Rhythm: A Unified Measurement Platform for Human Organizations

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Rhythm: A Unified Measurement Platform for Human Organizations

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***Abstract*—To understand and manage complex organizations, we must develop tools capable of measuring human social interaction accurately and uniformly. Current technologies that measure face-to-face communication do not measure interaction in a unified manner and often ignore remote interaction, an increasingly common communication modality. In this paper we present Rhythm, a platform that combines wearable electronic badges and online applications to capture team-level and network-level interaction patterns in organizations. The platform measures conversation time, turn-taking behavior, and the physical proximity of both co-located and distributed members. Our goal is to empower organizations and researchers to measure formal and informal social interaction across teams, divisions, and locations. We describe two pilot studies that use this platform and discuss how measurement systems like Rhythm may further the fields of computational social science and organizational design.**

***Keywords*—Organizational management and coordination, Computer-supported collaborative work, Social and Behavioral Sciences, Social science methods or tools, Nonverbal signals, Wearable computers, Video analysis**

I. Introduction

Large-scale and complex problems solved by today's modern organizations are not solved by individuals, but by teams of people working together to achieve common goals. Academic research is a heavily studied example of such dynamics, where teams have come to dominate individual authors, both in quantity and impact of results [1]. This pattern of organizational behavior and structure, where teams serve as the basic unit of work, has transformed modern organizations in many fields [2], [3].

As team-based work becomes central to organizations, understanding the effectiveness of groups has become an active area of social, managerial, and psychological research. Some of the most promising group studies leverage wearable sensors to quantify signals such as speaking patterns and body language [2]. These signals, which represent the internal structure and communication patterns of a group, have been shown to be highly predictive of group performance in some laboratory tasks [4]. In naturalistic settings, the face-to-face cohesion of physically co-located teams is an important factor in group productivity [5]. Team communication and behavior can be measured and used effectively to predict group performance in a variety of tasks.

However, modern teams don't perform tasks, solve problems, or generate creative solutions independently from the highly networked systems that they are a part of. Members of teams that are part of larger organizational networks are invariably influenced by other groups and individuals that they communicate with. This communication brings with it network effects that greatly impact the success and behavior of teams. Prior work on group dynamics and organizational structure has shown that it is these inter-group network ties, combined with the dynamics of each individual group that, fully characterizes an organization [6].

It is clear that to work towards a more fully informed organizational network science, tools must be developed that measure not just the intra-communication patterns within teams, but the interactions between teams in an organization. Prior literature has attempted to do this by using email and text-based communication networks as a proxy for inter-team ties, as these modalities are easy to instrument and analyze. However, interaction patterns, the quality of information flow, and the trust dynamics of a group are influenced by the richness of the communication modality used. Networks constructed from email, a non-rich modality of communication, have been found to misrepresent the true flow of information in an organization when compared to face-to-face interaction, the richest communication modality available to humans [5], [7]. To accurately represent communication networks in an organization, face-to-face interaction has to be measured.

While prior systems can quantify face-to-face interactions between individuals that are co-located, organizations are increasingly leveraging video conferencing as a communication medium. Video conferencing has been shown to closely mimic the dynamics of face-to-face interaction, suggesting that this modality may be more representative of idea flow between individuals and teams than text-based chat or email [8]. Capturing these rich team interactions may provide a more complete understanding of an organization's dynamics than co-located face-to-face communication and email alone.

We present our open source hybrid software-hardware platform, Rhythm, capable of measuring face-to-face interaction in co-located and distributed contexts. Rhythm captures team-level and network-level interactions in organizations; wearable electronic badges measure in-person interaction and online applications measure remote communication. This system is the first unified cohesive organizational measurement tool that instruments both distributed and co-located interactions seamlessly. This innovation in instrumentation allows for a more

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complete and accurate representation of the interaction patterns and social "rhythm" of organizations, including those that span multiple physical locations. Tools like Rhythm may help us design, engineer, and experiment within today's modern organizations.

II. Background, previous work, and motivation

A. Co-Located Interaction Using Electronic Badges

In co-located spaces, many interactions are informal or unintentional; People run into each other in corridors, have discussions at the coffee machine, or stop at each others' offices to talk. Data gathered from such interactions provides valuable insights into the underlying structure of organizations, communication between different teams, and other measures of organizational health [2]. Measuring these interactions within large organizations and spaces using traditional methods (e.g. activity journals) can be impractical, and often biased.

Recent technological advances have made it possible to gather longitudinal data on face-to-face interaction. Electronic wearable devices, typically in the form factor of a conference badge, use RFID, Bluetooth, and infrared sensors to collect detailed interaction data using proximity. The Sociometric Badge incorporates the addition of a microphone, used for measuring non-linguistic communication patterns[9].

The open source Rhythm Badge [10], part of the Rhythm platform, further advances the state of the art. It has a longer battery life and a smaller form factor as compared to the Sociometric Badge, and its minimalist design makes it much more affordable to make. The Rhythm Badge enables the automatic measurement of social interaction in a form factor similar to employee name tags, making it more socially acceptable to wear and easier to use.

B. Distributed Interaction Using Online Platforms

Distributed teams are an indispensable reality of organizations today, and video conferencing is fast becoming the dominant way these teams interact. While video conferencing allows members to communicate non-verbal cues that voice-only communication lacks, the dynamics of video conferencing groups are very different from co-located teams [11]. Prior work on measuring distributed interaction in organizations mostly examines email and other text-based communication, not rich face to face interaction. Much of the research on virtual teams is also based on lab experiments examining groups with prescribed team sizes and meeting goals, rather than naturalistic interaction. The Rhythm platform includes a web-based client that measures and augments distributed group communication at scale in natural organizational settings [12].

C. Electronic Interaction Through Email

Email-based social network analysis has been used to measure social ties between members of an organization. It provides easily quantifiable metrics in the form of who sent an email, to whom and when. Email analysis has provided insights into the structure of the informal and formal social networks of organizations, revealing central nodes, key influencers, and hierarchy [13]. Developments in natural language processing, word spotting and sentiment analysis can further help provide additional insights into the team dynamics and network structure of organizations. However, previous studies have demonstrated that the social network represented through email alone differs from that obtained through face-to-face interaction [7]. With important and information-rich communications usually being face-to-face [9], measuring and influencing teams within a broader organizational context requires an integrated approach that can combine multiple communication channels.

III. Technical Overview

For clarity, we define four kinds of face-to-face interactions that may occur between members of an organization: informal face-to-face interaction in a co-located space, formal face-to-face meetings in a co-located space, face-to-face meetings where all participants communicate remotely through video-conference, and mixed face-to-face meetings, where a group of co-located members communicate with other co-located groups or individuals over video-conference. We use a novel combination of a wearable electronic badge and a web-client to measure social interaction for the above face-to-face interactions in a unified manner. Figure 1 shows the Rhythm platform.

We use a wearable electronic badge to instrument both informal face-to-face interactions and co-located formal meetings. These badges continuously capture an individual member's vocal activity and her proximity to other members who are wearing a badge. These badges can be easily deployed in any location scalably and cost-effectively.

For distributed meetings, we use a web client that allows the instrumentation of on-line voice and video-conference interaction. The client captures vocal activity and facial expressions.

Finally, for mixed face-to-face meetings, we combine the two subsystems – members at each distributed location join the meeting using the web client, and badges are used to distinguish the vocal activity of members who are at the same location.

All three configurations of the system make use of a back-end server and support real-time feedback to augment the social interaction.

A. Measuring Co-Located Informal Interaction

Informal interaction patterns in organizations are an important signal that we aim to measure using Rhythm Badges (Figure 2a). To measure co-located informal interaction in organizations, the platform uses badges in conjunction with a network of stationary "hubs" that collect sensing data from the badges in real-time.

Each badge collects three types of data - vocal activity, proximity to other badges, and location (using location beacons). In order to detect speaking activity, the badge samples the microphone signal at $700Hz$ and creates an average amplitude reading every 50 milliseconds. No audio is recorded and the

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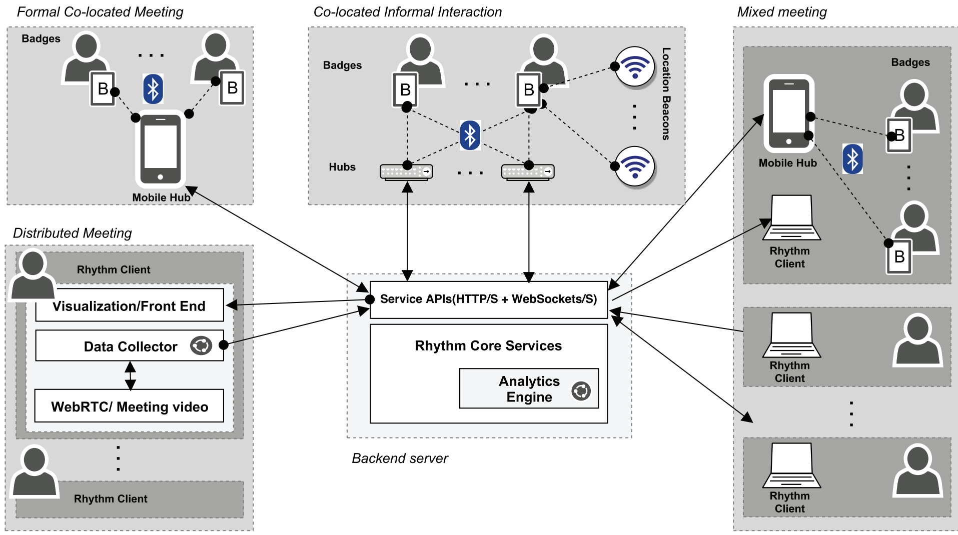
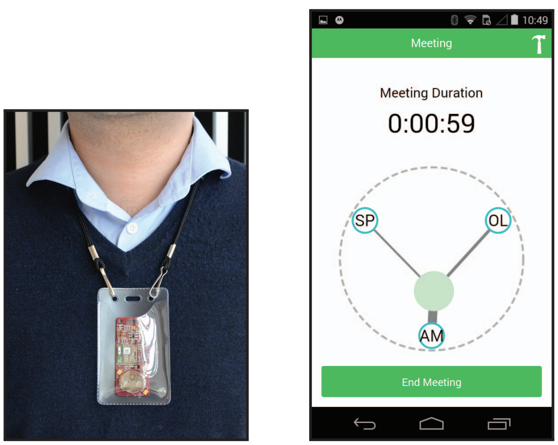


Fig. 1: The Rhythm framework. Measuring co-located informal interactions uses electronic badges as data collectors, location beacons for localization, and hubs for transferring the data from the badges to the server. Measuring Co-located formal meetings requires electronic badges and a mobile hub. Measuring distributed meeting makes used of on-line clients. Measuring mixed-meetings uses both the badges sub-system and on-line clients.



(a) (b)

Fig. 2: Components of the badge sub-system. A Rhythm Badge in a plastic holder, worn around the neck (Figure 2a) and an example of the real-time visualization in the mobile hub Figure 2b.

audio cannot be re-generated from the stored samples. This data is used for measuring communication patterns.

A multi-step voice activity detection (VAD) algorithm is then applied to the raw data. To reduce noise, we compute the power of each badge's audio signal over a sliding window using Equation 1, where P_n is the power of signal x at sample n, and where w is the window size. We set w equal to one minute in our experiments. We use an experimentally set threshold on this signal to determine if a participant is speaking. If more than one active speaker is detected for a given sample n in a group, we consider only the speaker with the highest signal power as speaking. This approach assumes that groups have a single speaker at any given time, but it also makes our speech detection more robust to false positives from background noise or the attenuated speech of nearby participants.

$$P_n = \frac{1}{w} \sum_{i=n-w+1}^{n} x_i^2 \tag{1}$$

To determine proximity to other badges and beacons, badges scan for nearby Bluetooth devices every sixty seconds, and record the RSSI values of each device. We found that a signal strength of -59dB produced the best results to identify pairs of badges that are up to four feet apart.

The Rhythm badges can run for five to six days on a single charge, and can collect several hours of vocal activity and proximity data before needing to wirelessly sync to a hub. Hubs receive transmitted data from badges, transfer it to a back-end server offsite, and monitor badges' status.

B. Measuring Co-Located Formal Meetings

Scheduled meetings are another common kind of face-to-face interaction in co-located spaces. The data from these meetings is similar to the data presented in the previous section, but it usually describes longer and more formal interactions.

Here, we use the same badges and a mobile app as a hub. In the mobile app, the members can see which badges are in range, add relevant badges to the meeting, and collect data

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from the badges. The app is also capable of providing real-time feedback to users (Figure 2b).

The mobile hub can collect meeting data in any location, even when there is no Internet connection - the data is cached on the mobile device and sent to a server once a connection can be established. The mobile hub is also useful for ad-hoc meetings and for settings where deployment of stationary hubs is impractical.

C. Measuring Distributed Face-to-Face Meetings

Many modern organizations are composed of distributed teams that communicate in formal meetings using video conferencing solutions. To measure these meetings and provide feedback to team members, we have created a web-based client with three main parts. The system consists of a video chat client, a data collector that processes the raw interaction data from the client, and a tool capable of visualizing this data to users of the system. Together, these pieces enable us to collect interaction data and quickly develop prototype interventions in the form of real time visualizations.

The modular design of the data collection system allows for integration with a wide range of video chat clients. We have developed open-source example systems that use commercial video conference applications such as Google Hangouts and custom-built video conferencing systems built on the open-source WebRTC protocol. Our custom-built system uses WebRTC as it is an emerging web standard in peer-to-peer communication that can easily scale without significant investment in infrastructure. It has also allowed us to fully customize a user experience without relying on limited APIs offered by commercial video conferencing solutions.

The data collector uses the API exposed by video-chat platform to retrieve interaction data in real-time. The data gathered is dependent on the underlying video conferencing platform, but the primary data collected is speaker history, excluding the linguistic content of speech. To detect and isolate voiced speech, we first apply a band-pass filter to isolate signal between 85Hz and 583Hz. We use an experimentally-set threshold of 40dB as a speaking threshold, and treat any segment of time under the threshold longer than 500ms as silence. This is done independently for each speaker, which allows us to identify overlapping speaking events, a signal that may reveal important social relationships between group members [14].

If the custom WebRTC platform is used, additional data such as tonal information and face tracking data are also collected, providing quantitative data on expressed emotions and body language. We use a constrained local models approach to calculate important feature points of the face [15]. Figure 3 illustrates example audio and facial statistics computed from two separate three-person meetings using the WebRTC platform.

D. Measuring Mixed Face-to-Face Meetings

Mixed face-to-face meetings present a unique challenge. To understand the dynamics of a mixed meeting, a system has to differentiate between multiple speakers on the same end-point of a video call. Traditional diarization methods necessitate either training using voice samples or the usage of multiple microphones. While effective, these techniques require additional work on the part of the user or significant infrastructure investment.

The Rhythm framework provides an accessible and user-friendly system that is able to perform diarization. When two or more people join a video-chat from the same end-point, each of them is required to wear a badge, and register the badge as part of the meeting using the mobile hub app. A computer is used for the video-feed, sound, and real-time visualization. The mobile hubs perform pre-processing on the raw badges data and send the data to the back-end server where it can be used by the analytics engine.

While the use of both a mobile app and a web browser might seem cumbersome, we find it to be the most convenient solution at this time. We expect future version of Rhythm to replace the mobile app with a browser-based solution using the Web Bluetooth API, which is currently in an early beta.

E. Back-end server

Data collected by the system is stored in a secure server, processed in real-time by the analytics engine, and then made available through an API. The server also provides APIs for managing and tracking meeting attendance and badges' ownership.

The Analytics Engine is a small server-side application that analyzes and aggregates interaction and event data collected from the platform. It exposes a secure, real-time API, allowing authorized researchers and applications to access the computed data. The data collected by the Rhythm system is by nature intensely personal; to ethically scale frameworks like Rhythm, it will be important to consider personal data ownership and security in future system designs.

The Analytics Engine currently generates aggregate statistics such as (i) number of speaking events per person (ii) response patterns between members (iii) frequency of turn-taking, a measure of engagement in team communication [16], and (iv) percentage of overlapped speaking time.

F. Socially Aware Feedback

In remote interactions in particular, crucial non-verbal and non-linguistic social cues are often lost or misinterpreted [16]. This can lead to confusion and frustration between team members as they miss cues used to signal turn taking, participation, and emotions [8], [11].

To overcome these challenges, researchers have developed tools to augment social interaction with the goal of improving awareness of these social cues and the information they convey. Past work on small team dynamics showed that post-hoc and real-time feedback help increase interaction balance, decrease dominant behavior, and improve collaboration in co-located meetings [14], [16]. The Meeting Mediator system was also shown to increase the effectiveness of distributed collaboration[16].

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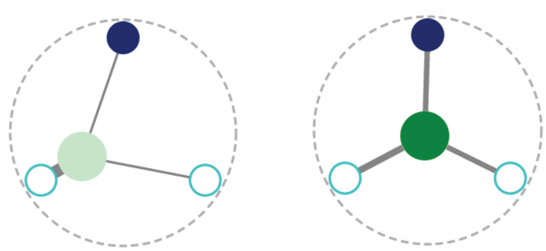
Fig. 3: Example data collected and processed by the Analytics Engine for two 3-person face-to-face remote meetings with the custom WebRTC platform. Face movement indicates the average absolute change of tracked facial points for each participant. Speech Activity is the number of utterances spoken by group members. Values are binned and averaged for each minute of the meeting.

We have included an intervention and augmentation system in the Rhythm platform with visualizations that are designed to compensate for the potential loss of social cues in remote and co-located interaction. The visualizations are designed to raise individual awareness of group social dynamics using data and statistics provided by the Rhythm platform.



(a) (b)

Fig. 4: Examples of the custom Meeting Mediator (MM) visualization used in the current system. Figure 4a shows an example of the MM visualization in a group with one dominant member and low team engagement, while 4b shows a group with high team engagement and no strongly dominant members. The solid blue dot at the top of the visualization indicates the speaker viewing the personal visualization, while other nodes represent other group members.

Figure 4 shows an example visualization currently built-in to the system that provides an overview of the turn-taking behavior between meeting members. This visualization is based on prior group interaction research, and has been shown to improve group performance, trust, and engagement, while not increasing cognitive load [16]. In this visualization, each node on the outer edge of the circle represents a meeting member, with the solid blue nodes representing the speaker who is viewing the visualization. As members take more frequent turns as a whole, the color of the green ball in the center becomes more intense. The ball moves closer to nodes (members) who take more turns, offering an ambient, objective representation of the group dynamics. Finally, the thickness of the lines between member nodes and the center ball corresponds with level of participation of each member.

The real-time visualization is shown on the mobile hub in co-located meetings and next to the video chat feed in distributed settings. The Rhythm platform can be further expanded to develop successful intervention strategies to improve team effectiveness of both co-located and distributed teams.

IV. System Usage & Evaluation

With the goal of measuring social interaction in an entire organization in mind, we evaluated the system in a series of deployments. This allowed us to gradually build and test the platform in environments that simulate the different types of interactions in real organizations. Here, we describe two field tests we performed and the data collected.

A. *Measuring Interaction In a Three Days Workshop*

Badges and hubs were used to measure team dynamics and inter-team communication during a three day workshop. The workshop had six teams with each team from a different country, with the goal of each team to develop an entrepreneurship and innovation strategy for their respective regions. Each team included one or more representatives from four sectors - government, entrepreneurship, university, and risk capital. The workshop consisted of a mix of lectures, where participants attend a group seminar, and breakout sessions, where each country's team met independently.

Each participant received a name tag that contained an electronic badge. Seven stationary hubs were placed in key locations (meeting rooms, common areas, lecture hall) to ensure good coverage and data integrity. Location beacons were placed in several areas in an attempt to discern when participants were in lecture vs in team breakout sessions.

We collected three days of data from fifty active participants (no participants opted-out).

To validate our data collection strategy, we analyzed the RSSI values reported by each badge during the workshop to automatically discover when breakout sessions occurred. Our data collection provided us with RSSI values for each badge-badge and badge-location beacon pairing every minute.

To detect breakout sessions, we are interested in discovering periods of time where the distance between group members is smaller than the general distance between participants as a whole. One approach to this problem might triangulate the position of badges in the dataset using the position of the beacons, but this requires precise measurement of the placement of hubs in a field test. We instead take an approach more robust to the position of beacons, and apply Multidimensional Scaling (MDS) to the pairwise distances between badges. We calculate

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this using Equation 2, an established method of computing distance from RSSI values, where p and n are parameters set through experimentation, and r is the observed RSSI value. For missing pairwise distances, we impute the maximum distance observed between badges.

$$d = 10^{\frac{p-r}{10n}} \tag{2}$$

We then apply Multidimensional Scaling, which discovers a two-dimensional embedding that retains the pairwise distances calculated from RSSI. Figure 5 shows embeddings for two 30-minute windows; one during a known lecture time, and one during a breakout session. There is clear visual separation between group members during the breakout session.

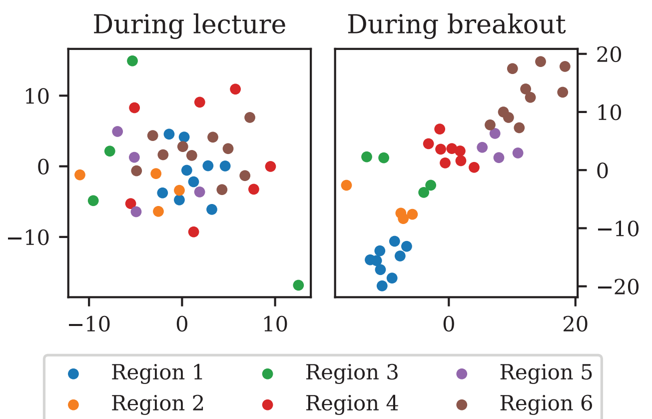

Fig. 5: An example of an MDS embedding of badge-badge pairwise distances, computed from RSSI values.

To attempt to automatically discover breakout meetings, we perform a cluster analysis, defining each group as a cluster. We compute the ratio of within-cluster mean distance to the total mean distance for each window of time. In the example given above, this ratio is computed to be 0.834 during lecture, and 0.294 during a breakout. To assess the significance of these results, we perform a two-tailed t-test on 20 hours of these ratios, computed over one-minute time bins. It shows, with a very high level of confidence ($p < 10^{-6}$), that the two distributions have unequal means. These preliminary results suggest that it may be possible to create a robust system for meeting discovery using the proximity data collected by the system.

A key requirement in this workshop was to have all stakeholders contribute to the discussion. After the workshop we used the vocal activity to generate participation reports for each team to help them reflect on their team dynamics. Figure 6 shows the contribution by stakeholders in Region 1. While all stakeholders contributed to the discussion, the figure shows that the Government stakeholders became more dominant on the third day.

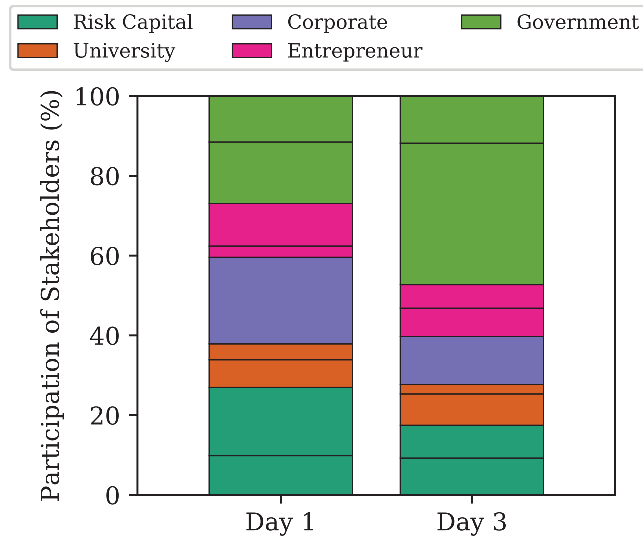

Fig. 6: Contribution to the discussion, by stakeholder, in Region 1

B. Mixed Face-to-Face Meetings

We set up a short user study to evaluate how the system can be used when multiple members join a video-conference meeting from distributed locations. In this experiment, we have five members joining the meeting from three different end-points – two members join from the first meeting room, two members join from a second meeting room, and a fifth member joins from home.

Figure 7 depicts the setting. Each member in the multi-member location wears a badge so that their vocal activity can be measured and distinguished from each other. The data from these badges is sent to the back-end server using a mobile phone equipped with our hub app. A laptop is used for the video streams and real-time visualization. The last member uses his or her laptop to join the call.

To start a meeting, one of the members creates a new meeting and shares the meeting ID with the other end-points. The participants in each end-point open the Rhythm WebRTC page and enter the meeting id in order to join the video chat. Finally, members in each end-point with multiple participants put on their badges, open the mobile app, and join the meeting so that badge data can be sent to the server.

As the members join the meeting, the end-points start sending data to the back-end server. The server, in turn, process the data and send aggregate statistics back to all the clients. These statistics is used for updating the visualization in real-time. Figures 8a and 8b show two co-located members using the system in a meeting, and a screenshot of the view from their web client, respectively.

This study helped us evaluate the quality and usability of the system. From a technical prospective, the system worked as expected – the real-time visualization reflected the contribution of each member, successfully distinguishing between members

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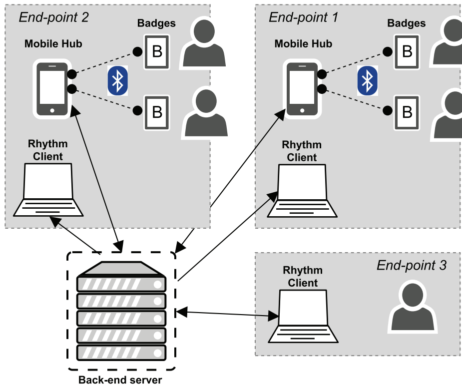
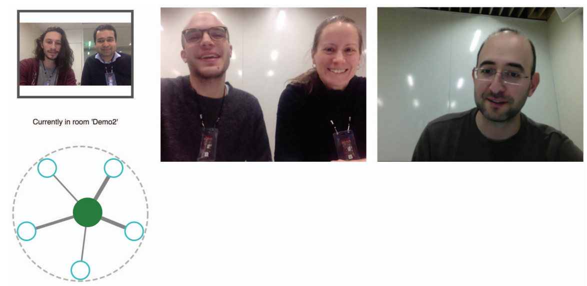


Fig. 7: Experimental Setting. Two participants join the meeting from one meeting room (end-point 1). Two participants join from s second office (end-point 2). One participant joins from home (end-point 3)

(a)



(b)

Fig. 8: An example of a mixed endpoint in a meeting using the Rhythm platform. The two members at the mixed endpoint in Figure 8a are using badges to collect information on their speaking patterns while using the Rhythm online system to communicate with other remote members. Figure 8b shows a screenshot of an example meeting using the Rhythm online system. In this meeting, there are two mixed endpoints that have multiple members wearing badges.

located at the same end-point.

From a usability prospective there is room for improvement. Initiating a meeting is still a cumbersome task, requiring both a mobile phone and a computer at multi-member end-points. To solve this issue, we are planning to consolidate the roles of the mobile phone and the computer into one device by creating a web application that can both support WebRTC and can connect to badges using the new Web Bluetooth API. However, at the time of writing, the Web Bluetooth API was still in its early stages of development and only supported by limited number of operating systems.

V. Conclusion

To understand and manage complex human organizations and networks, we must first be able to measure them effectively. In this paper, we present Rhythm, an open-source mixed software-hardware sensing platform that is capable of measuring face-to-face communication within organizations in real-time. The major innovation that the Rhythm system contributes is the ability to collect real-time, accurate empirical data that describes an organization's communication structure, even when such communication is spread across multiple modalities. We hope that systems like Rhythm may be used to develop a new paradigm of experimental inquiry into the nature of complex human systems.

Much of the prior work examining how network structure affects organizational behavior is firmly based in computational modeling and simulations [17]. With systems like Rhythm, such models may be empirically validated in naturalistic ”living labs” that are simply instrumented organizations. Past work that has empirically measured organizations in the way we describe has been technologically limited to conducting post-hoc analyses in order to understand network effects [9]. The sensing platform we present here is instead able to collect high-resolution interaction data in real time, a technological improvement that not only eases the technical burden on researchers and data collectors in the field, but also allows for the rapid development and measurement of interventions in complex social systems.

The ability to rapidly develop and measure system-level interventions has the potential to change how human organizations are constructed. By leveraging real-time interaction data collected from a living human network, researchers may be able to construct socially intelligent systems that are capable of identifying and implementing network-level interventions in organizational living labs. Examples of such interventions may be as simple as real-time user-level recommendation systems. Such a system may suggest other organization members that an individual might interact with in order to improve overall information flow in the network. In this way, organizations of the future may be co-created with socially intelligent systems. To begin exploring this future, however, we have to first develop ubiquitous and accessible social measurement tools.

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