge was 7.18 hours per day (std = ± 4.17).

At the end of each day the participants were asked to answer a job performance survey that included the following questions:

- Q1. How would you rate your workload today?
- Q2. How hard was it to obtain the information that you needed to do your job?
- Q3. How would you rate the quality of your work group interaction today?
- Q4. How satisfied do you feel with your job performance today?
- Q5. How productive do you think you were today?
- Q6. How much stress were you under today?

Each question could be answered according to the following 5-point likert scale: (1 = very low) (2 = low) (3 = average) (4 = high) (5 = very high). In total we collected 226 valid surveys. At the end of the study 39 participants also answered a NEO-FFI (NEO Five Factor Inventory) questionnaire (Costa & McCrae 2008) that contains 60 questions and is designed to measure the five personality traits described in the background section.

6.2.5 Measures

Table 6.7 shows the list of features that were calculated on a per-minute basis from the sensor data grouped by behavior description. The daily average and standard deviation of the per-minute features were calculated for each participant. Table 6.8 shows the notation that we use when we refer to the daily features. We used correlation analysis to identify personality traits from the individual daily features, and stepwise multiple linear regression analysis to predict the overall perception of workload, difficulty to obtain information, quality of work group interaction, job performance, productivity, and stress, as well as the average patient recovery time and number of delays from the daily features aggregated across subjects.

6.2.6 Findings

A correlation analysis of the daily badge features with each subject's answers to the daily job performance survey revealed weak but significant correlations ($r \leq 0.2$ with $p \leq 0.05$). However, when we aggregated the sensor features across subjects, the overall group perception of job performance (average of daily surveys across subjects) was highly correlated with the daily group behavior in the PACU. In order to do this, the answers to the daily survey were standardized across participants and the mean and standard deviation across subjects of the daily badge features described in table 6.8 were calculated. We will use the following notation to distinguish between daily features calculated across days and daily features calculated across subjects:

$\mu(F^n)_D$ denotes the average of daily feature F^n across days for a particular subject.

$\sigma(F^n)_D$ denotes the standard deviation of daily feature F^n across days for a particular subject.

$\mu(F^n)_S$ denotes the average of daily feature F^n across subjects for a particular day.

$\sigma(F^n)_S$ denotes the standard deviation of daily feature F^n across subjects for a particular day.

Table 6.7: Per-minute sensor features

Behavior Description	**Variable**	**Sensor features calculated every minute**
Physical activity	Intensity	(F^1) Mean signal magnitude (F^2) Standard deviation of signal magnitude (F^3) Power or energy per minute
Speech activity	Speech volume	(F^4) Mean volume modulation (F^5) Standard deviation of volume modulation
	Speaking time	(F^6) Speaking time in minutes
	Voiced speaking time	(F^7) Voiced speaking time in minutes
Face-to-face interaction (f2f)	f2f time	(F^8) f2f time in minutes
	Number of people with f2f	(F^9) Number of different people
Proximity	Time in close proximity to other people	(F^{10}) Time in minutes
	Time in close proximity to a bed	(F^{11}) Time in minutes
	Time in close proximity to a phone	(F^{12}) Time in minutes
Social network	Degree centrality	(F^{13}) Using f2f network (F^{14}) Using proximity to bed network
	Contribution index	(F^{15}) Using f2f network (F^{16}) Using proximity to bed network
	Betweenness centrality	(F^{17}) Using f2f network (F^{18}) Using proximity to bed network

Table 6.9 shows the correlation coefficients found between the daily badge features (mean and standard deviation across days) from each participant's sensor data and the results of their personality test grouped by behavior description.

These results support Hypothesis 1: *Personality traits can be identified from behavioral sensor data*. The results can be interpreted in terms of each personality trait (without implying causality) as follows:

- Neuroticism. The higher the daily percentage of f2f time, and the more variation across days in the daily percentage of f2f time, the more neurotic. These results are in accordance with (Hough 1992), who found that Emotional Stability (the opposite of Neuroticism) is correlated with effective teamwork (balanced f2f time and low variation over time).

- Extroversion. The lower the daily average time in close proximity to a bed the more

Table 6.8: Daily sensor features, where $h(k) = 1$ if $F^1(k) > 1$ (when wearing the badge), and $h(k) = 0$ if $F^1(k) \leq 1$ (when not wearing the badge)

Daily feature	**Notation**	**Calculation**
Average	F^n_μ	$\frac{1}{\sum_{k=1}^{K} h(k)} \sum_{k=1}^{K} F^n(k)h(k)$
Standard deviation	F^n_σ	$\sqrt{\frac{1}{\sum_{k=1}^{K} h(k)} \sum_{k=1}^{K} [F^n(k)h(k) - F^n_\mu(k)]^2}$
Percentage of time	$F^n_\%$	$\frac{1}{\sum_{k=1}^{K} h(k)} \sum_{k=1}^{K} F^n(k) > 0$

Table 6.9: Correlation coefficients between monthly badge features and personality traits. $* = p < 0.05$, $** = p < 0.01$.

		Personality Dimension				
Behavior Description	**Feature**	N	E	O	A	C
Physical activity	$\mu(F^2_\sigma)_D$	-0.03	-0.07	0.37*	-0.14	-0.09
Speech activity	$\sigma(F^5_\mu)_D$	0.07	-0.16	-0.18	-0.43**	-0.006
	$\sigma(F^5_\sigma)_D$	0.09	-0.13	-0.24	-0.41**	0.12
	$\sigma(F^6_\sigma)_D$	0.11	-0.006	-0.36*	-0.18	0.02
Face-to-face	$\mu(F^8_\%)_D$	0.35*	-0.08	0.004	0.06	-0.18
	$\sigma(F^8_\%)_D$	0.41*	-0.09	0.02	0.06	-0.26
Proximity	$\sigma(F^{11}_\%)_D$	0.06	-0.18	-0.16	-0.34*	0.16
	$\mu(F^{11}_\mu)_D$	-0.003	-0.36*	0.11	-0.26	0.18
Social Network	$\sigma(F^{17}_\mu)_D$	0.30	-0.07	0.46**	-0.16	-0.42**
	$\mu(F^{18}_\mu)_D$	0.18	0.01	0.26	-0.28	-0.37*
	$\sigma(F^{18}_\mu)_D$	0.13	-0.0008	0.20	-0.28	-0.36*

extrovert. One could interpret these results as the nurses having more time to interact and talk with others when they are not in close proximity to a bed looking after a patient therefore being more sociable (or extrovert).

- Openness. The higher the daily variation in physical activity, the less variation across days in daily variation in speaking time, and the more variation across days in the daily average betweenness centrality (f2f network) across days, the more open. There is evidence for the benefit of physical activity on cognitive performance (openness to experience being a trait-based contributor to predicting cognitive performance) (Lochbaum et al. 2002). The betweenness centrality correlation coincides with that obtained by (Gloor et al. 2010), who used our sensing platform in a bank and found that people who exhibit more fluctuating betweenness centrality also tend to exhibit higher levels of openness.

- Agreeability. The less variation across days in the daily average speech volume modulation, the less variation across days in the daily variation in speech volume modulation, and the less variation across days in the daily percentage of time in close proximity to a bed, the more agreeable. Previous research indicates that speech is perceived as more agreeable or accommodating when it is well modulated (Pentland 2007).

- Conscientiousness. The less variation across days in the daily average betweenness (f2f network), the lower the daily average betweenness (f2f network), and the less variation across days in the daily average betweenness (bed proximity network), the more conscientious. These results seem to be in accordance with those found by (Wehrli 2008): Conscientiousness is negatively correlated with betweenness centrality.

Tables 6.10 to 6.14 show the results of the multiple linear regression analysis for the overall group perception of workload ($R^2 = 0.49$), difficulty to obtain information ($R^2 = 0.42$), quality of group interaction ($R^2 = 0.69$), productivity ($R^2 = 0.63$), and stress ($R^2 = 0.77$) from the aggregated daily features across subjects.

Table 6.10: Group's perception of workload (Q1) using badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\sigma(F_\sigma^3)_S$	-0.61	0.37	0.30	10.16	0.005	0.39	4.54
$\sigma(F_\mu^7)_S$	0.47	0.49	0.40	7.71	0.004	0.37	-3.54

Table 6.11: Group's perception of difficulty to obtain information (Q2) using badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_\mu^3)_S$	0.50	0.25	0.16	5.62	0.03	0.28	-15.82
$\sigma(F_\mu^{11})_S$	-0.51	0.42	0.32	5.87	0.01	0.25	5.90

In the case of workload, the variation across subjects in physical activity and in speech activity were statistically significant. Likewise, in the case of difficulty to obtain information, the average physical activity intensity, and the variation across subjects in the time in close proximity to a bed were statistically robust. For quality of group interaction, the group's physical activity, speech activity, proximity to other people, proximity to a bed, and social

Table 6.12: Group's perception of quality of group interaction (Q3) using badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_{\mu}^{1})_S$	-0.52	0.27	0.18	6.21	0.02	0.37	91.44
$\mu(F_{\mu}^{3})_S$	-0.50	0.35	0.22	4.22	0.03	0.36	-34.55
$\sigma(F_{\sigma}^{10})_S$	-0.51	0.61	0.51	7.88	0.002	0.28	6.15
$\sigma(F_{\mu}^{11})_S$	0.47	0.66	0.52	6.67	0.003	0.28	-5.14
$\mu(F_{\mu}^{15})_S$	0.56	0.67	0.52	5.24	0.007	0.28	-0.66
$\mu(F_{\mu}^{16})_S$	0.48	0.69	0.52	4.55	0.01	0.28	0.52

Table 6.13: Group's perception of productivity (Q5) using badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\sigma(F_{\mu}^{7})_S$	0.71	0.50	0.44	16.84	0.0007	0.17	-1.84
$\mu(F_{\sigma}^{7})_S$	0.74	0.63	0.56	13.58	0.0003	0.15	-2.25

Table 6.14: Group's perception of stress (Q6) using badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_{\mu}^{1})_S$	0.67	0.45	0.38	13.82	0.002	0.44	-218.247
$\sigma(F_{\mu}^{1})_S$	-0.55	0.45	0.34	6.50	0.008	0.45	-22.10
$\mu(F_{\mu}^{3})_S$	0.65	0.61	0.51	7.93	0.002	0.39	77.78
$\mu(F_{\%}^{7})_S$	0.46	0.64	0.51	6.15	0.004	0.39	417.85
$\sigma(F_{\mu}^{7})_S$	0.49	0.75	0.63	7.80	0.001	0.34	-5.78
$\mu(F_{\mu}^{9})_S$	0.58	0.76	0.63	6.45	0.003	0.34	-0.03
$\sigma(F_{\mu}^{12})_S$	0.46	0.77	0.63	5.38	0.007	0.34	-7.02

network attributes were highly significant. Voiced speech activity seemed to be strongly associated with group's perception of productivity. Finally, several attributes seemed to play an important role in determining the group's stress level: physical activity, speech activity, face-to-face interaction, and proximity to a phone.

Tables 6.15 and 6.16 show that it is possible to explain the variation in the daily average LOS in minutes ($R^2 = 0.79$) and the daily average number of outgoing delays ($R^2 = 0.56$) from the aggregated features across subjects. In the case of LOS, the variation in physical activity intensity, face-to-face interaction time, and time in close proximity to a phone across subjects played an important role. Low variation across the nurses' level of physical activity (either all nurses having high levels of activity or low levels of activity) and high variation across the nurses' face-to-face interaction time was an indication of extended LOS. In the context of the PACU these results can be interpreted as either most PACU nurses being busy (high activity levels) or waiting for bed availability (low activity levels). The variation across the nurses' face-to-face interaction time could be an indicator of poor communication among nurses. The variation in the detection of nurses in close proximity to a phone could be an indicator of lack of advanced notification to the receiving unit of an impending patient transfer.

When estimating the daily number of delays the variation across subjects in their individual physical activity variation throughout the day and the average time they are in close proximity to a phone (which could be related to phone call length) were the most predictive features. This means that a high variation across the nurses' daily activity levels (having alternate periods of high activity and low activity during the day), coupled with the variation in the time they spend in close proximity to a phone, is an indication of increased number of delays in the PACU.

Table 6.15: Daily average LOS in minutes using badge features across subjects ($p < 0.005$)

Predictors	R	R^2	F	RMSE	β
$\sigma(F^1_\mu)_S$	-0.72	0.52	18.11	36.32	-1387.52
$\sigma(F^8_\%)_S$	0.53	0.71	19.39	29.07	2909.17
$\sigma(F^{12}_\%)_S$	0.16	0.79	19.21	25.24	-53.5

Table 6.16: Daily average number of delays (going out of the PACU) using badge features across subjects ($p < 0.05$)

Predictors	R	R^2	F	RMSE	β
$\sigma(F^2_\mu)_S$	0.46	0.21	4.48	3.95	-189.53
$\sigma(F^{12}_\mu)_S$	-0.60	0.56	10.37	3.02	206.63

These results favor Hypothesis 2: *Aggregate group behavior is predictive of group performance* (subjective in the case of the job performance survey, and objective if we consider the patient's length of stay and the daily number of outgoing delays in the PACU as the group's outcome).

6.2.7 Social Network Optimization

To demonstrate the social network simulation and optimization methodology proposed in section 5.5 we will attempt to find the optimal operational region for the group-level predictor variables tie strength ($x_1 = F^8/F^9$) and betweenness centrality ($x_2 = F^{17}$) that minimize the daily average patient LOS (y_1) and at the same time minimize daily nurse stress ratings (y_2). Table 6.17 shows the quality characteristics (patient LOS and nurse stress ratings) and their optimal specifications. Note that we again have specified a 10% decrease in the average patient LOS (currently 231 minutes) as the performance target value, and a 10% decrease in stress ratings (currently 3.21 on a scale from 1 to 5) as the target value for stress. The maximum acceptable value is the current average, and the minimum acceptable value is twice the optimal increase/decrease from the current value. This allows us to constrain the search space for a optimal operational region.

Table 6.17: Optimal quality characteristics

Quality characteristics	**Specification**	**Target value**
Patient LOS (y_1)	$184.77 \leq y_1 \leq 230.96$	$y_1^{target} = 207.87$
Nurses' stress (y_2)	$2.56 \leq y_2 \leq 3.21$	$y_2^{target} = 2.88$

In order to obtain multiple sets of simulated regression coefficients for the multiple responses, the bootstrap method was used. At each iteration, a unique set of operational conditions was obtained with its corresponding desirability functions. The maximum D with its corresponding operational condition was selected.

The bootstrapped regression coefficients are:

$$\begin{aligned} \hat{y_1} = &\quad 248.97 + 26.20x_1 + 23.19x_2 + 19.01x_1x_2 + 6.19x_1^2 + 6.39x_2^2 \\ \hat{y_2} = &\quad 3.36 - 0.19x_1 + 0.45x_2 + 0.83x_1x_2 - 0.621x_1^2 - 0.07x_2^2 \end{aligned} \tag{6.10}$$

The desirability functions d_1 and d_2 for every set of operational condition during the bootstrap method were calculated. At each iteration b, the trust-region method was used to solve the non-linear programming equation:

$$\text{Maximize } D(b) = \sqrt[2]{d_1(b) \times d_2(b)}, \tag{6.11}$$

where

$$d_1(b) = \begin{cases} \left[\frac{\hat{y}_1 - 184.77}{207.87 - 184.77}\right] & 184.77 \leq \hat{y}_1 \leq 207.87 \\ \left[\frac{\hat{y}_1 - 230.96}{207.87 - 230.96}\right] & 207.87 < \hat{y}_1 \leq 230.96 \\ 0 & \hat{y}_1 < 184.77 \text{ or } \hat{y}_1 > 230.96 \end{cases} \tag{6.12}$$

Table 6.18: Optimal operational regions (OOR) from simulation.

Variable	**OOR (coded units)**	**OOR(original units)**
Tie strength (x_1)	$[-0.99, -0.75]$	$[0.31, 0.49]$
Centrality (x_2)	$[-0.58, 0.29]$	$[0.05, 0.10]$
D value	$[0.54, 1]$	
Patient LOS (y_1)		$[207.87, 226.82]$
Nurses' stress level (y_2)		$[2.88, 3.05]$

$$d_2(b) = \begin{cases} \left[\frac{\hat{y}_2 - 2.56}{2.88 - 2.56}\right] & 2.56 \leq \hat{y}_2 \leq 2.88 \\ \left[\frac{\hat{y}_2 - 3.21}{2.88 - 3.21}\right] & 2.88 < \hat{y}_2 \leq 3.21 \\ 0 & \hat{y}_2 < 2.56 \text{ or } \hat{y}_2 > 3.21 \end{cases} \tag{6.13}$$

subject to the following constraints:

$$\begin{aligned} 0 < d_1(b), d_2(b) < 1, \\ -1 < x_j(b) < 1, j = 1, 2 \end{aligned} \tag{6.14}$$

in order to find the optimal set of operational conditions for the network properties. Table 6.18 shows the results that were obtained after 1000 iterations of the bootstrap method.

Figure 6-3 shows a contour plot for response variable y_1 (patient LOS), while figure 6-4 shows the contour plot for response variable y_2 (nurses' stress level). A dotted rectangle shows the optimal operational region (OOR) that maximizes performance (by 10% of the current average value) and minimizes stress levels (by 10% of the current average value) at the same time.

6.2.8 Discussion

We have shown how to obtain high level descriptions of human behavior in terms of physical activity, speech activity, face-to-face interaction, proximity and social network attributes from sensor data. We presented experimental results that show that it is possible to identify individual personality traits as well as subjective and objective group performance metrics from low level sensor data. While we could not estimate the individual perception of job performance from sensor data for each individual, we were able to estimate the overall group

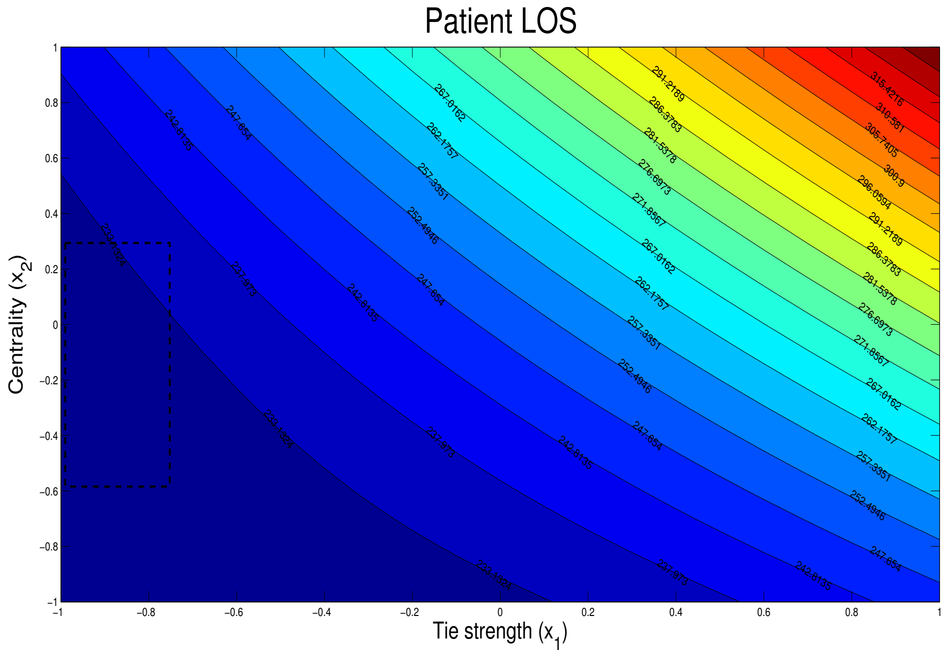


Figure 6-3: Contour plot displaying areas filled with constant colors between isolines for response variable y_1 (patient LOS)

performance by aggregating the daily sensor features across subjects. This is a first attempt to measure and model organizational behavior at the individual and group levels.

The use of pervasive technology in healthcare management has the potential to improve organizational performance by allowing healthcare providers to identify bottlenecks and ineffective behaviors. Our results argue in favor of using wearable sensors to study group behavior, and incorporating behavioral data into patient scheduling systems to reduce the patient's LOS and save costs by minimizing the number of delays. We plan to extend this research to multiple groups and entire organizations. Future work includes modeling, simulation and optimization of individual and group behavior from sensor data.

An optimal operational region for two network properties (daily average tie strength and daily average centrality across nurses) that achieves a 10% increase in performance (or 10% decrease in the average patient LOS), and a 10% decrease in nurse stress ratings was found, offering support for hypothesis H2-3. Two clear regions in both figures 6-3 and 6-4 can be distinguished. The lower left corner (low centrality and low tie strength) which results in lower patient LOS and lower stress, and the upper right corner (high centrality and high

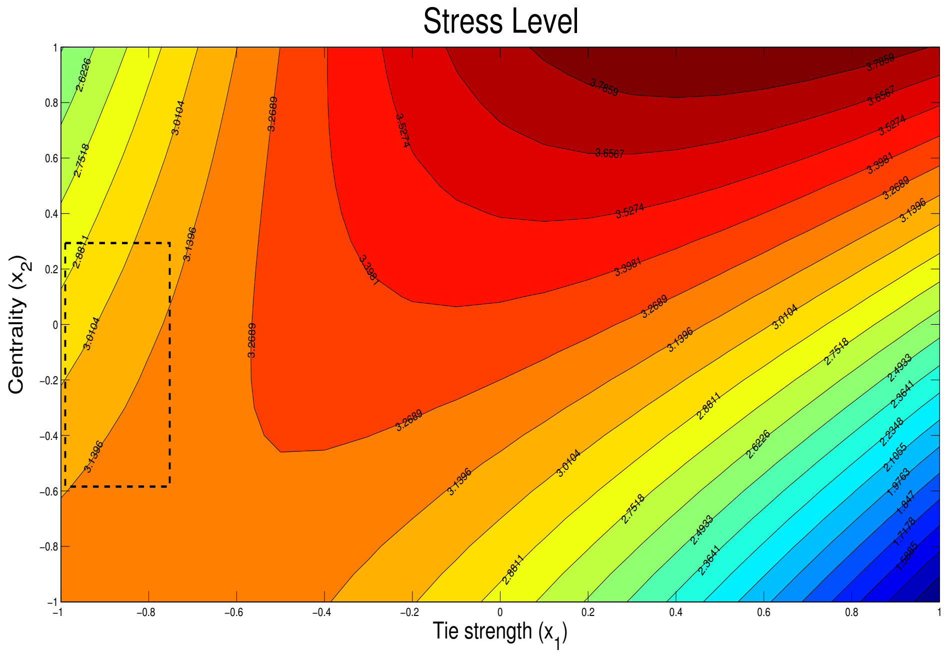


Figure 6-4: Contour plot displaying areas filled with constant colors between isolines for response variable y_2 (nurses' stress level)

tie strength) which results in higher patient LOS and higher stress. As both centrality and tie strength across nurses increase, the average daily patient LOS also increases. Another interesting region in figure 6-4 is the lower right corner which achieves the lowest stress levels. A more decentralized network with high tie strength would reduce the nurses' stress levels and achieve a moderate patient LOS. This shows that it is possible to find a trade-off between performance and job quality characteristics by exploring surface response plots.

6.2.9 Proposed Organizational Intervention

In the context of the PACU these results can be interpreted as either most PACU nurses being busy (high activity levels) or waiting for bed availability (low activity levels). The variation across the nurses' face-to-face interaction time could be an indicator of poor communication among nurses, slowing down patient transfer. A possible organizational design intervention would be to incorporate behavioral sensor data from the nurses' activity levels, face-to-face interaction, and time they spend in close proximity to beds into existing patient scheduling systems. This could potentially save costs to the hospital by minimizing the number of delays, reducing the patients' LOS, and providing better care to the patients. Another potential intervention would be to install a display that shows a map of the PACU and overlays information about the nurses' location, displacement patterns, activity levels, and beds with patients, in real-time. This would give instantaneous feedback to the nurses and PACU managers about the current activity and stress levels in the PACU, and help them manage their capacity in a more efficient way.

6.3 Case Study 3: Call Center

6.3.1 Introduction

A two-phase study at a call center with over 3,000 employees from a major North American bank was carried out. We deployed our organizational-engineering system at the bank's call center, where a group of 80 employees (working in four different teams) and managers used sociometric badges for 6 weeks. The purpose of this phase of the study was to identify social behaviors that could lead to a behavioral intervention that would enhance productivity. The executives in charge of the call center unit of this bank had the intuition that limiting interaction for the call center employees during break periods had negative effects on the mental well being of the employees and may lead to higher turnover (Waber et al. 2010).

6.3.2 Hypotheses

For the first phase of this study, we wanted to discover whether or not face-to-face interactions had any affect on productivity or stress levels. The objective of the study was to use data collected using the sociometric badges to correlate temporal changes in social interaction patterns with performance of individual actors and groups.

Hypothesis H3-1

Face-to-face network attributes (e.g. centrality, cohesion, and f2f time) are correlated with individual performance.

Hypothesis H3-2

It is possible to find an optimal range of network properties (e.g. centrality and face-to-face interaction time) that optimizes several job quality characteristics (e.g. performance and stress) at the same time.

6.3.3 Experimental Setting

During the first phase of the study, four teams consisting of 20 employees each used sociometric badges all day while they were at the call center for a period of six weeks. On average we collected more than 9,500 hours of data. We placed base stations in the hallways in order to detect when the employees were in close proximity to their work station and track their location and displacement patterns. There were approximately 12 base stations in total, which allowed us to map the four team areas. The four teams were each headed by a single manager, who had a desk in the group area. Employees sat in cubicles in front of a computer terminal taking customer calls on a variety of banking issues. The break structure for these employees, as in many call centers, was designed to reduce as much as possible the overlap between breaks for people on the same team. Each employee was given one 15-minute break per day in addition to a 30 minute lunch break (Waber et al. 2010).

6.3.4 Measures

In addition to the sociometric badge data, several daily productivity metrics were made available to us, including number of phone calls handled, average call handle time (AHT), speaking time, and system use time, among others. The bank also gave the employees surveys as part of their regular monthly employee assessment, and we were also able to obtain them as part of the case study.

6.3.5 Analysis

A linear correlation analysis to determine the relationship between badge features and performance was performed. Multiple linear regression was also used to estimate the variation in average handle time using correlated badge features as predictor variables.

6.3.6 Findings

Preliminary results seem to indicate that cohesion in the face-to-face social network is negatively correlated with the average handle time ($r = -0.61$, $p < 0.001$). This has several implications for the call center's operations, as we will discuss later. Stress was also negatively correlated with cohesion and betweenness centrality, but these results were not statistically significant.

6.3.7 Social Network Optimization

To demonstrate the social network simulation and optimization methodology proposed in section 5.5 we find the optimal operational region for the predictor variables tie strength (x_1) and betweenness centrality (x_2) that minimize the daily average handle time (y_1) and at the same time minimize daily stress ratings (y_2). Table 6.19 shows the quality characteristics (AHT and stress ratings) and their optimal specifications. Note that we specified a 10% decrease in the AHT (currently 268 seconds) as the performance target value, and a 10% decrease in stress ratings (currently 3.26 on a scale from 1 to 5) as the target value for stress. Once again, the maximum acceptable value is the current average, and the minimum acceptable value is twice the optimal increase/decrease from the current value. This allows to constrain the search space for a optimal operational region.

Table 6.19: Optimal quality characteristics

Quality characteristics	**Specification**	**Target value**
Average Handle Time (AHT) (y_1)	$214.5 \leq y_1 \leq 268.13$	$y_1^{target} = 241.31$
Stress Level (y_2)	$2.61 \leq y_2 \leq 3.26$	$y_2^{target} = 2.94$

In order to obtain multiple sets of simulated regression coefficients for the multiple responses, the bootstrap method was used. At each iteration, a unique set of operational conditions was obtained with its corresponding desirability functions. The maximum D with its corresponding operational condition was selected.

The bootstrapped regression coefficients are:

$$
\begin{aligned}
\hat{y_1} = &\quad 223.91 - 51.98x_1 - 25.19x_2 - 102.96x_1x_2 + 60.94x_1^2 + 11.49x_2^2 \\
\hat{y_2} = &\quad 2.77 + 0.53x_1 + 0.12x_2 - 0.14x_1x_2 + 1.61x_1^2 + 0.16x_2^2
\end{aligned}
\tag{6.15}
$$

The desirability functions d_1 and d_2 for every set of operational condition during the bootstrap method were calculated. At each iteration b, the trust-region method was used to solve the non-linear programming equation:

$$
\text{Maximize } D(b) = \sqrt[2]{d_1(b) \times d_2(b)}, \tag{6.16}
$$

where

$$
d_1(b) = \begin{cases} \left[\frac{\hat{y}_1 - 214.5}{241.31 - 214.5}\right] & 214.5 \leq \hat{y}_1 \leq 241.31 \\ \left[\frac{\hat{y}_1 - 268.13}{241.31 - 268.13}\right] & 241.31 < \hat{y}_1 \leq 268.13 \\ 0 & \hat{y}_1 < 214.5 \text{ or } \hat{y}_1 > 268.13 \end{cases} \tag{6.17}
$$

$$
d_2(b) = \begin{cases} \left[\frac{\hat{y}_2 - 2.61}{2.94 - 2.61}\right] & 2.61 \leq \hat{y}_2 \leq 2.94 \\ \left[\frac{\hat{y}_2 - 3.26}{2.94 - 3.26}\right] & 2.94 < \hat{y}_2 \leq 3.26 \\ 0 & \hat{y}_2 < 2.61 \text{ or } \hat{y}_2 > 3.26 \end{cases} \tag{6.18}
$$

subject to the following constraints:

$$
\begin{gathered}
0 < d_1(b), d_2(b) < 1, \\
-1 < x_j(b) < 1, j = 1, 2
\end{gathered}
\tag{6.19}
$$

in order to find the optimal set of operational conditions for the network properties. Table 6.20 shows the results that were obtained after 1,000 iterations of the bootstrap method.

Figure 6-5 shows a contour plot for response variable y_1 (AHT), while figure 6-6 shows the contour plot for response variable y_2 (stress level). A dotted rectangle shows the optimal operational region (OOR) that jointly maximizes performance (10% increase from the current average value) and minimizes stress levels (10% decrease from the current average value).

Table 6.20: Optimal operational regions (OOR) from simulation

Variable	**OOR (coded units)**	**OOR(original units)**
Tie strength (x_1)	$[-0.66, 0.35]$	$[0.30, 1.15]$
Centrality (x_2)	$[-0.99, 0.99]$	$[0.04, 4.57]$
D value	$[0.56, 1]$	
AHT (y_1)		$[223.85, 258.23]$
Stress Level (y_2)		$[2.83, 3.10]$

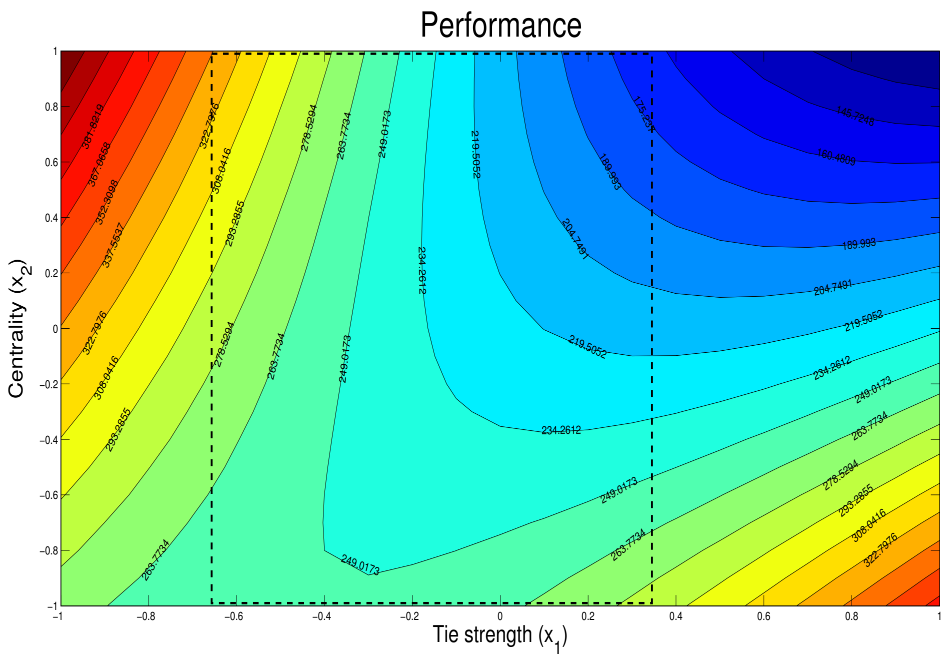


Figure 6-5: Contour plot displaying areas filled with constant colors between isolines for response variable y_1 (AHT)

6.3.8 Discussion

By looking at figures 6-5 and 6-6, one can observe that centrality does not play a major role in determining performance and stress levels in the call center. The rectangle enclosing the optimal operational region includes the whole range of observed centrality values. On the other hand, there is an optimal range of tie strength values that minimizes both the average handle time (AHT) and the call center's stress levels.

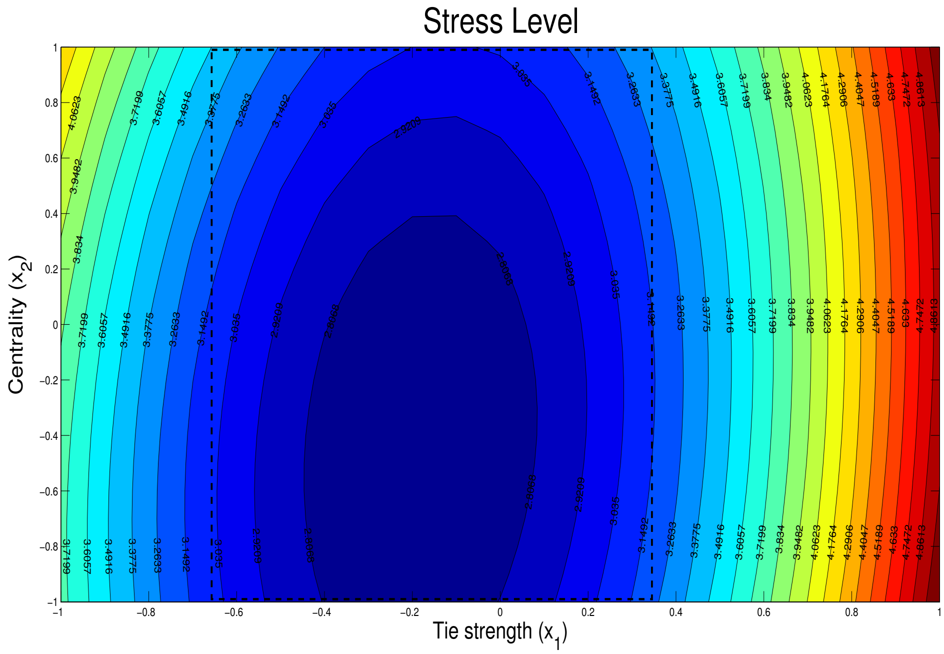


Figure 6-6: Contour plot displaying areas filled with constant colors between isolines for response variable y_2 (stress level)

6.3.9 Proposed Organizational Intervention

Feedback systems that present real-time information to managers could be used to improve the performance of the call center. One suggested intervention was to change the way employee's breaks were scheduled. Instead of minimizing the number of people taking a break at the same time, changing the break structure so that more people working in the same team could take a break at the same time would allow members of the teams to form more cohesive ties over time. This would also allow more knowledge sharing, which in turn would lead to a reduction in the average call handle time.

Chapter 7

Conclusions and Future Work

We have discussed several technologies for sensing and modeling human behavior, and proposed a sensor-based organizational design and engineering approach. By bringing together computational models, human sensing, data mining, and social network analysis, we believe it is possible to create a closed loop system that uses digital information, sensor data, performance and productivity data as inputs. Data mining algorithms and social network analysis can be applied to these inputs, and computational models created from the results of the data analysis. Simulations and feedback mechanisms would be reported to the users of the system in order to design interventions aimed at improving organizational outcomes. These changes may include: restructuring the organizational chart, restructuring teams, changing the physical office layout in order to facilitate communication and mobility patterns, or promoting specific behaviors.

Our proposed approach to measure human behavior has several advantages over existing methods such as direct observation by humans, the use of pervasive cameras to videotape social interactions, or the use of surveys. Direct observation of humans by humans is expensive and limited to a few people per observer, and observers do not always agree. Deploying pervasive cameras is generally expensive and their range of measurement is constrained to a particular place. Surveys may be subjective, inaccurate, and time consuming, especially in situations when particular aspects of social interactions are trying to be measured. In contrast, it is a great advantage to be able to automatically capture the behavior of hundreds of people at the same time with unobtrusive sensors. The use of pervasive sensors has allowed us to study human behavior with unprecedented levels of detail. By capturing individual behaviors such as the amount of face-to-face interaction, speaking patterns, and non-linguistic social signals; and aggregating them at the group level, it is possible to assess group performance and design organizational interventions aimed at improving performance.

We presented results from several case studies in which we looked at face-to-face communication patterns and found correlations between behavioral sensor data, performance outcomes and several job quality characteristics such as job satisfaction and stress. We proposed a social-network simulation and optimization technique based on the response surface methodology and the bootstrap method and we showed that it is possible to obtain an operational region that optimizes several job quality characteristics simultaneously. We discussed several organizational interventions to promote face-to-face interaction and reduce communication overload for each case study. In the first study we were able to observe different group dynamics and job attitudes in three branches of a retail bank and estimate the monthly number of sales from the f2f network features. The results from the second study showed that it was possible to assess the overall performance of a post-anesthesia care unit by analyzing aggregated behavioral features across all nurses working in the unit as a group. Finally, the third study looked at group configurations that maximize performance and minimize stress levels in a call center.

Even though we have only discussed a few application scenarios, we believe the possibilities for the proposed sensor-based approach are much broader. A few limitations of these case studies along with questions for future research should be noted. Even though the case studies demonstrate associations between variables, they cannot fully establish causality. We have only described some potential organizational interventions that could be designed for each of the discussed scenarios. Simulating and implementing the proposed organizational interventions using the proposed method may give us a better understanding and knowledge about the causality of the relationships.

There is an enormous potential in applying data mining techniques to the domain of organizational design. People working in large companies usually find it difficult to identify other people working on similar projects or with specific skills or knowledge. Text mining of digital documents (websites, profiles, working papers, reading papers, e-mail) would make it possible to update or automatically create a users profile based on mined expertise from the text contained in these documents. Information obtained in this way could be combined with information from sensor data and allow people to connect with others who have the required know-how to help them solve a specific problem. Individuals should be able to set their own privacy rules and specify which documents can be used for text mining by storing them in a specific directory for example.

7.1 Contributions

Among the contributions of this thesis are:

- The conceptualization, design and implementation of a sensor-based organizational engineering approach.
- The sociometric badge research platform and required infrastructure to study human behavior in organizations.
- Several behavioral datasets collected in collaboration with my colleagues in real organizations.
- A Simulation and optimization methodology that uses behavioral sensor data.
- The design of organizational interventions based on behavioral sensor data and simulation models.
- The possibility to confirm social-science theories based on human observation using automatic tools and methods on larger populations.
- The possibility to create feedback and visualization tools based on behavioral sensor data and simulation models for organizational performance.

7.2 Future Work

Future work includes designing, simulating and implementing organizational interventions, as well as validating them in a second sociometric measurement phase. Applying longitudinal social network analysis and simulation techniques would allow analysts to take into account the time dependencies inherent to social interactions. Further extensions of this work include automatic clustering of people to maximize team performance as well as dynamic visualizations of team processes. Some implications that this work has for future studies and future technologies for organizational design and engineering are:

- The emergence of new collaboration tools and technologies that make use of behavioral sensor data to promote collective intelligence in organizations.
- A deeper understanding of human behavior within organizations. Most of the required infrastructure and sensors are already in place (sensors, location, software, etc.) and eventually will be exploited.
- An awareness that users should have the right to manage their privacy settings, have access to their data, know what kind of data is being collected, and decide how their data will be utilized.
- Privacy concerns, which will be overcome by the potential benefits for the users and the organizations.

Bibliography

Ahuja, M. K., Galletta, D. F. & Carley, K. M. (2003), 'Individual centrality and performance in virtual r&d groups: An empirical study', *Management Science* **49**(1), 21–38.

Alder, G. S. (2007), 'Examining the relationship between feedback and performance in a monitored environment: A clarification and extension of feedback intervention theory', *Journal of High Technology Management Research* **17**, 157–174.

Allen, T. (1971), 'Communication networks in r&d laboratories', *R&D Management* **1**, 14–21.

Allen, T. (1997), *Architecture and Communication among Product Development Engineers*, The MIT Press, Cambridge, MA.

Baken, R. (1987), *Clinical Measurement of Speech and Voice*, Taylor and Francis Ltd, London, UK.

Bao, L. & Intille, S. S. (2004), Activity recognition from user-annotated acceleration data, *in* 'Proc. of the 2nd International Conference on Pervasive Computing', pp. 1–17.

Barrick, M. R. & Mount, M. K. (1994), 'The big five personality dimensions and job performance: A meta-analysis', *Personnel Psychology* (44), 1–26.

Blum, M., Pentland, A. & Troster, G. (2006), 'Insense: Interest-based life logging', *IEEE MultiMedia* **13**(4), 40–48.

Bonacich, P. (1987), 'Power and centrality: A family of measures', *AJS* **92**(5), 1170–1182.

Boonstra, J. J. (2004), *Some reflections and perspectives on organizing, changing, and learning. In Boonstra, J.J. (ed.), Dynamics of Organizational Change and Learning*, John Wiley & Sons, West Sussex, England.

Borovoy, R., Martin, F., Vemuri, S., Resnick, M., B., S. & Hancock, C. (1998), Meme tags and community mirrors: Moving from conferences to collaboration, *in* 'Proceedings of the 1998 ACM Conference on Computer Supported Cooperative Work', pp. 1–10.

Borovoy, R., McDonald, M., Martin, F. & Resnick, M. (1996), 'Things that blink: Computationally augmented name tags', *IBM Systems Journal* **35**(3), 488–495.

Bowditch, J. L. & Buono, A. F. (2005), *A Primer on Organizational Behavior*, John Wiley & Sons, Inc., Danvers, MA.

Bowers, C. A., Jentsch, F., Salas, E. & Braun, C. C. (1998), 'Analyzing communication sequences for team training needs assessment', *Human Factors* pp. 672–679.

Brandes, U., Lerner, J. & Snijders, T. A. B. (2009), Networks evolving step by step: Statistical analysis of dyadic event data, *in* 'Proc. of Advances in Social Network Analysis and Mining'.

Brass, D. (2011), *A social network perspective on organizational psychology. In Kozlowski, S. W. J. (ed.), The Oxford Handbook of Organizational Psychology*, Oxford University Press, New York, NY.

Burk, W. J., Steglich, C. E. G. & Snijders, T. A. B. (2007), 'Beyond dyadic interdependence: Actor-oriented models for co-evolving social networks and individual behaviors', *International Journal of Behavioral Development* **31**(4), 397–404.

Carley, K. M. (1995), 'Computational and mathematical organization theory: perspective and directions', *Computational and Mathematical Organization Theory* pp. 39–56.

Carley, K. M. (2002), 'Computational organizational science and organizational engineering', *Simulation Modeling Practice and Theory* pp. 253–269.

Carley, K. M. & Kamneva, N. Y. (2004), A network optimization approach for improving organizational design, Technical report, Carnegie Mellon University.

Carrol, T. & Burton, R. M. (2001), 'Organizations and complexity: Searching for the edge of chaos', *Computational & Mathematical Organization Theory* **6**, 319–337.

Castro Melo Godinho de Matos, M. M. (2007), Organizational engineering: an overview of current perspectives, *dissertao para a obteno de grau de mestre em engenharia informtica e de computadores*, Master's thesis, Instituto Superior Tecnico, Lisbon, Portugal.

Chang, M. H. (2006), *Agent-based models of organizations. In Tesfatsion, L. and Judd, K. L. (eds.), Handbook of Computational Economics*, Elsevier, The Netherlands.

Choudhury, T. (2004), Sensing and Modeling Human Networks, PhD thesis, Massachusetts Institute of Technology, Media Laboratory.

Choudhury, T. (2008), 'The mobile sensing platform: An embedded activity recognition system', *Pervasive* **7**(2), 32–41.

Choudhury, T. & Pentland, A. (2003), Sensing and modeling human networks using the sociometer, *in* 'Proceedings of the 7th IEEE International Symposium on Wearable Computers', pp. 216–222.

Costa, P. T. & McCrae, R. R. (2008), 'Neo five-factor inventory'. Psychological Assessment Resources, Inc. [http://www3.parinc.com/products/ product.aspx?Productid=NEO_FFI]. Accessed on: 09/18/2008.

Cummings, T. G. & Worley, C. G. (2009), *Organization Development and Change*, South-Western College Publishing, Cincinnati, OH.

Derringer, G. & Suich, R. (1980), 'Simultaneous optimization of several response variables', *Journal of Quality Technology* **12**(4), 214–219.

Dietz, J. L. (2002), 'Demo: towards a discipline of organization engineering', *European Journal of Operational Research* pp. 351–363.

DiMicco, J. M., Pandolfo, A. & Bender., W. (2004), Influencing group participation with a shared display, *in* 'Proc. of the ACM Conference on Computer Supported Cooperative Work', pp. 614–623.

Dong, W., Mani, A., Pentland, A., Lepri, B. & Pianesi, F. (n.d.), 'Modeling group discussion dynamics'. Submitted to IEEE Transactions on Autonomous Mental Development, 2009.

Dunbar, R. I. M. (2003), 'The social brain: Mind, language and society in evolutionary perspective', *Annual Review of Anthropology* **32**, 163–181.

Eagle, N. & Pentland, A. (2005), 'Reality mining: sensing complex social systems', *Personal and Ubiquitous Computing* **10**(4), 255–268.

Ellis, R., Yoo, H., Graham, D. W., Haseler, P. & Anderson, D. V. (2002), A continuous-time speech enhancement front-end for microphone inputs, *in* 'Proceedings of the IEEE International Symposium on Circuits and Systems'.

Eppler, M. J. & Mengis, J. (2004), 'The concept of information overload: A review of literature from organization science, accounting, marketing, mis, and related disciplines', *The Information Society* **20**, 325–344.

Fang, C., Lee, J. & Schilling, M. A. (2010), 'Balancing exploration and exploitation through structural design: The isolation of subgroups and organizational learning', *Organization Science* pp. 625–642.

Farringdon, J., Moore, A. J., Tilbury, N., Church, J. & Biemond, P. (1999), 'Wearable sensor badge & sensor jacket for context awareness', *Proceedings of the 3rd International Symposium on Wearable Computers* pp. 107–113.

Foltz, P. W. & Martin, M. J. (2009), *Automated communication analysis of teams. In Salas, E., Goodwin, G. F. and Burke, S. (eds.), Team Effectiveness in Complex Organizations*, Taylor & Francis Group, New York, NY.

Freeman, L. C. (1978), 'Centrality in social networks: Conceptual clarification', *Social Networks* **1**, 215–239.

Gabbai, J. M. E., Wright, W. A. & Allinson, N. M. (2003), Measuring and visualizing organizations by relating structure to performance, *in* 'Proc. of the IEEE International Conference on Industrial Informatics'.

Gatica-Perez, D. (2006), Analyzing group interactions in conversations: a review, *in* 'Proc. of the International Conference on Multisensor Fusion and Integration for Intelligent Systems'.

Gatica-Perez, D. (2009), 'Automatic nonverbal analysis of social interaction in small groups: a review', *Image and Vision Computing* **27**(12), 1775–1787.

Gellersen, H. W., Schmidt, A. & Beigl, M. (2002), 'Multi-sensor context-awareness in mobile devices and smart artefacts', *ACM Journal on Mobile Networks and Applications* **7**(5), 1–17.

Gibson, J. L., Ivancevich, J. M., Donnelly, J. H. & Konopaske, R. (2009), *Organizations: Behavior, Structure, Processes*, McGraw-Hill Irwin, New York, NY.

Girvan, M. & Newman, M. E. (2002), 'Community structure in social and biological networks', *PNAS* pp. 7821–7826.

Gloor, P. A., Oster, D., Raz, O., Pentland, A. & Schoder, D. (2010), 'The virtual mirror: Reflecting on the social and psychological self to increase organizational creativity', *Int. Studies of Mgt. & Org.* **40**(2), 74–94.

Gloor, P., Laubacher, R., Dynes, R. & Zhao, S. (2003), Visualization of communication patterns in collaborative innovation networks: Analysis of some w3c working groups, *in* 'Proceedings of the ACM CKIM International Conference on Information and Knowledge Management'.

Granovetter, M. S. (1973), 'The strength of weak ties', *American Journal of Sociology* (6), 1360–1380.

Greve, A., Benassi, M. & Dag-Sti, A. (2010), 'Exploring the contributions of human and social capital to productivity', *International Review of Sociology* **20**(1), 35–58.

Guo, F., Hanneke, S., Fu, W. & Xing, E. P. (2007), Recovering temporally rewiring networks: A model-based approach, *in* 'Proc. of the 24th International Conference on Machine Learning'.

Hanneke, S., Fu, W. & Xing, E. P. (2010), 'Discrete temporal models of social networks', *Electronic Journal of Statistics* **4**, 585–605.

Harrison, R., Lin, Z., Carroll, G. R. & Carley, K. M. (2007), 'Simulation modeling in organizational and management research', *Academy of Management Review* pp. 1229–1245.

Harter, A., Hopper, A., Steggles, P., Ward, A. & Webster, P. (1999), The anatomy of a context-aware application, *in* 'Proc. of the 5th Annual ACM/IEEE International Conference on Mobile Computing and Networking', ACM Press, New York, NY, pp. 59–68.

Heubach, J. G., Montgomery, J. C., Weimer, W. C. & Heerwagen, J. H. (1995), A case study: Integrated work environment and organisational change, *in* 'Proc. of the Third International Symposium on Productivity & Quality Improvement Conference', pp. 1–9.

Hodges, S. (2006), 'Sensecam: a retrospective memory aid', *Ubicomp 2006, LNCS* **4206**, 177–193.

Hoegl, M. & Proserpio, L. (2004), 'Team member proximity and teamwork in innovative projects', *Research Policy* **3**, 1153–1165.

Hough, L. M. (1992), 'The "big five" personality variables - construct confusion: Description versus prediction', *Human Performance* **5**(1), 139–155.

Hunter, J. E. & Schmidt, F. L. (1996), 'Intelligence and job performance: Economic and social implications', *Psychology, Public Policy, and Law* **2**(3-4), 447–472.

Jackson, M. O. (2008), *Social and Economic Networks*, Princeton University Press, Princeton, NJ.

Jamal, M. (1984), 'Job stress and job performance controversy: An empirical assessment', *Organizational Behavior and Human Performance* **33**(1), 1–21.

Jiang, B. C., Wang, C. C., Lu, J., Jen, C. H. & Fan, S. K. (2009), 'Using simulation techniques to determine optimal opterational region for multi-responses problems', *International Journal of Production Research* **47**(12), 3219–3230.

Johnson, D. W. & Johnson, R. T. (1999), 'Making cooperative learning work', *Theory into Practice* **38**(2), 67–73.

Jones, G. J. F. & Brown, P. J. (2002), Challenges and opportunities for context-aware retrieval on mobile devices, *in* 'Proc. of the Workshop on Mobile Personal Information Retrieval at Twenty-Fifth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval', pp. 47–56.

Judge, T. A., Thoresen, C. J., Bono, J. E. & Patton, G. K. (2001), 'The job satisfaction-job performance relationship: A qualitative and quantitative review', *Psychological Bulletin* **127**(3), 376–407.

Karantonis, D. M., Narayanan, M. R., Mathie, M., Lovell, N. H. & Celler, B. G. (2006), 'Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring', *IEEE Transactions on Information Technology and Biomedicine* **10**(1), 156–167.

Kauffman, S. (1993), *The Origins of Order*, Oxford University Press, New York, NY.

Kern, N. & Schiele, B. (2003), Context-aware notification for wearable computing, *in* 'Proc. of the 7th International Symposium on Wearable Computers', pp. 223–230.

Kilduff, M. & Brass, D. J. (2010), 'Job design: A social network perspective', *Journal of Organizational Behavior* **31**, 309–318.

Kim, T., Bian, L., Hinds, P. & Pentland, A. (2010), Encouraging cooperation using sociometric feedback, *in* 'Proc. of the ACM Conference on Computer Supported Cooperative Work'.

Kim, T., Chang, A., Holland, L. & Pentland, A. (2008), Meeting mediator: enhancing group collaboration using sociometric feedback, *in* 'Proc. of the ACM Conference on Computer Supported Cooperative Work', pp. 457–466.

Kim, T., Olguín-Olguín, D., Waber, B. N. & Pentland, A. (2009), Sensor-based feedback systems in organizational computing, *in* 'Proc. of the Workshop on Social Computing with Mobile Phones and Sensors at the IEEE International Conference on Social Computing', pp. 1–4.

Kim, T. & Pentland, A. (2009), Understanding effects of feedback on group collaboration, *in* 'Proc. of the AAAI Spring Symposium on Human Behavior Modeling', pp. 1–6.

Kluger, A. N. & DeNisi, A. (1998), 'Feedback interventions: Toward the understanding of a double-edged sword', *Current Directions in Psychological Science* **7**(3), 67–72.

Kozlowski, S. W. J. & Ilgen, D. R. (2006), 'Enhancing the effectiveness of work groups and teams', *Psychological Science in the Public Interest* **7**(3), 77–124.

Krebs, V. (n.d.), 'Social network analysis', *Retrieved on April 26, 2008 from:* ¡http://www.orgnet.com/sna.html¿.

Kuhn, H. (1955), 'The hungarian method for the assignment problem', *Naval Research Logistics Quarterly* **2**(1/2), 83–97.

Laibowitz, M., Gips, J., Aylward, R., Pentland, A. & Paradiso, J. A. (2006), A sensor network for social dynamics, *in* 'Proceedings of the 5th International Conference on Information Processing in Sensor Networks', pp. 483–491.

Lazer, D. & Friedman, A. (2007), 'The network structure of exploration and exploitation', *Administrative Science Quarterly* **52**, 667–694.

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D. & et al. (2009), 'Computational social science', *Science* pp. 721–723.

Lee, S. W. & Mase, K. (2002), 'Activity and location recognition using wearable sensors', *Pervasive Computing* **1**(3), 24–32.

Lochbaum, M. R., Karoly, P. & Landers, D. M. (2002), 'Evidence for the importance of openness to experience on performance of a fluid intelligence task by physically active and inactive participants', *Research Quarterly for Exercise and Sport* pp. 1–12.

Magalhães, R. & Rito Silva, A. (2009), Organizational design and engineering (ode). working paper no. 1, Technical report, Center for Organizational Design and Engineering. Lisbon, Portugal.

Mantyjarvi, J., Himberg, J., Kangas, P., Tuomela, U. & Huuskonen, P. (2004), Sensor signal data set for exploring context recognition of mobile devices, *in* 'Proc. of the 2nd International Conference on Pervasive Computing', pp. 1–6.

Mantyjarvi, J., Himberg, J., Seppanen, T. & Center, N. (2001), Recognizing human motion with multiple acceleration sensors, *in* 'Proc. of the IEEE International Conference on Systems, Man, and Cybernetics', pp. 747–752.

March, J. G. & Sutton, R. I. (1997), 'Organizational performance as a dependent variable', *Organization Science* **8**(6), 698–706.

Martin, J. (1995), *The Great Transition: Using the Seven Disciplines of Enterprise Engineering*, AMACOM, New York, NY.

Mathie, M. J., Coster, A. C. F., Lovell, N. H. & Celler, B. G. (2004), 'Accelerometry: providing an integrated, practical method for long-term ambulatory monitoring of human movement', *Physiological Measurement* **25**(4), R1–R20.

Meyer, M. A. (2006), Use of location data for the surveillance, analysis, and optimization of clinical processes, Master's thesis, Massachusetts Institute of Technology.

Mishra, N., Schreiber, R., Stanton, I. & Tarjan, R. (2007), 'Clustering social networks', *Lecture Notes in Computer Science* **4863**(2007), 56–67.

Monge, P. R., Rothman, L. W., Eisenberg, E. M., Miller, K. I. & Kirste, K. K. (1985), 'The dynamics of organizational proximity', *Management Science* **31**(9), 1129–1141.

Mouchtaris, A., Cao, Y., Khan, S., der Spiegel, J. V. & P.Mueller (2005), Combined software/hardware implementation of a filterbank front-end for speech recognition, *in* 'Proceedings of the IEEE Workshop on Signal Processing Systems Design and Implementation'.

Mount, M. K. & Barrick, M. R. (1998), 'Five-factor model of personality and performance in jobs involving interpersonal interactions', *Human Performance* **11**(2/3), 145–165.

Myers, R. H., Montgomery, D. C. & M., A.-C. C. (2009), *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*, John Wiley & Sons, Hoboken, NJ.

Nemati, H. R. & Barko, C. D. (2004), *Organizational Data Mining: Leveraging Enterprise Data Resources for Optimal Performance*, Idea Group Publishing, London, UK.

Niinimaki, T., Piri, A., Hynninen, P. & Lassenius, C. (2009), Studying communication in agile software development: a research framework and pilot study, *in* 'Proc. of the ICMI-MLMI Workshop on Multimodal Sensor-Based Systems and Mobile Phones for Social Computing', pp. 1–4.

Ntag Interactive (n.d.). http://www.ntag.com/.

Olguín-Olguín, D. (2007), Sociometric badges: wearable technology for measuring human behavior, Master's thesis, Massachusetts Institute of Technology.

Olguín-Olguín, D., Gloor, P. A. & Pentland, A. (2009), Wearable sensors for pervasive healthcare management, *in* 'Proc. of the 3rd International Conference on Pervasive Computing Technologies for Healthcare', pp. 1–4.

Olguín-Olguín, D. & Pentland, A. (2008), Social sensors for automatic data collection, *in* 'Proc. of the 14th Americas Conference on Information Systems', pp. 1–10.

Olguín-Olguín, D. & Pentland, A. (2010*a*), Assessing group performance from collective behavior, *in* 'Proc. of the CSCW 2010 Workshop on Collective Intelligence in Organizations', pp. 1–5.

Olguín-Olguín, D. & Pentland, A. (2010*b*), 'Sensor-based organisational design and engineering', *International Journal of Organisational Design and Engineering* **1**(1/2), 69–97.

Olguín-Olguín, D., Waber, B., Kim, T., Mohan, A., Ara, K. & Pentland, A. (2009), 'Sensible organizations: technology and methodology for automatically measuring organizational behavior', *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics* **39**(1), 43–55.

Oliver, N., Garg, A. & Horvitz, E. (2004), 'Layered representations for learning and inferring office activity from multiple sensory channels', *Computer Vision and Image Segmentation* **96**, 163–180.

Organizational-Engineering-Institute (2007), 'Organizational research and knowledge', *Retrieved on December 19, 2007 from:* [http://www.oeinstitute.org/index.htm].

Osborne, J. W. (2000), 'Prediction in multiple regression', *. Practical Assessment, Research & Evaluation* **7**(2), 1–9.

Otte, E. & Rousseau, R. (2002), 'Social network analysis: a powerful strategy, also for the information sciences', *Journal of Information Science* **28**(6), 441–453.

Palla, G., Barabasi, A. L. & Vicsek, T. (2007), 'Quantifying social group evolution', *Nature* pp. 664–667.

Pantic, M., Pentland, A., Nijholt, A. & Huang, T. S. (2007), 'Human computing and machine understanding of human behavior: a survey', *Human Computing* **4451**(2007), 47–71.

Paradiso, J., Gips, J., Laibowitz, M., Sadi, S., Merrill, D., Aylward, R., Maes, P. & Pentland, A. (2010), 'Identifying and facilitating social interaction with a wearable wireless sensor network', *Personal and Ubiquitous Computing* **14**(2), 137–152.

Park, S., Locher, I., Savvides, A., Chen, A., Muntz, R. & Yuen, S. (2002), 'Design of a wearable sensor badge for smart kindergarten', *Proceedings of the 6th International Symposium on Wearable Computers* pp. 231–238.

Pentland, A. (2005), 'Socially aware computation and communication', *IEEE Computer* **38**(3), 33–40.

Pentland, A. (2007), 'On the collective nature of human intelligence', *Adaptive Behavior* **15**(2), 189–198.

Pentland, A. (2008), *Honest Signals: How they Shape our World*, The MIT Press, Cambridge, MA.

Pentland, A., Choudhury, T., Eagle, N. & Singh, P. (2004), 'Human dynamics: computation for organizations', *Pattern Recognition Letters* **26**(2005), 503–511.

Poole, M. S., Hollingshead, A. B., McGrath, J. E., Moreland, R. L. & Rohrbaugh, J. (2004), 'Interdisciplinary perspectives on small groups', *Small Group Research* **35**(1), 3–16.

Reijswound, V. v. & Lind, M. (1998), Comparing two business modeling approaches in the language action perspective, *in* 'Proc. of the International Workshop on Communication Modeling', pp. 1–17.

Richard, P. J., Devinney, T. M., Yip, G. S. & Johnson, G. (2008), Measuring organizational performance as a dependent variable: Towards methodological best practice, Technical report, University of New South Wales. Available at SSRN: http://ssrn.com/abstract=814285.

Rivkin, J. W. & Siggelkow, N. (2007), 'Patterned interactions in complex systems: Implications for exploration', *Management Science* **53**(7), 1068–1085.

Robbins, S. P. (2005), *Essentials of Organizational Behavior*, Pearson Prentice Hall, Upper Saddle River, NJ.

Robins, G., Snijders, T., Wang, P., Handcock, M. & Pattison, P. (2007), 'Recent developments in exponential random graph (p*) models for social networks', *Social Networks* **29**(2), 192–215.

Rothwell, W. J., Stavros, J. M. & Sullivan, R. L. (2010), *Practicing Organization Development: A Guide for Leading Change*, John Wiley & Sons, San Francisco, CA.

Rulke, D. L. & Galaskiewicz, J. (2000), 'Distribution of knowledge, group network structure, and group performance', *Management Science* **46**(5), 612–625.

Sahinler, S. & Topuz, D. (2007), 'Bootstrap and jackknife resampling algorithms for estimation of regression parameters', *Journal of Applied Quantitative Methods* **2**(2), 188–199.

Samarth, C. N. (2007), It adoption in hospitals: Social networking, governance and the clockspeed of change, Master's thesis, Massachusetts Institute of Technology.

Shpuza, E. (2006), Floorplate Shapes and Office Layouts: A Model of the Effect of Floorplate Shape on Circulation Integration, PhD thesis, Georgia Institute of Technology, Atlanta, GA.

Slaughter, A. J., Yu, J. & Koehly, L. M. (2009), *Social network analysis: understanding the role of context in small groups and organizations. In Salas, E., Goodwin, G. F. and Burke, S. (eds.), Team Effectiveness in Complex Organizations*, Taylor & Francis Group LLC, New York, NY.

Smith, E. R. & Conrey, F. R. (2007), 'Agent-based modeling: A new approach for theory building in social psychology', *Personality and Social Psychology Review* pp. 87–104.

Snijders, T. A. (2001), 'The statistical evaluation of social network dynamics', *Sociological Methodology* pp. 361–395.

Snijders, T. A., Pattison, P. E., Robins, G. L. & Handcock, M. (2006), 'New specifications for exponential random graph models', *Sociological Methodology* pp. 99–153.

Snijders, T. A., van de Bunt, G. G. & Steglich, C. E. G. (2010), 'Introduction to stochastic actor-based models for network dynamics', *Social Networks* **32**(1), 44–60.

Sparrowe, R. T., Liden, R. C., Wayne, S. J. & Kraimer, M. L. (2001), 'Social networks and the performance of individuals and groups', *The Academy of Management Journal* **44**(2), 316–325.

Stocker, R., Green, D. G. & Newth, D. (2001), 'Consensus and cohesion in simulated social networks', *Journal of Artificial Societies and Social Simulation* **4**(4), 1–14.

Sycara, K. & Lewis, M. (2008), Agent-based approaches to dynamic team simulation, Technical report, Bureau of Naval Personnel.

Tosi, H. L., Mero, N. P. & Rizzo, J. R. (2000), *Managing Organizational Behavior*, Blackwell Publishers Inc., Cambridge, MA.

Tourish, D. & Hargie, O. (2009), *Communication and organizational success. In Hargie, O. and Tourish, D. (eds.), Auditing Organizational Communication*, Routledge, New York, NY.

Tushman, M. L. & Nadler, D. A. (1978), 'Information processing as an integrating concept in organizational design', *Academy of Management Review* pp. 613–624.

Tushman, M. L. & Nadler, D. A. (1997), 'Social structure and competition in interfirm networks: The paradox of embeddedness', *Administrative Science Quarterly* **42**(1), 35–67.

Van de Bunt, G. G. & Groenewegen, P. (2007), 'An actor-oriented dynamic network approach: The case of interorganizational network evolution', *Organizational Research Methods* **10**(3), 463–482.

Van Laerhoven, K., A., S. & W., G. H. (2002), Multi-sensor context aware clothing, *in* 'Proc. of the 6th IEEE International Symposium on Wearable Computers', pp. 49–56.

Van Laerhoven, K. & Cakmakci, O. (2000), What shall we teach our pants?, *in* 'Proc. of the 4th International Symposium on Wearable Computers', pp. 77–83.

Waber, B. N., Olguín-Olguín, D., Kim, T. & Pentland, A. (2008), Organizational engineering using sociometric badges, *in* 'Proc. of the Academy of Management Annual Meeting', pp. 1–36.

Waber, B. N., Olguín-Olguín, D., Kim, T. & Pentland, A. (2010), Productivity through coffee breaks: Changing social networks by changing break structure, Technical report, MIT Media Laboratory. Available at SSRN: http://ssrn.com/abstract=1586375.

Want, R., Hopper, A., Falcao, V. & Gibbons, J. (1992), 'The active badge location system', *ACM Transactions on Information Systems* **10**(1), 91–102.

Wasserman, S. & Faust, K. (1994), *Social Network Analysis: Methods and Applications*, Cambridge University Press, London, UK.

Wasserman, S. & Faust, K. (2005), *Social Network Analysis: Methods and Applications*, Cambridge University Press, Cambridge, UK.

Wehrli, S. (2008), Personality on social network sites: An application of the five factor model, Eth zurich sociology working papers, ETH Zurich.
URL: *http://ideas.repec.org/p/ets/wpaper/7.html*

Weick, K. & Quinn, R. (2004), *Organizational change and development. In Boonstra, J. J. (ed.), Dynamics of Organizational Change and Learning*, John Wiley & Sons, West Sussex, England.

Williams-Woolley, A., Chabris, C. F., Pentland, A., Hashmi, N. & Malone, T. W. (2010), 'Evidence for a collective intelligence factor in the performance of human groups', *Science* **DOI: 10.1126/science.1193147**, 1–5.

Winograd, T. (1986), A language action perspective on the design of cooperative work, *in* 'Proc. of the ACM Conference on Computer-Supported Cooperative Work', pp. 203–220.

Winter, R. & Fisher, R. (2007), 'Essential layers, artifacts, and dependencies of enterprise architecture', *Journal of Enterprise Architecture* pp. 1–12.

Wu, L., Waber, B. N., Aral, S., Brynjolfsson, E. & Pentland, A. (2008), Mining face-to-face interaction networks using sociometric badges: predicting productivity in an it configuration task, *in* 'Proc. of the International Conference on Information Systemse', pp. 1–19.

Yang, H. L. & Tang, J. H. (2003), 'Effects of social network on students' performance: A web-based forum study in taiwan', *Journal of Asynchronous Learning Networks* pp. 93–107.

Yuan, Y. C., Fulk, J., Monge, P. R. & Contractor, N. (2010), 'Expertise directory development, shared task interdependence, and strength of communication network ties as mulitlevel predictors of expertise exchange in transactive memory workgroups', *Communication Research* **37**(1), 20–47.

Yuan, Y. C., Monge, P. R. & Fulk, J. (2007), 'The impact of social capital on the development of transactive memories in multilevel group knowledge systems'.

Zagenczyk, T. J., Murrell, A. J. & Gibney, R. (2007), 'Effects of the physical work environment on the creation of individual- and group-level social capital', *International Journal of Organizational Analysis* **15**(2), 119–135.

Zollinger, T. W. & Saywell, R. M. J. (1999), 'Delays in patient transfer: postanesthesia care nursing', *Nursing Economics* **17**(5), 283–290.