Human Action Interpretation by Body Pressure Sensing with Application to a Physical Assist Device

by

Mitsuichi Hiratsuka

Bachelor of Engineering, Applied Mathematics and Physics
Kyoto University, 1990

Master of Engineering, Applied Systems Science
Kyoto University, 1992

Submitted to the Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degree of

Mater of Science in Mechanical Engineering

at the

Massachusetts Institute of Technology

June 2000

Signature of Author ______________________________
Department of Mechanical Engineering
May 5, 2000

Certified by ______________________________
Haruhiko H. Asada
Ford Professor of Mechanical Engineering
Thesis Supervisor

Accepted by ______________________________
Ain A. Sonin
Chairman, Department Committee on Graduate Students

Human Action Interpretation by Body Pressure Sensing with Application to a Physical Assist Device

Mitsuichi Hiratsuka

Submitted to the Department of Mechanical Engineering on May 5, 2000 in Partial Fulfillment of the Requirements for the Degree of Master of Science in Mechanical Engineering

ABSTRACT

A physical assist device, *i*PASS (Integrative Physical Assist for Seamless Services), has been developed to provide a solution to the people in needs of various assistance in their daily lives. Since *i*PASS is capable of changing its configuration to cover the range of physical assistance needs, i.e. a bed, a walker, a standing-up and seating assist as well as a wheelchair, it can provide seamless services for bedridden patients without changing equipment. In order to provide an appropriate service to the patient properly and safely, *i*PASS is equipped with a human-machine interface that understands and adapts to a physical and mental state of the patient.

First, This thesis details a method to recognize human intentions by monitoring human actions in operating the *i*PASS system. Since physical assist devices such as *i*PASS directly interact with a patient, it is important to monitor human actions and to recognize human intentions in order to provide an appropriate physical support to the patient. *i*PASS detects a human action through a pattern of pressure distribution on the seat surface. By developing statistical models of the pressure distribution patterns associated with human actions, the Bayes classifier recognizes a particular human action through the detected pressure distribution pattern. This method is applied to the standing-up assist of *i*PASS. This method assumes that there is a correlation between a human action and a human intention. Through the experiment of this approach with the standing-up assist of *i*PASS, it is verified that a human intention comes out as a muscular exertion and it results in a human action.

In addition, this thesis presents the assessment of *i*PASS for a practical implementation. To make the *i*PASS system acceptable for the end users at hospitals, nursing facilities, and homes, the assessment is needed from the end user's point of view. Since the people who can benefit from physical assist devices are physically and mentally different from the normal people, the system should be carefully tested and assessed by the real end users. This thesis describes several redesign issues of *i*PASS that we found through the collaborative work between MIT and the Bedford Veterans Administration Medical Center.

Thesis Supervisor: Haruhiko H. Asada
Title: Ford Professor of Mechanical Engineering

ACKNOWLEDGEMENTS

I would like to thank Prof. Haruhiko H. Asada, my thesis adviser for giving me the opportunity to work on this project. I am grateful for his advice and patience throughout this thesis project.

I also would like to thank Dr. Volicer, Dr. Hurley, and other clinical staff at Bedford VAMC for giving me precious comments on this project.

Thanks to my daughter, Sanako, for giving me noisy encouragement at home.

Thanks to Akiko for everything, without your support and encouragement, none of this would have been possible.

Thanks to Kawasaki Heavy Industries, LTD., whose financial support is gratefully acknowledged.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 PROBLEM STATEMENT

Physical aids are a helpful and necessary component to support the daily lives of the elderly and non-ambulatory patients. Various pieces of equipment have been developed to facilitate their daily activities and to adapt to the day-to-day changes in their physical condition. For this reason there is a wide variety of equipment available on the market to provide physical assist to the elderly or non-ambulatory patients. The current commercial offerings, however, are specialized pieces of equipment that are useful in certain physical scenarios, but have limited utility. The lack of an efficient, compact, and multi-functional piece of equipment to serve the diverse needs of patients and caregivers is the fundamental motivation behind this thesis.

A physical assist device, *i*PASS (Integrative Physical Assist for Seamless Services), has been developed to provide a solution to the people in needs of various assistance. *i*PASS is capable of changing its configuration to cover the broad range of physical assistance needs, i.e. a bed, a walker, a standing-up and seating assistance as well as a wheelchair. *i*PASS can provide seamless services for the elderly or non-ambulatory patients without changing equipment. Changing equipment may be a problem for both patients and caregivers. Changing equipment may frighten the patient, and it may ends up with a chain of behaviors culminating in resisting the transfer and increasing the risk of falls. Changing equipment requires debilitating physical strain on caregivers when transferring a patient from one piece of equipment to another. *i*PASS eliminates these laborious transfers and provides seamless aid for diverse needs, including sleep in a spacious bed, moving with a powered wheelchair, walking with an instrumented walker, and assistance in standing-up and seating.

While physical assist devices such as *i*PASS requires high standards of safety, such a sophisticated system often creates higher possibilities of human mistakes with resultant serious consequences, such as injury and costly repair. Since *i*PASS directly and physically interacts with people with physical impairment, the elderly, and demented people who tend to have difficulties to operate machines properly, an improper physical support may cause accidents and result in injuries for users. It needs special cares in the system operations for safety requirements. Otherwise, *i*PASS would not be accepted by the end users. Therefor, *i*PASS must understand and adapt to the end users to provide appropriate support and to ensure the safety in operations.

In addition, to make the *i*PASS system acceptable for the end users at hospitals, nursing facilities, and homes, the assessment is needed from the end user's point of view. Since the people who can benefit from physical assist devices are physically and mentally different from the normal people, the system should be carefully tested and assessed by the real end users. It is important to find out what the patients and caregivers need in their daily lives and provide proper equipment for them. The aim of development of *i*PASS is not only combining several functions into one system, but also providing patients flexible and coordinated assistance in a variety of daily lives.

1.2 OBJECTIVES OF THE THESIS

First, this thesis presents a method for monitoring human actions to recognize underlying human intentions in order to provide appropriate and safe support to a patient with the *i*PASS system. Our basic assumption is that a human intention comes out as an active muscular exertion and it results in an observable human action. Each human action generates a measurable signal that has a certain pattern corresponding to a human intention.

*i*PASS has a pressure sensor array embedded in the seat to measure pressure distribution patterns generated by human actions. This thesis details a method for classifying patterns of pressure distribution on the seat surface in order to recognize a human action and to understand a human intention or desire. The method assumes that there is a correlation between a human action and a human intention. Based on feature vectors extracted from measured signals of pressure distribution patterns, statistical models of the pressure distribution patterns associated with human actions are developed. By using the Bayes classifier, a human action is recognized through an observed pressure distribution pattern by taking a maximum discriminant computed from the statistical models. This method is applied the standing-up assist of *i*PASS in order to recognize human actions and to understand an underlying human intention through the recognized human action. Through the experiment, it is verified that there is some correlation between a human intention and a resultant human action.

This thesis also presents the assessment of *i*PASS for practical implementation. After developing the first prototype of *i*PASS with the fundamental functions described above, the *i*PASS project group at MIT and clinicians/researchers at the Bedford Veterans Administration Medical Center (Bedford VAMC) initiated the redesign of *i*PASS to make the system accepted by end users at hospitals or nursing homes. Meetings were held with clinical staff and nurses working with bedridden patients at the Bedford VAMC to obtain comments from the point of view of the end user, both as proxy informant for the patient and customer of the product. The basic concept of *i*PASS is widely considered useful and helpful to support bedridden patients, but some modifications and additions are needed for practical implementation. This thesis describes several redesign issues arising obtained from the collaborative work between MIT and the Bedford VAMC for practical implementation of *i*PASS. Our focus of this assessment is to redesign the *i*PASS system to make it usable and acceptable for patients and caregivers at the Bedford VAMC. To this end, an improved design of *i*PASS is proposed.

2 HUMAN ACTION INTERPRETATION BY BODY PRESSURE SENSING

2.1 INTRODUCTION AND RELATED WORK

There is an increasing need for assisting humans in operating complex systems in the home as well as in hospitals and factories. While high standards of safety are required, a sophisticated system often creates higher possibilities of human mistakes with resultant serious consequences, such as injury and costly repair. In particular, systems for home use and healthcare applications need special care in the system operations due to safety requirements and involvement of people with physical impairment, the elderly, and demented people who tend to have difficulties to operate machines properly. Physical assist devices, such as active beds, reconfigurable chairs, and omni-directional wheelchairs, would not be accepted by end users unless the system is very easy to operate and safe.

Since the end users of physical assist devices such as *i*PASS are vulnerable patients, it could not be expected that the patients could adapt to the system well. Instead, the system must understand and adapt to the patients, and it must provide appropriate support to the patients according to their physical and mental states. Therefor, the human-machine interfaces that enable smooth and flexible communication between the human and the machines need to be studied.

In the last several years, the new technology for the human-machine interface is emerging that understands human intention through human behavior to establish smooth communications between machines and the human. Sato *et al.* [1] developed a teleoperation robot that understands human intention through unconscious behavior of user's hand. The robot utilized this information of human intention to change its control mode and make its manipulation more effective and easier. Nishida *et al.* [2] developed a bed system that detect posture and respiration of the patient on the bed by using pressure sensors. The information of the patient is not exploited by the system but provided to doctors or nurses. Yang *et al.* [3] focused on modeling of a simple human action such as a gesture, sign language, or manual controller command by using a hidden Markov model. A human action is differentiated base on HMM, and intention of the human action can be inferred from which HMM is the most likely to match sensory data of a human action. This approach was applied to modeling of human actions of hand control in teleoperation of a robot. Sharma *et al.* [4] proposed a system that gave instructions to a human in manual assembly tasks in accordance with the assembly states. This human-machine interface provided an assisting function to correct a wrong human operation by detecting an improper assembly state.

2.2 iPASS (INTEGRATIVE PHYSICAL ASSIST FOR SEAMLESS SERVICES)

*i*PASS can meet diverse physical assistance needs and provide seamless services to bedridden patients without changing of equipment. *i*PASS eliminates laborious job associated with transfers of a patient and provides seamless aid for diverse needs, including sleep in a spacious bed, moving with a powered wheelchair, walking with an instrumented walker, and assistance in standing-up and seating. Figure 1 shows an overview of the first prototype of *i*PASS.

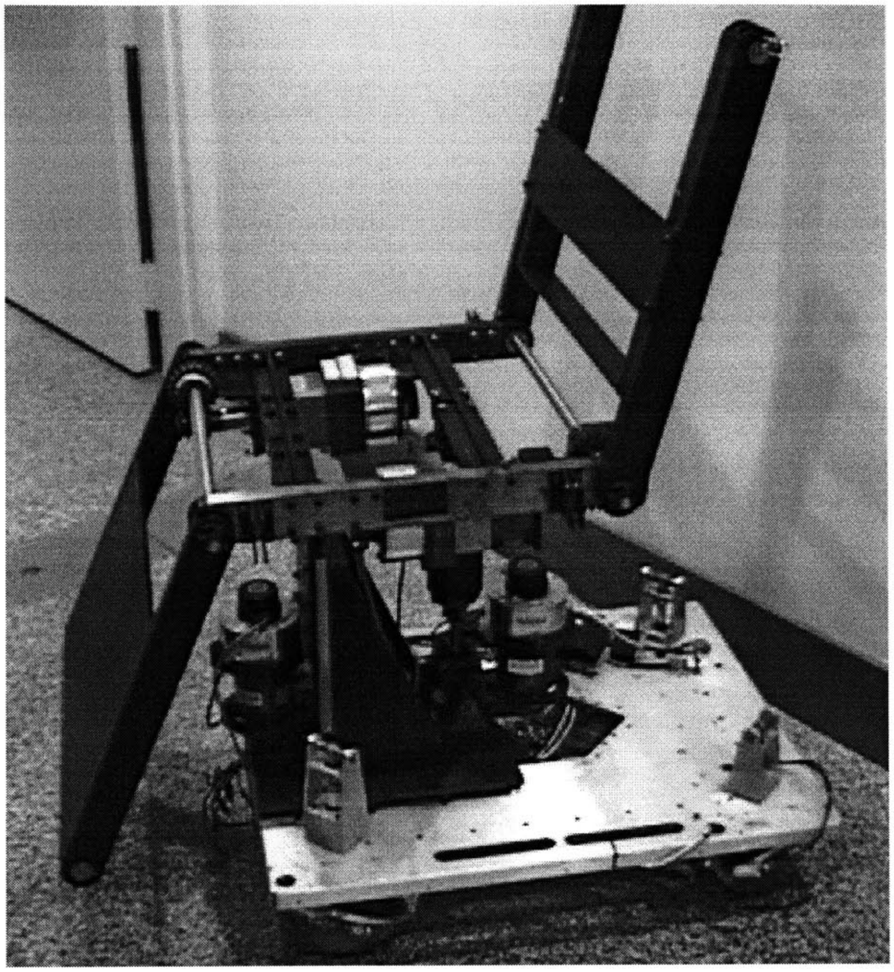
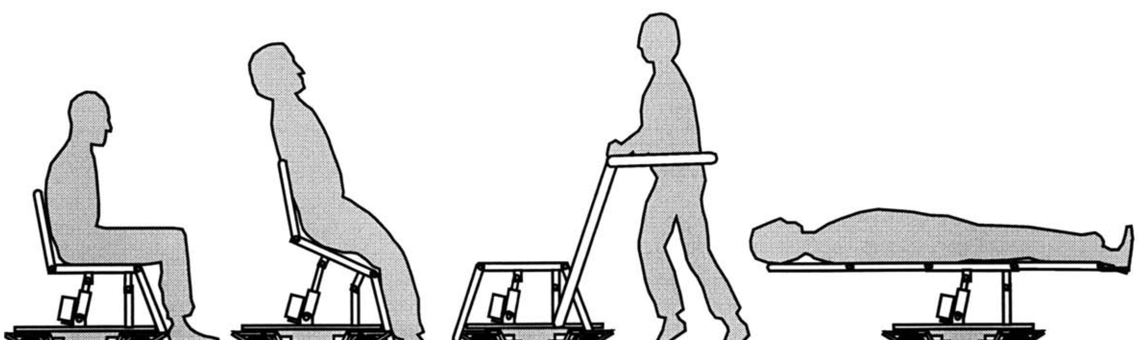


Figure 1. First Prototype of iPASS. (seat cover is removed)



(a) (b) (c) (d)

Figure 2. iPASS Basic Functions

Figure 2 illustrates the diverse functionality of *i*PASS. It transports a patient in a wheelchair configuration, Figure 2-(a); it assists a patient in standing up or being seated, Figure 2-(b); it assists a patient in walking in a walker configuration, Figure 2-(c); it provides a patient with a spacious bed for sleep, Figure 2-(d).

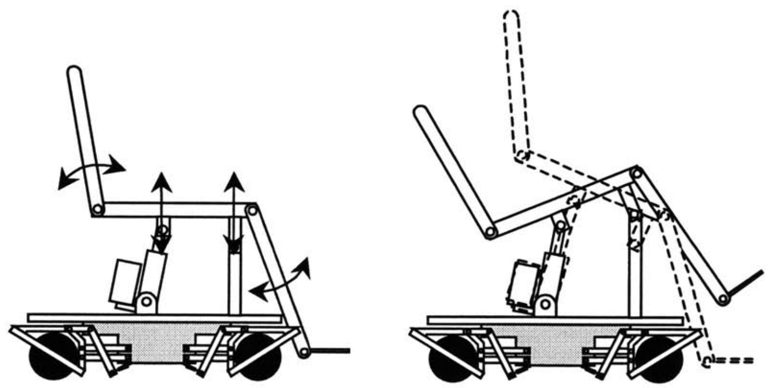


Figure 3. Degree of Freedom of Reconfigurable chair

*i*PASS has a five degree-of-freedom chair and a three degree-of-freedom moving platform. As shown in Figure 3, the seat of the chair can be lifted and tilted with two axes of actuators, while the back leaf and the footrest can be folded independently by two actuators. In addition, the entire chair can be shifted longitudinally relative to the vehicle. As a matter of fact, the desired posture depends on the patient and it may vary frequently and widely. This chair can offer a wide range of the chair configuration to provide a desired posture of a patient. The detailed design of the reconfigurable chair is shown in [5]. The vehicle is a holonomic, omni-directional platform having four ball wheels that allow the platform to move in an arbitrary direction and orientation from an arbitrary configuration without kinematic singularity. The vehicle has the ability to move in any direction without changing the direction of wheels. It can move diagonally and side to side with keeping the direction of the vehicle. It also can rotate in place. This moving platform provides flexible and smooth maneuverability to patients. The detailed design of the ball-wheel, holonomic, omni-directional wheelchair is shown in [6].

2.3 HUMAN-MACHINE INTERACTION ON *i*PASS

2.3.1 PROBLEM STATEMENT

It is important for physical assist devices to provide a support for a patient in a proper and safe manner. Since *i*PASS directly and physically interact with people with physical impairment, the elderly, and demented people who tend to have difficulties to operate machines properly, an improper physical support may cause accidents and result in injuries for patients. It needs special care in the system operations for safety requirements. Otherwise, *i*PASS would not be accepted by the end users in hospitals or nursing homes. Therefor, *i*PASS must understand and adapt to the end users through interactions in order to provide appropriate support and to ensure the safety.

Here we focus on a physical interaction when using the standing-up assist of *i*PASS as an example. Through the collaboration with researchers, clinical staff, and nurses at the Bedford VAMC to assess the feasibility of *i*PASS in practical situations such as hospitals and nursing home, the design concept of *i*PASS was found widely useful and helpful for both of patients and caregivers. However, to maintain patients' mobility as long as possible, the patients had better leave *i*PASS and walk on their own if possible. In addition to it, even though *i*PASS covers several services for patients, there are some unavoidable daily situations in which patients have to be transferred from *i*PASS to another equipment. For example, when they want to use bathroom or to take a shower, patients have to stand up and move from *i*PASS to another devise such as a toilette chair or a shower chair. In the current practice, caregivers play a role to initiate a patient to stand up and pull and push the patient up to the standing-up position. The standing-up assist is useful for patients having difficulty to stand up on their own. Also, it is helpful for caregivers to reduce laborious job of aiding patients in standing up. Figure 4 illustrates the current practice and the use of *i*PASS to assist a patient in standing up.

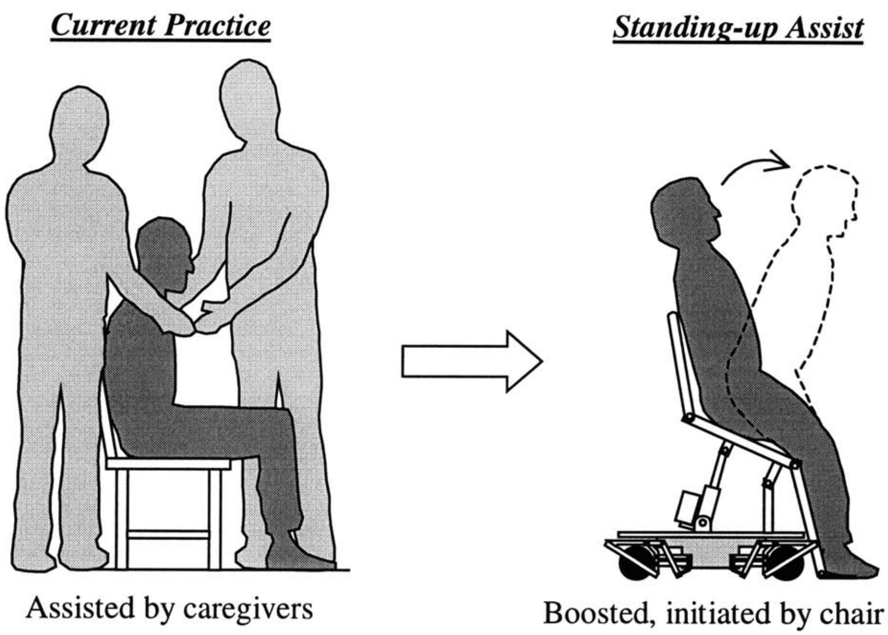


Figure 4. Assist from Caregivers and Assist from *i*PASS

*i*PASS is able to change its configuration, and it can provide a patient an appropriate posture that makes it easier to stand up. To assist a patient to stand up safely, the system has to make sure whether the patient is ready to stand up or not. If the patient is not ready to stand up or doesn't want to do so, *i*PASS should not force him to stand up and has to move back to the sitting configuration for the safety. If the system ignores a physical or mental state of the patient and pushes him up to the standing-up position regardless of his physical and mental state, the patient may not be able to stand stably and it may result in a serious accident such as falling down or sliding off from the chair. Therefor, the system needs to understand an intention or a desire of the patient and to provide a physical support properly and safely. Figure 5 depicts the typical accidents that the standing-up assist might cause.

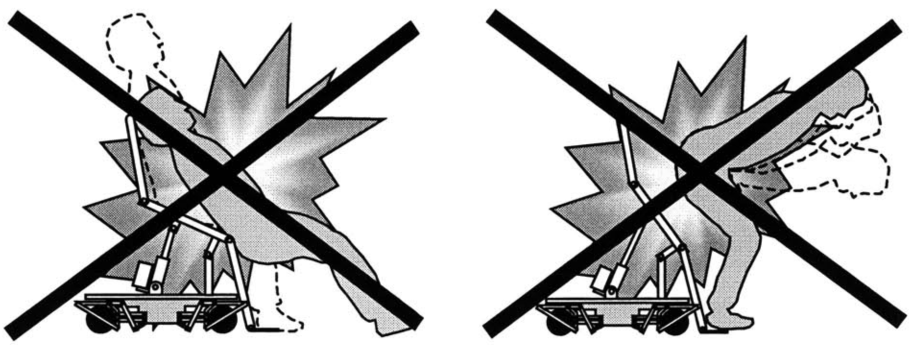


Figure 5. Potential Accidents with Standing-up Assist

2.3.2 TASK DEFINITION

To understand a human intention, it is important to monitor human actions continuously. The basic assumption is that a human intention comes out as a certain muscular action, and the muscular action appears as an observable human action which can be measured by using appropriate sensors. By detecting and identifying a certain pattern of signals from sensors, it is possible to infer a human intention through a human action. For example, when a patient has an intention to stand up, the patient should take a certain action. The patient should change the posture properly according to the chair support, and shift the center of the mass forward and upward in accordance with the chair motion. The patient's action should be cooperative with the chair motion. On the other hand, when the patient doesn't have an intention to stand up, the patient doesn't take an appropriate action and the center of the mass stays on the chair. Moreover, when the patient doesn't want to stand up, the patient resists against the chair motion. The patient applies force to the seat surface to express his intention of resistance. The force generated by the human muscles indicates an intention or a desire of the patient. Figure 6 illustrates the concept of the system to recognize a human intention though a human action.

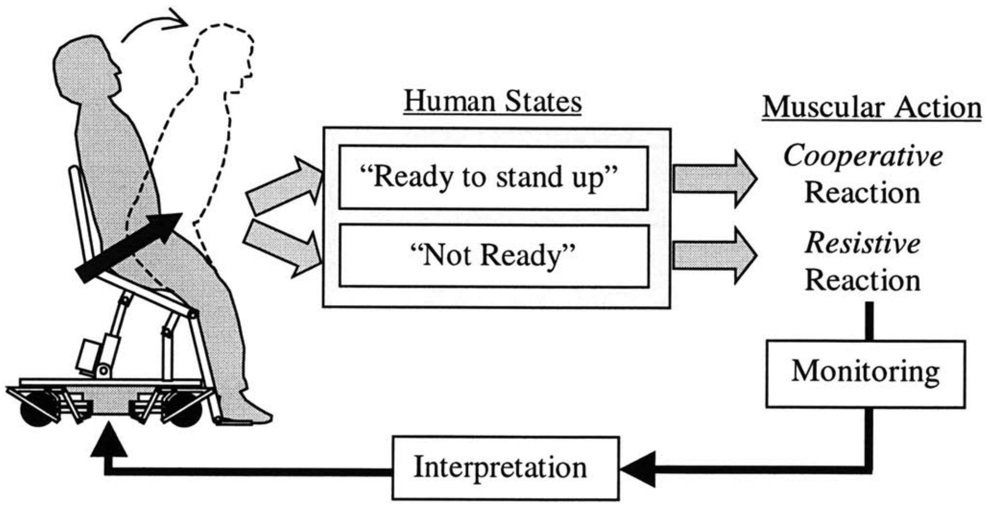


Figure 6. Concept of Human Action Interpretation System

The goal is development of the system that monitors a human action through observable signals and recognizes an underlying human intention through the human action. By recognizing an underlying human intention, the system can provide a proper physical assist to the patient according to the human intention and avoid a potential accident.

To make *i*PASS acceptable in the practical situation, a scenario of *i*PASS operation should be considered carefully. Since the interpretation of the patient's action through body pressure sensing is very sensitive and subtle, there might be some difficult cases to make a decision automatically on which action the patient is taking. In such a case, a manual decision of a caregiver is needed to recognize the patient's reaction and to determine the next operation of the support. Therefor, it is supposed that one caregiver should attend to monitor the patient's action in order to avoid the serious accident in the practical operation of *i*PASS. Even though *i*PASS needs one attending caregiver to meet the high standards of safety, *i*PASS can decrease the number of the caregivers and reduce the laborious job of the caregivers during assistance of the patient. Figure 7 illustrates the change of the operation mode of *i*PASS according to the result of the human action interpretation.

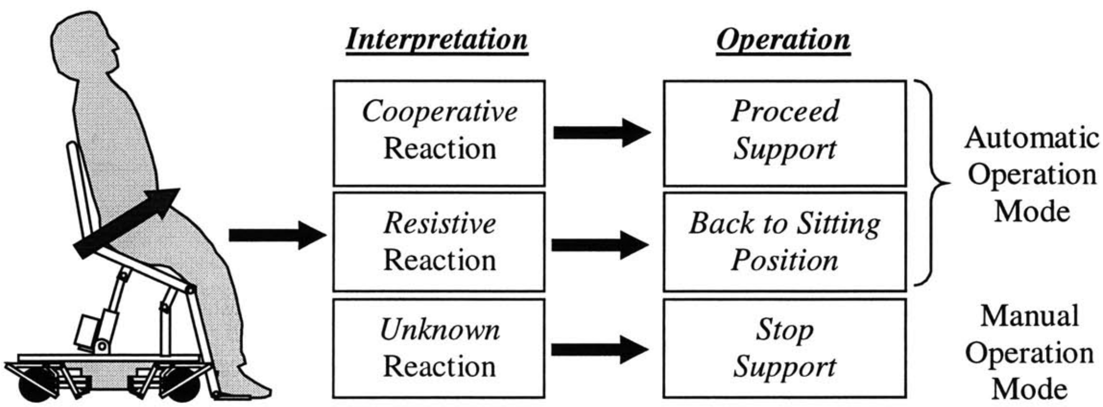


Figure 7. Operation Modes in Standing-up Process

2.4 BODY PRESSURE SENSING

To monitor signals generated by human actions, an appropriate sensor should be selected. Since patients are expected to use *i*PASS at most for several hours and continuous monitoring is needed during their use, invasive sensing makes them uncomfortable. Also, the sensor must not constrain the patient's motion. While the patient is using *i*PASS, it is preferable that the patient takes a desired posture on the chair. Therefor, the sensor must measure signals from the patient non-invasively and without constraining the patient's motion for continuous and long-tem monitoring.

Since a patient has a contact with the *i*PASS during seating, *i*PASS has a pressure sensor array on the seat in order to detect a pattern of a pressure distribution generated by a patient's action. The pressure sensor array consists of 64 pressure sensors called Force Sensing Resisters (FSRs). FSR provides us easy implementation and provides repeatable and linear force responses, which is suitable for our application. In addition to it, low cost and commercial availability are good for practical implementation. While this FSR is not able to measure accurate pressure, it is not a problem for our application as long as the measurements are consistent with each other.

This sensor array is utilized to monitor the time profile of the pressure measurements. If the patient takes an action on the chair, it comes out as the change of the pressure distribution. In addition it can monitor the static location of the patient on the sear during seating. Since the location of the patient on the chair is important information to keep the safety of the patient, the pressure sensors can be utilized to make sure if a patient properly stay on the chair. If the patient is not located on the seat properly, the chair sends a warning to a caregiver in order to correct the patient's location and to avoid an accident such as falling down from the chair.

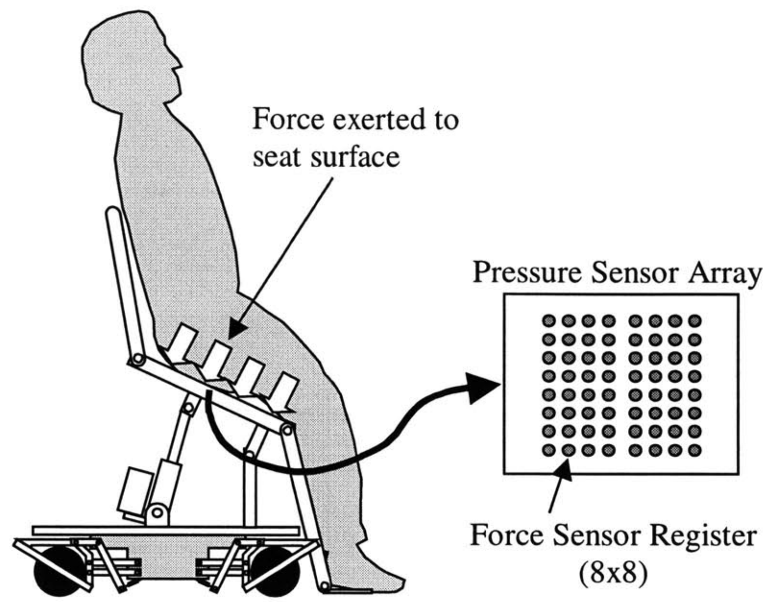


Figure 8. Implemented Sensor Array

2.5 MODELING AND CLASSIFICATION OF PRESSURE DISTRIBUTION PATTERN

2.5.1 PRESSURE DISTRIBUTION PATTERN

To differentiate the pressure distribution patterns effectively and correctly, some features well characterizing patterns should be extracted from measured signals form the pressure sensor array. Here we focus on the changes of the pressure distribution pattern associated with the changes of the upper body posture and the muscular force caused by a human intention. Figure 9 illustrates the block diagram of the entire system including *i*PASS system and a patient. There is the interaction between *i*PASS and the patient's body, and the patient controls the body and the force exerted to the seat surface to express his intention through this interaction.

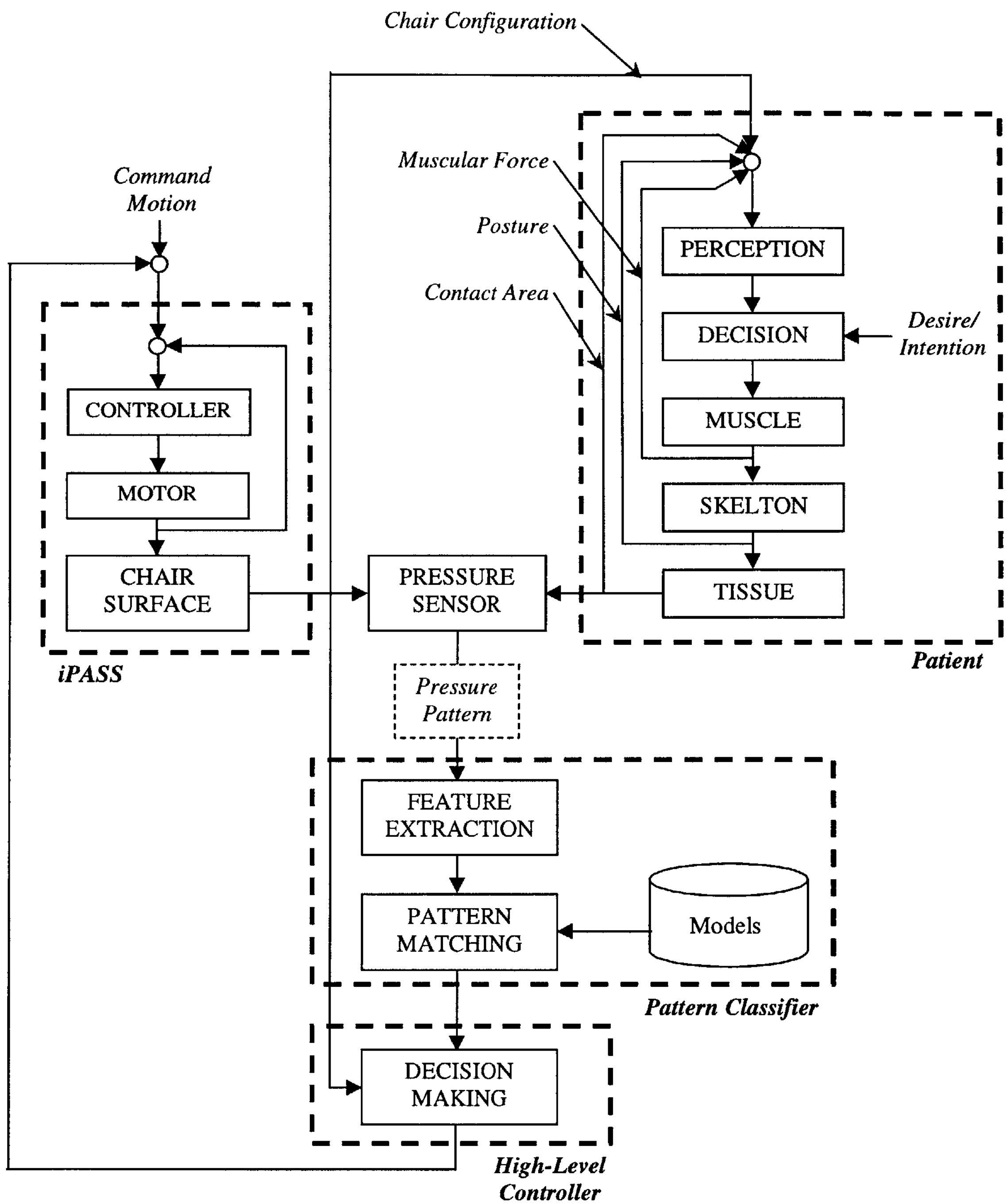


Figure 9. Block Diagram of Entire System

In the operation of *i*PASS, when the patient perceives the motion of *i*PASS, the patient decides his next action in accordance with his intention or desire. Based on this decision, the muscles are commanded to move and the muscular force is generated. The muscular force changes the patient's posture, and it propagates through the skeletal system to the soft tissue, and eventually the force is exerted to the seat surface. This force is measured as a pressure distribution pattern by the pressure sensor array. Because of the skeletal structure inside the human body, the way of the propagation of the force onto the seat surface depends on the upper body posture. This changes not only the magnitude of the force and the contact area but also the pattern of the pressure distribution on the seat surface. Figure 10 illustrates the arrangement of pressure sensors in the pressure sensor array. Figure 11 – 13 show some patterns of the pressure distribution. Data are interpolated to draw the graphs. These figures show that the pressure distribution pattern changes when a patient on the chair takes some actions. When the patient is sitting on the chair, the pressure distribution is located in the center of the pressure sensor array, Figure 11. When the patient is taking a "resistive" action and applying the force against the chair, the pressure distribution moves backward, Figure 12. When the patient is following the support from the chair and moving the posture forward, the pressure distribution moves forward according the motion of the patient, Figure 13.

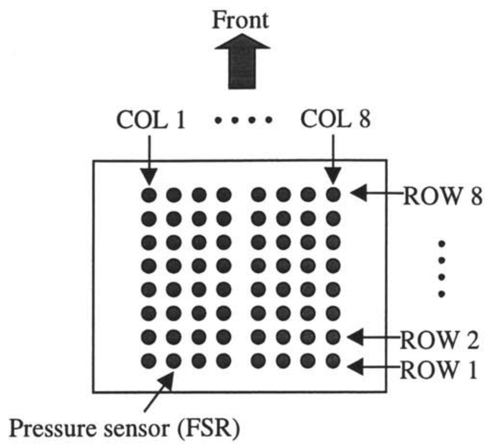


Figure 10. Pressure Sensor Array

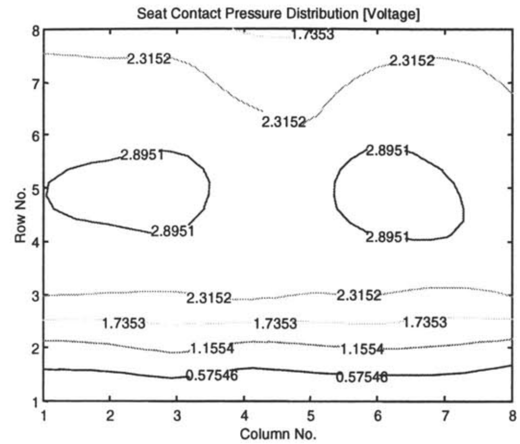


Figure 11. Pressure Pattern (1)

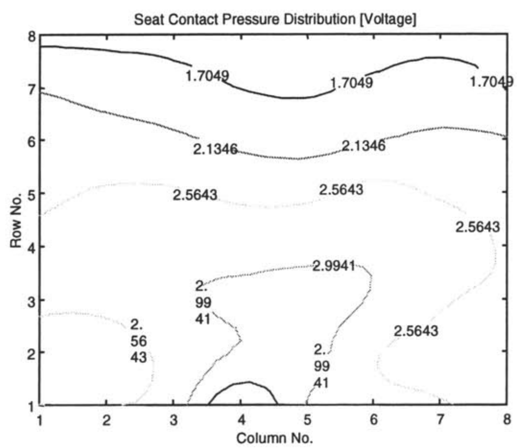


Figure 12. Pressure Pattern (2)

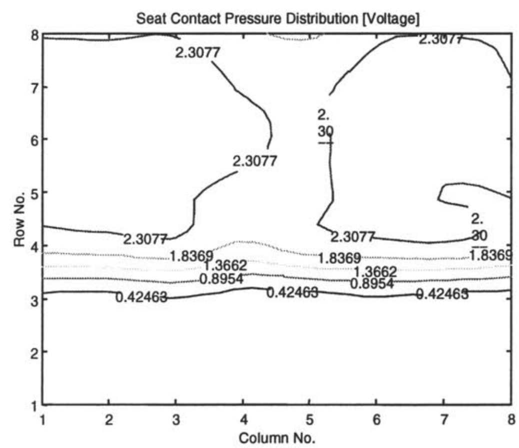


Figure 13. Pressure Pattern (3)

As shown above, the pressure distribution pattern changes by the change of the upper body posture. The muscular force propagates through the bones to the soft tissue, and it is eventually exerted to the seat surface. Because of the skeletal structure inside the human body, the way of the propagation of the force onto the seat surface depends on the upper body posture. See Figure 14. When the patient leans forward, the force is mainly exerted through the pelvis to the seat. On the other hand, when the patient lean backward, the force is mainly exerted though the spine to the seat. These human actions change the location of maximally pressurized points and the shape of the pressurized area. Figure 15 illustrates how the pattern changes according to the change of the patient's posture.

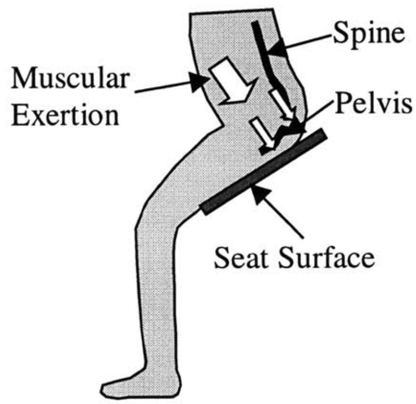


Figure 14. Ways of Propagation of Muscular Force

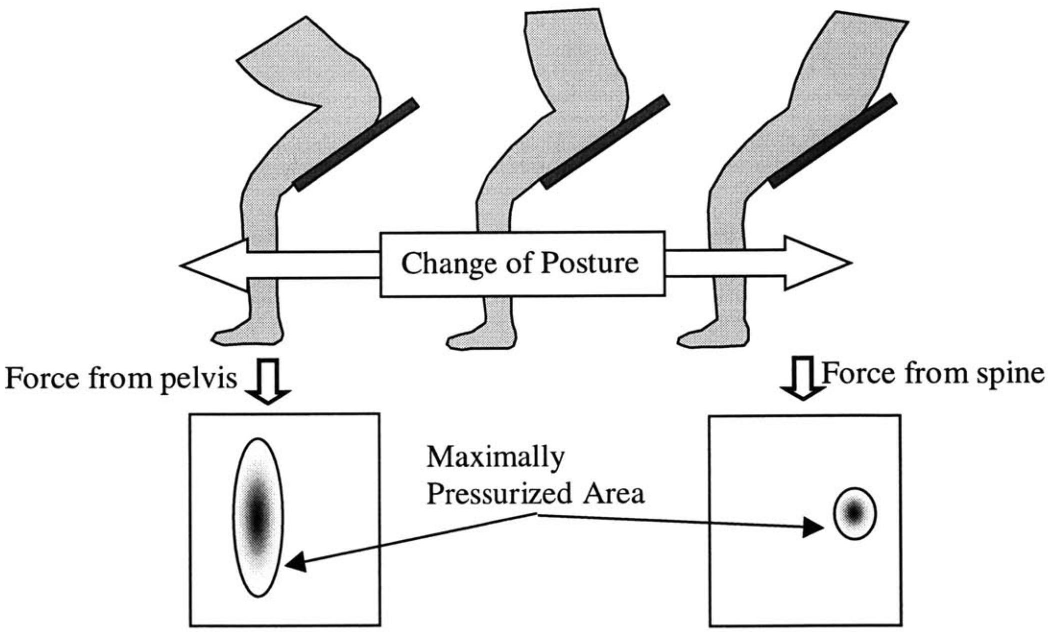


Figure 15. Change of Pressure Distribution by Posture

In addition to the location of the pressurized area, the intensity of the pressure changes according the change of the force exerted onto the seat. Therefor, it is an important factor to infer the patient's intention. However, because of the functional limitation of the pressure sensors, the pressure measures of some pressure sensors are sometimes saturated when the large force is exerted to the seat. In addition to it, since the buttock is covered with the soft tissue, the muscular force deforms the shape of the buttock and changes the size of the contact area. The change of the area is also very sensitive to other factors such as the posture and the clothing of the patient. In order to measure the intensity of the pressure and reduce the deviation caused by the external factors, the average pressure in the area pressurized more than 95% of the maximum pressure is measured instead of the average pressure inside the whole contact area.

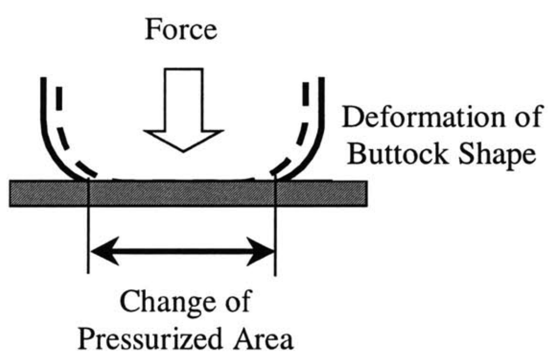


Figure 16. Change of Pressurized Area by Force Exertion

2.5.2 FEATURE EXTRACTION

Based on the observation mentioned above, three features are extracted as variables in order to characterize the pressure distribution pattern. Figure 17 shows the features of the pressure distribution pattern.

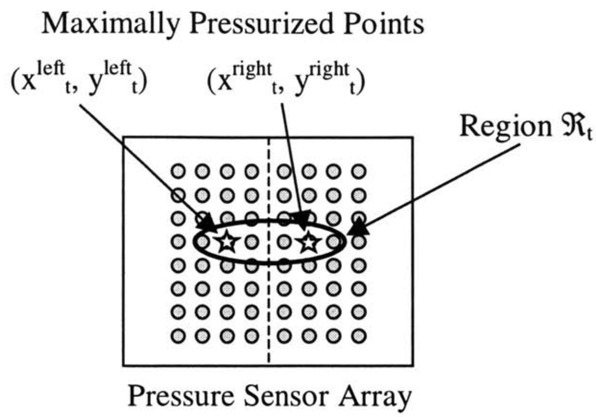


Figure 17. Features of Pressure Distribution

Deviations of maximally pressurized points: A maximally pressurized point is identified in each half region of the pressure sensor array. The initial position of the maximally pressurized point can be localized while the patient is sitting on the chair. Because the seating position can be slightly different each time the patient sits on the chair, the deviation from the initial position of the point is measured to characterize the movement of the pressurized area. Since the position change in the y-direction is not much deviated while the pressure distribution pattern changes, only the position change in the x-direction is taken as a feature variable. Given the initial positions of the maximally pressurized points at time *0*, the deviations of the points at time *t* are computed as

$$\begin{aligned} dx^{right}{}_t &= x^{right}{}_t - x^{right}{}_0 \\ dx^{left}{}_t &= x^{left}{}_t - x^{left}{}_0 \end{aligned} \qquad (1)$$

Width between maximally pressurized points: To measure the shape of the pressurized area, the width between maximally pressurized points is taken as a feature variable. From the preliminary experiments we conducted, the length of the pressurized area in the longitudinal direction doesn't change much while the pressure distribution changes.

Therefor, the shape is well characterized by the width of the maximally pressurized points. The width w_t between maximally pressurized points at time t are computed as

$$w_t = \left| y^{left}{}_t - y^{right}{}_t \right| \tag{2}$$

Averaged pressure: Averaged intensity of the pressure is measured in the area pressurized more than 95% of the maximum pressure. The averaged pressure I_t at time t is given as

$$I_t = P_t / A_t \tag{3}$$

where P_t is the sum of the pressure in region $\Re_t$ at time t, and A_t is the area of region $\Re_t$ at time t.

2.5.3 BAYES CLASSIFIER

The Bayes classifier provides a systematic way to develop a method to make a decision on which action the patient is taking. There is also another way to determine a human action heuristically. Based on the future vector extracted from an observation, a threshold or a range for each element of the feature vector has to be estimated beforehand. However, it is not easy to determine the threshold or the range of the value in order to obtain a reasonable performance of decision-making. Compared with this heuristic method, the Bayes classifier provides a systematic way to estimate parameters of the classifier.

In order to develop the Bayes classifier based on these feature variables, it is assumed that a feature vector consisting of feature variables has a normal density. The multivariable normal density is written as

$$p(\mathbf{F}) = \frac{1}{(2\pi)^{m/2} |\mathbf{\Sigma}|^{1/2}} \exp\left[-\frac{1}{2} (\mathbf{F} - \boldsymbol{\mu})^T \mathbf{\Sigma}^{-1} (\mathbf{F} - \boldsymbol{\mu}) \right] \tag{4}$$

where **F** is an m-component column feature vector, μ is the m-component mean vector, Σ is the m-by-m covariance matrix, and $|\Sigma|$ is the determinant of Σ. It is also assumed that all a priori probabilities are equal. Since it is hard to estimate the probability of any of the human action occurring, this assumption is made and all a priori probabilities are set to be equal.

The Bayes classifier [8] is developed to classify human actions based on feature variables described above. A loss function $\lambda(\alpha_i|\omega_j)$ is defined when a decision α_i is made and the true class of a human action is ω_j. The decision α_i is a decision that the true class of a human action is ω_i. The expected risk R of making a decision α_i based on a given feature vector $\mathbf{F}_t$ at time t is defined as

$$R(\alpha_i | \mathbf{F}_t) = \sum_j \lambda(\alpha_i | \omega_j) P(\omega_j | \mathbf{F}_t) \tag{5}$$

A posteriori probability of a feature vector obtained from a measurement can be computed by using the Bayes rule.

$$P(\omega_i | \mathbf{F}_t) = \frac{p(\mathbf{F}_t | \omega_i) P(\omega_i)}{\sum_j p(\mathbf{F}_t | \omega_j) P(\omega_j)} \tag{6}$$

where $p(\mathbf{F}_t|\omega_i)$ is a conditional probability density function, and $P(\omega_i)$ is a priori probability. To minimize the average probability of wrong decision, for example, a loss function is given as

$$\lambda(\alpha_i \mid \omega_j) = \begin{cases} 0 & i = j \\ 1 & i \neq j \end{cases} \tag{7}$$

In this case, the expected risk corresponding to the loss function is

$$\begin{aligned} R(\alpha_i \mid \mathbf{F}_t) &= \sum_j \lambda(\alpha_i \mid \omega_j) P(\omega_j \mid \mathbf{F}_t) \\ &= \sum_{j \neq i} P(\omega_j \mid \mathbf{F}_t) \\ &= 1 - P(\omega_i \mid \mathbf{F}_t) \end{aligned} \tag{8}$$

Therefor, to minimize the average probability of wrong decision, i should be selected which maximizes the a posteriori probability $P(\omega_i|\mathbf{F}_t)$. The discriminant function of the Bayes classifier is given by

$$g_i(\mathbf{F}_t) = -R(\alpha_i \mid \mathbf{F}_t) \tag{9}$$

At any time t, a decision is made to minimize the expected risk of the decision-making, and it results in maximizing the discriminant value. Therefor, a detected human action i is described as

$$i = \arg\max(g_1, g_2, \cdots, g_r) \tag{10}$$

Figure 18 illustrates the Bayes classifier.

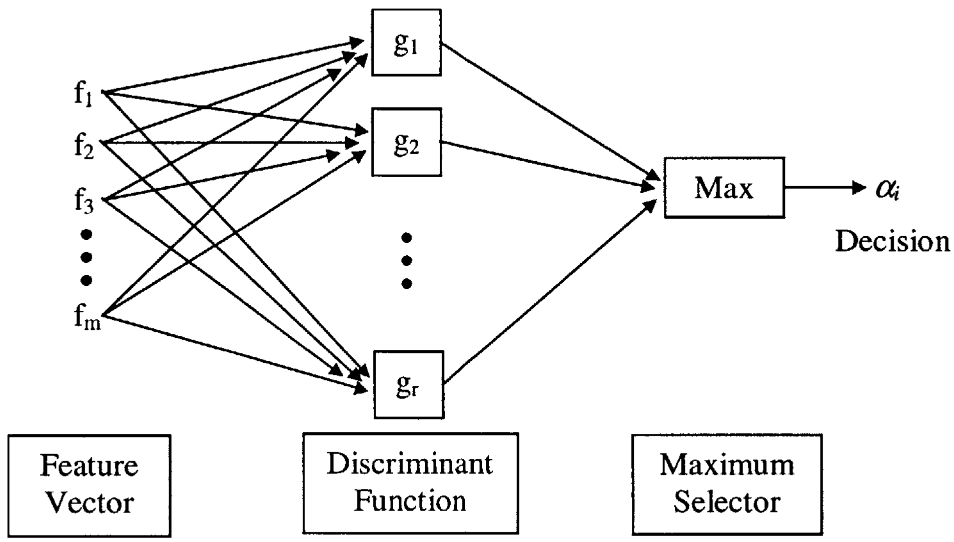


Figure 18. Bayes Classifier

2.5.4 Bayes Classifier with Sequential Probability Revision

When monitoring the pressure distribution, the Bayes classifier described in the previous section finds the most likely class of a human action based on an observation $\mathbf{F}_t$ at time t. If the discriminant of the equation (9) is almost *0.0* for the feature vector F_t, a decision can be made confidentially. On the other hand, if the discriminant value is not closed to *0.0*, a conservative decision should be made for the safety. In this case, the decision should be a less risky one in terms of a resultant chair motion. However, as the time proceeds, the number of observations can be made. These observations should be exploited to make a decision at some point, because the sequence of the observations provides richer information rather than just one observation.

Based on obtained observations, a priori probability can be revised by applying the Bayes rule sequentially [9]. From the equation (6), after making t observations of feature vectors $\mathbf{F}_1 \ldots \mathbf{F}_t$, a posteriori probability is given as

$$P(\omega_i \mid \mathbf{F}_1 \cdots \mathbf{F}_t) = \frac{p(\mathbf{F}_t \mid \omega_i, \mathbf{F}_1 \cdots \mathbf{F}_{t-1}) P(\omega_i \mid \mathbf{F}_1 \cdots \mathbf{F}_{t-1})}{\sum_j p(\mathbf{F}_t \mid \omega_j, \mathbf{F}_1 \cdots \mathbf{F}_{t-1}) P(\omega_j \mid \mathbf{F}_1 \cdots \mathbf{F}_{t-1})} \tag{11}$$

Let the conditional probability after t observations be defined as

$$P_t(\omega_i) = P(\omega_i \mid \mathbf{F}_1 \cdots \mathbf{F}_t) \tag{12}$$

The equation (11) is rewritten as

$$P_t(\omega_i) = \frac{p(\mathbf{F}_t \mid \omega_i, \mathbf{F}_1 \cdots \mathbf{F}_{t-1}) P_{t-1}(\omega_i)}{\sum_j p(\mathbf{F}_t \mid \omega_j, \mathbf{F}_1 \cdots \mathbf{F}_{t-1}) P_{t-1}(\omega_j)} \tag{13}$$

If it is assumed that observations are independent each other, the conditional probability density is

$$p(\mathbf{F}_t \mid \omega_i, \mathbf{F}_1 \cdots \mathbf{F}_{t-1}) = p(\mathbf{F}_t \mid \omega_i) \tag{14}$$

A priori probability of ω_i is $P_0(\omega_i)$. One benefit of using this probability revision is that a priori probability can be updated based on sequential observations even if a priori probability could not be estimated precisely beforehand. This revised conditional probability can be replaced with original a priori probability in the equation (8) to compute the discriminant.

$$\begin{aligned} g_i(\mathbf{F}_1 \cdots \mathbf{F}_t) &= -R(\alpha_i \mid \mathbf{F}_1 \cdots \mathbf{F}_t) \\ &= P(\omega_i \mid \mathbf{F}_1 \cdots \mathbf{F}_t) - 1 \end{aligned} \tag{15}$$

Another benefit of the probability revision is that an ambiguous decision-making based on only one observation can be eliminated to some extent. For example, in the case of two-category classification, the decision boundary is defined as the boundary satisfying

$$g_1(\mathbf{F}) = g_2(\mathbf{F}) \tag{16}$$

If a feature vector is located close to the decision boundary, it is hard to make a confidential decision based on this feature vector. However, when sequential observations are made, and the observations of the feature vectors stay in the same region and they show some tendency, this information can increase the confidence of decision making. See Figure 19.

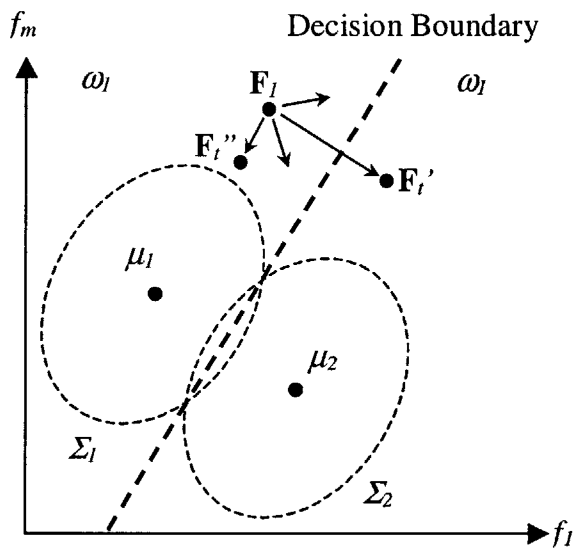


Figure 19. Feature Vector Space and Decision Boundary

Even though the discriminant based on one observation of a feature vector provides how likely the distribution pattern matches the model at a particular time, this doesn't necessary shows a real current human action because the human actions have some deviation. In addition, even though a human action can not be clearly decided which class it belongs to in terms of the value of the discriminants, the likeliness of the class of the human action would increase if the sequence of the feature vectors stay within one side of the decision boundary in some time period. The discriminant based on the sequential observations can take the tendency of the feature vectors into consideration and can eliminate such deviation of human actions. Therefor, the discriminant based on the sequential observations is utilized to make a more reliable decision.

2.6 EXPERIMENTS AND RESULTS

2.6.1 SYSTEM OVERVIEW

The method to recognize human intentions by body pressure sensing is applied to the standing-up assist of *i*PASS. Figure 20 illustrates the overview of the system hardware.

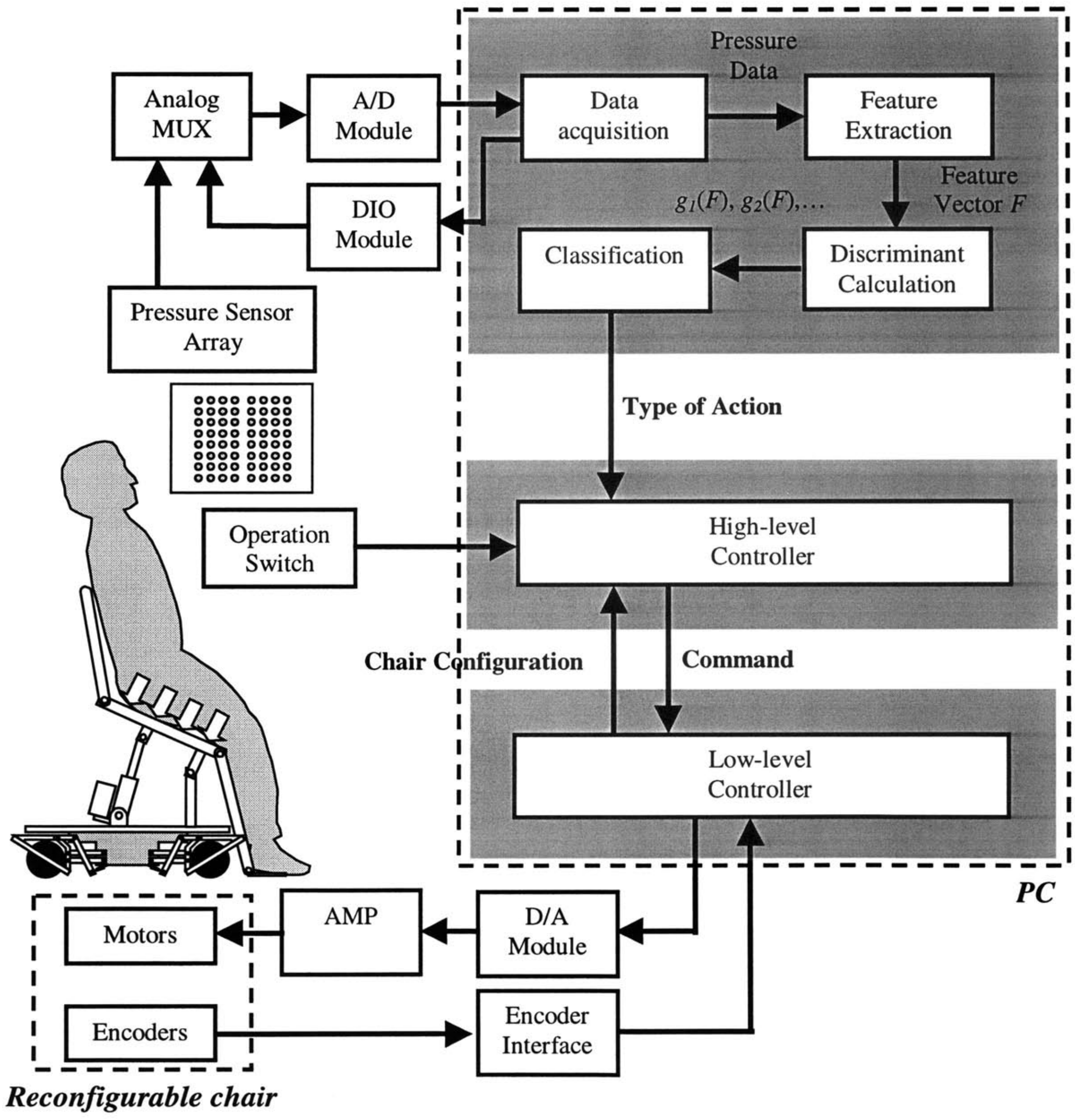


Figure 20. System Overview

The pressure sensor array is embedded in the seat, and it is covered with a cloth like a bed sheet. The pressure measurement of each pressure sensor is acquired by using the A/D module, and all sensors are scanned by using the analog multiplexer.

The controllers and the Bayes classifier are implemented as software for the PC with Real-time Linux [10]. The detail of the software implementation is described in Appendix A. The Bayes classifier detects a human action and passes it to the high-level controller of *i*PASS. The high-level controller supervises the low-level controller of *i*PASS and it changes the chair motion according the detected human action. If *i*PASS detects an improper human action while providing the physical support, it interprets the intention of resisting against the support and it moves back to the seating position for the safety of the patient. If *i*PASS detects a cooperative action of the patient, it recognizes the human intention to stand up and it proceeds the physical support up to the standing-up position.

2.6.2 Implementation of Human Action Interpreter

For the experiment, the Bayes classifier is developed to detect two types of human actions: a *cooperative* action and a *resistive* action. Each class of human actions is defined ω_1 and ω_2 respectively.

$$\omega_1 : \text{Class of } \textit{resistive} \text{ actions}$$
$$\omega_2 : \text{Class of } \textit{cooperative} \text{ actions}$$

These two types of human actions are treated as being exclusive each other. Figure 21 illustrates how the pressure distribution changes in each case. When the patient takes a *resistive* action, the patient applies the force against the chair and the pressure distribution moves backward to decline to stand up from the chair. When the patient takes a *cooperative* action, the patient follows the support from the reconfigurable chair and the pressure distribution moves forward according the motion of the patient.

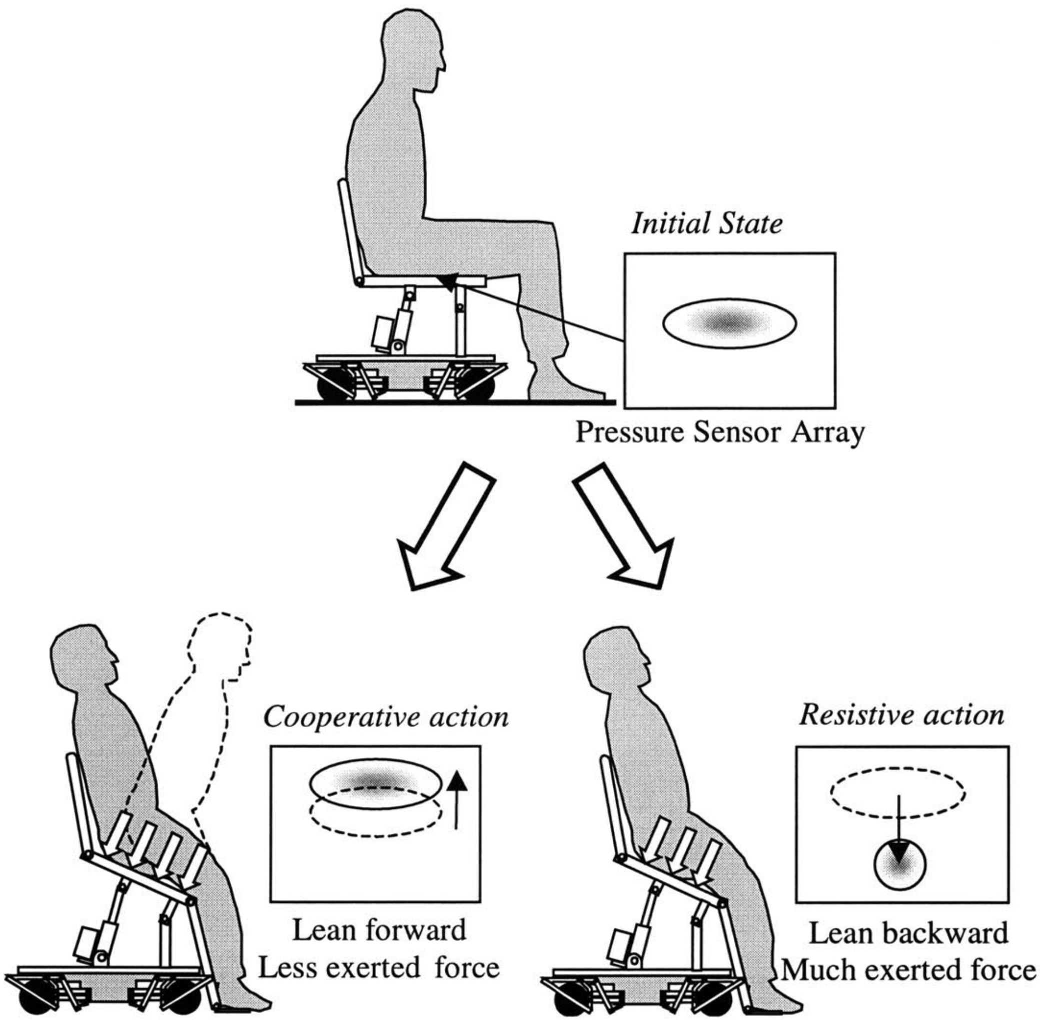


Figure 21. Human Action Interpretation

The Bayes classifier continuously monitors human actions from the beginning of the support to the final decision-making point. The Bayes classifier computes the discriminant g_S for the class of the *resistive* actions, and this discriminant utilizes the sequential observations from time *1* to *t*.

$$g_S(\mathbf{F}_1 \cdots \mathbf{F}_t) = P(\omega_1 \mid \mathbf{F}_1 \cdots \mathbf{F}_t) - 1 \tag{17}$$

Since *resistive* actions and *cooperative* actions are treated as being exclusive each other,

$$P(\omega_2 \mid \bullet) = 1 - P(\omega_1 \mid \bullet) \tag{18}$$

The discriminant for the class of the *cooperative* actions is easily computed from the discriminant (17). Therefor, the Bayes classifier needs to compute only the discriminant for the *resistive* action.

If the discriminant for the *resistive* actions becomes very high, *i*PASS concludes that the patient is likely to take a resistive action and the chair moves back to the sitting position to avoid a dangerous situation. Otherwise, *i*PASS proceeds the support for the patient. Again, since two human actions are treated as being exclusive each other, *i*PASS proceeds the support if the discriminant is very low for the *resistive* action. In the practical situation, there exist some cases in which it is difficult to make a decision. In such a case, *i*PASS stops the motion and leave the decision of next operation to a caregiver. Therefor, it is supposed that one caregiver should attend the patient.

The final decision-making point should be set at a point where the patient is not unstable yet and it is possible to move back to the sitting position safely. This point could be determined based on how much force applied to the seat surface. Figure 22 illustrates the process of decision making.

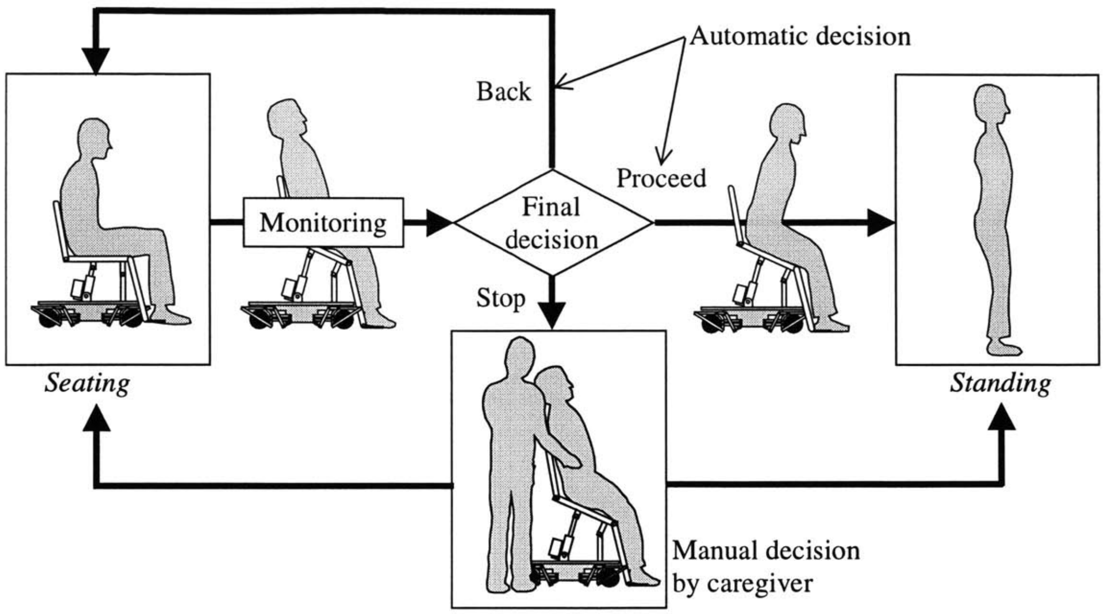


Figure 22. Decision-Making Process

2.6.3 EXPERIMENTAL RESULTS OF BAYES CLASSIFIER

In the experiment, a subject sits on the reconfigurable chair. The subject performs the trial to stand up with the standing-up assist. The speed of the chair tilt is about 10 degree/sec. It takes about 7 seconds to move from the seating position to the standing-up position. 7 seconds of data of the pressure distributions will be collected for each trial.

To estimate the parameters of the probability distribution of the feature vector for the *resistive* actions and the *cooperative* actions, 20 data were used for each human action. After obtaining the probability density of the feature vector of each action, newly observed human actions are evaluated with the developed Bayes classifier.

To evaluate the performance of the Bayes classifier with the sequential observation, the discriminant with the one observation at time t is also computed in the experiment. This discriminant g_O is given as

$$g_O(\mathbf{F}_t) = P(\omega_1 \mid \mathbf{F}_t) - 1 \tag{19}$$

The time profiles of the discriminant values of Bayes classifier are shown in Figure 23 and 24. Both of figures show the time profile of the two discriminants evaluating a *resistive* action, but Figure 23 shows the evaluation of a *resistive* action that has much more deviation than in Figure 24. The result shows that the probability revision extracts the tendency of human action and it is not affected by the deviation of human action.

In this experiment, when the subject took the *resistive* action against the chair motion, he ended up with a sliding down on the seat surface. If the subject is not prepared to stand up, the chair should move back to the seating position. Otherwise, this may result in a serious accident such as falling down.

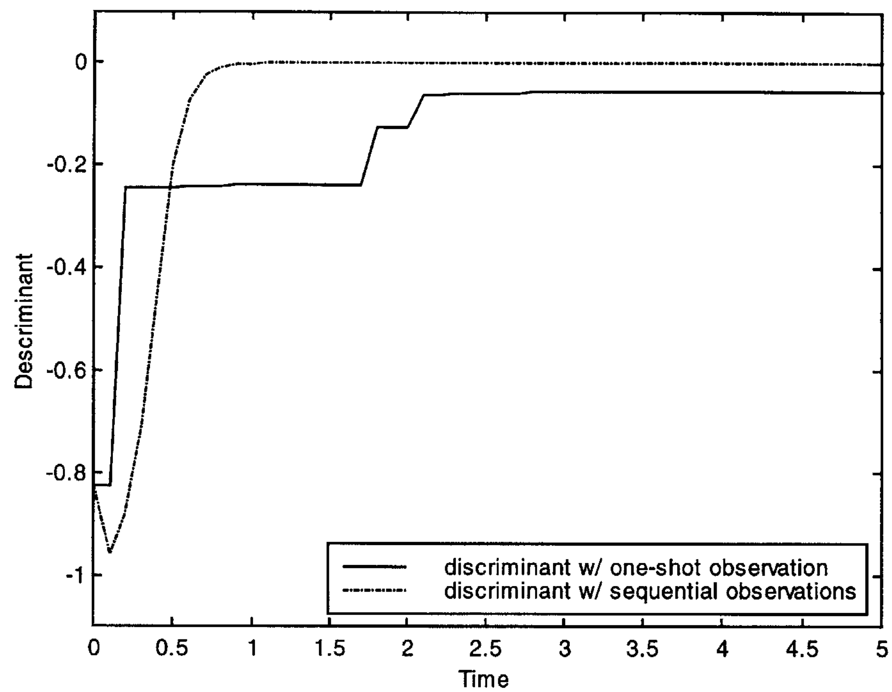


Figure 23. Discriminant Value of *Resistive* Action (1)

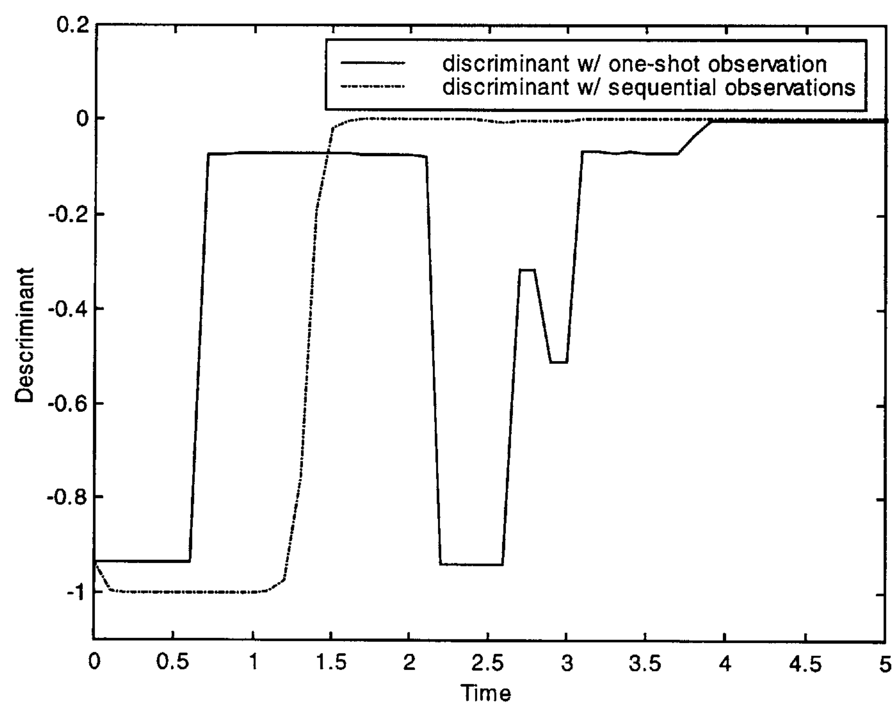


Figure 24. Discriminant Value of *Resistive* Action (2)

2.6.4 Discussion

Through the experiment, it was found out that a human action changed a pressure distribution pattern consistently. Therefor, the human action can be classified with the Bayes classifier based on the pressure distribution pattern. However, the final goal is to interpret a human intention or desire through a human action, the relationship between the action and the intention should be clarified.

Based on the observation in the experiment, the process of the human action generation can be described as follows. When the patient has an intention or a desire stimulated by physical interaction with *i*PASS, the intention or desire comes out as a muscular exertion. The muscular exertion changes the patient's posture and the exerted force to the seat surface, and finally the pressure distribution pattern changes. Therefor, a pressure distribution pattern can be associated with a muscular exertion and finally associated with a human intention or desire. Figure 25 illustrates the process from a human intention to the generation of the pressure distribution pattern.

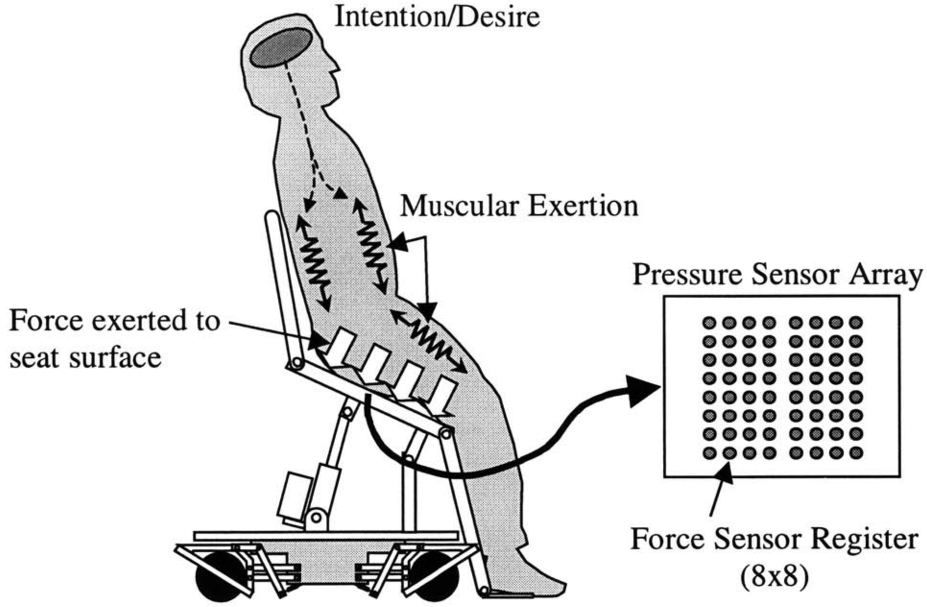


Figure 25. Process from Intention/Desire to Pressure Distribution Pattern

3 ASSESSMENT OF *i*PASS FOR PRACTICAL IMPLEMENTATION

3.1 INTRODUCTION

After developing the first *i*PASS prototype, the project group at MIT and researchers, clinical staff, and nurses at the Bedford VAMC started the redesign of *i*PASS. Our primary goal of the assessment of *i*PASS is making it usable and acceptable for demented patients and caregivers at the Bedford VAMC. Through this collaboration, some important improvements were highlighted to ensure acceptance of the system by patients and caregivers in hospitals or nursing homes.

We selected the male patients who have advanced progressive dementia and are receiving care at the Bedford VAMC for two reasons. (1) The patients are male and their height and weight mean that the final product will have the flexibility to serve a wide variety of persons. (2) The nature of the dementing illness suffered by the veterans makes them cognitively impaired as well as completely dependent in activities of daily living; working components to serve this very impaired population allows testing in the most extreme of patient difficulties with the physical assist device.

3.2 RECONFIGURABLE CHAIR

Functional Requirement: All five degrees-of-freedom of the reconfigurable chair are useful to adjust patient posture according to their physical condition and limitations. This function enables patients to take a preferable posture easily. A wide range of reclining positions and stable sitting positions was desired to adjust support pressure for maintenance of healthy skin tissue and promote healthy posture.

Chair Size Requirement: Minimum seat height from the floor should be from 16" to 19", and maximum height should be more than 25". The lowest position makes it easier for a patient to sit down, and the highest position makes it easier to transfer a patient to a bed. Seat width needs to be 18". Figure 25 illustrates these requirements of the chair size. It should be noted, however, that some caregivers need more space in the chair to take care of patients. See Additional Functions.

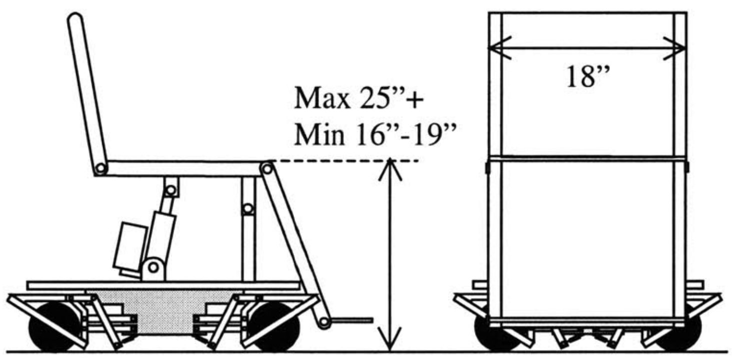


Figure 26. Requirement of Height and Width of Reconfigurable Chair

Expected Patient Weight: Average weight of patients at the Bedford VAMC is about 180 lbs. Some patients weigh more than 200 lbs. Even though the chair has many movable joints, it must be rigid enough to accommodate such patients.

Support for Patients: A head support is needed when taking a reclining position. A folding armrest is needed so it does not interfere with transferring a patient. Height adjustable foot platform is needed so that the patients can place their feet easily and comfortably. Almost all parts to support patients, such as armrests and chair frames, must be padded to promote comfort and prevent injury. Figure 26 illustrates the requirements of the parts to support the patients.

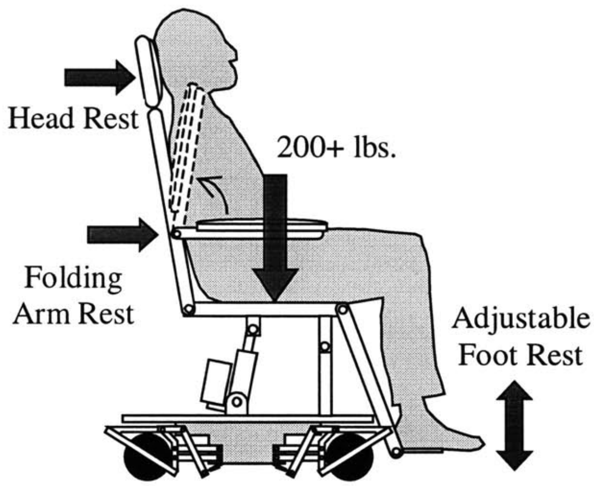


Figure 27. Required Functions to Support a Patient

3.3 HOLONOMIC OMNI-DIRECTIONAL WHEELCHAIR

Functional Requirement: The advantage of the holonomic, omni-directional wheelchair over a traditional one is its ability to move in any direction without changing the direction of wheels. It can move diagonally and side to side with keeping the direction of the chair. It also can rotate in place. In addition, ball wheels enable very smooth movement on the floor. This wheelchair provides more flexible and smooth movement to patients and caregivers than traditional wheelchairs. This maneuverability needs less effort to navigate in facilities such as hospitals and makes it easier to communicate with other people.

Controller Position: Controller needs to be put on handle in back, so it would be easy for caregivers to operate *i*PASS. Figure 27 shows a preferable position of the controller.

Maneuver Speed: Maximum speed should be slower than one of standard powered wheelchairs. Fast speed may frighten the patient and cause an accident because of slowing and impairment of information processing of the patient. Currently 4 inch/sec is set for maximum speed.

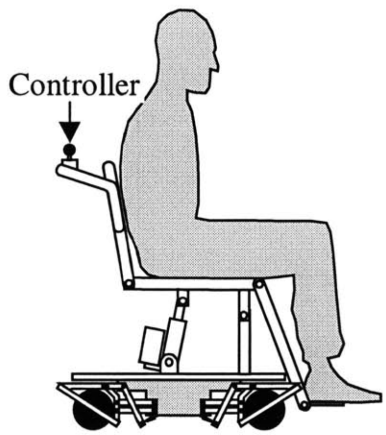


Figure 28. Controller Position of Wheelchair

3.4 STANDING-UP ASSIST

Functional Requirement: Standing-up is a common and necessary activity in daily life, and people need to take this action in various situations. As a matter of fact, to maintain patients' mobility as long as possible, the patients had better leave from *i*PASS and walk on their own if possible. Moreover, even if the patients can't stand on their own due to physical impairment, they can physiologically benefit from standing posture with a standing device. The patients that stand for 30 minutes or more per day will have fewer bed sores, fewer bladder infections, improved bowel regularity, and improved ability to straighten their legs compared with the patients who stand less time [7].

In addition to it, even though *i*PASS covers several services for patients, there are some unavoidable daily situations in which patients have to be transferred from *i*PASS to another equipment. Even if the patients lack their cognitive abilities, they can begin to take an action to stand up when some physical cue is provided. In the current practice, caregivers always play the role to initiate the patients to stand up and to push and pull the patients up to the standing-up position if needed. Some patients need physical assistance to be pushed up during their entire standing-up actions.

Using *i*PASS to aid a patient in standing-up, the patient can be transferred easily to a toilette chair, transferred to a shower chair, or walk around. Since patient weight sometimes exceeds 200 lbs. at the Bedford VAMC, assistance for standing-up is a laborious, dangerous job for caregivers. In addition to it, since the patients usually take a deep position on the chair, it is not easy to pull and push them from such a deep sitting position up to the standing-up position.

*i*PASS is able to change its configuration, it can provide a patient an appropriate posture that makes it easier to stand up, and it can provide a continuous support during standing up if the patient needs. Therefor, standing-up assistance can reduce the labor of caregivers and prevent back injuries and fear of injury. Fear of injury may be a reason why caregivers keep patients in bed. Standing-up assistance is useful to physically boost the patients while taking standing-up actions, to give the patients a cue to start standing up on their own, and to reduce the work load of caregivers.

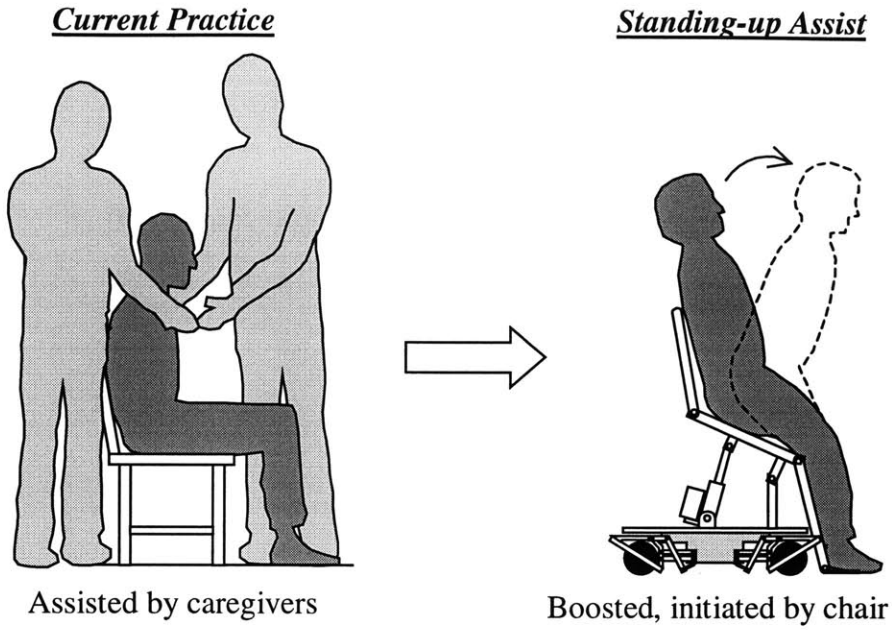


Figure 29. Benefits of Standing-up Assist

Support Handle: Some handles are needed so that the patients can grab the bar during the standing-up process. The shape and position of the bar is critical for patient safety. The shape of the bar should be easy and comfortable to grab, and the position should be suitable so patients can keep their stable posture. A possible idea is a bicycle like handle pointing outward so it does not interfere with the standing-up process. Another idea is a horizontal bar in front of a patient. This bar should move according to patient and chair motion to avoid interference with the standing-up process and make a patient feel secure and comfortable.

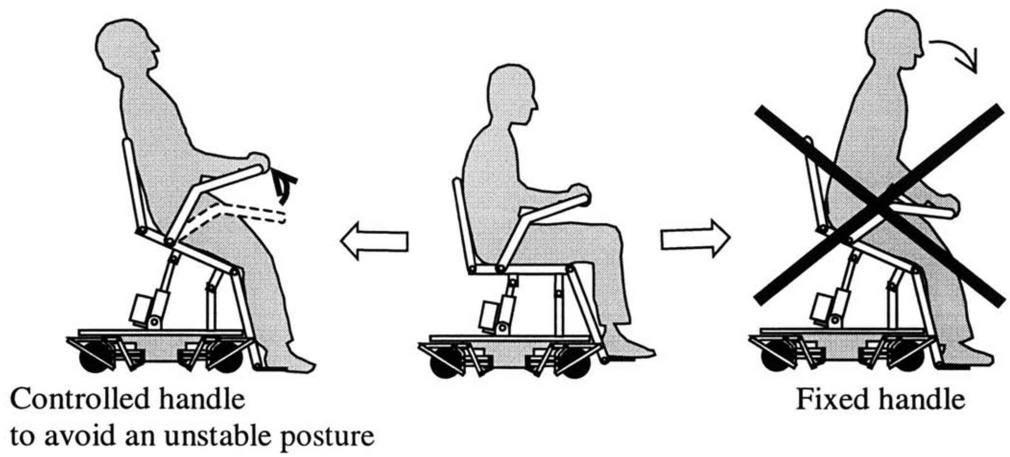


Figure 30. Support Handle for Standing-up Assist

An alternative method is to use a bar fixed to a wall for this purpose. This way is reasonably acceptable, because a patient can walk a short distance from a wall to the final destination if a patient can stand up.

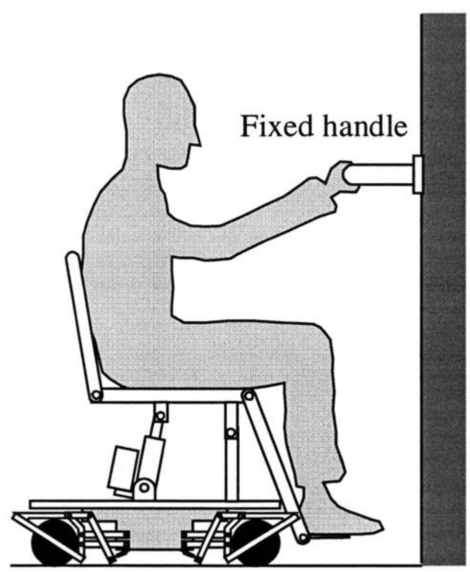


Figure 31. Standing-up Assist with Use of Fixed Handle

Support Belt: A seat belt is needed to avoid sliding down or falling down from the chair.

3.5 WALKER

Functional Requirement: About 1/3 of patients at the Bedford VAMC require assistance in walking and could benefit from this function. As a matter of fact, some patients use a traditional walker to maintain their mobility as long as possible. However, exclusion of the walker function could make the development of *i*PASS simple and shorten the development period. Since this function is not necessary for all the patients at Bedford VAMC, it could be left over for the next phase.

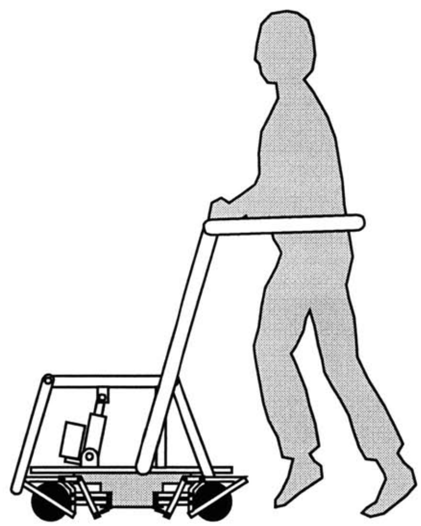


Figure 32. Walker Function of iPASS

3.6 ADDITIONAL FUNCTIONS

Additional Sensors: Sensors to detect a wall, such as an ultrasound sensor, might be useful to prevent accidental collisions. Weight scale embedded in the wheelchair platform might be useful to measure patients' weight continuously.

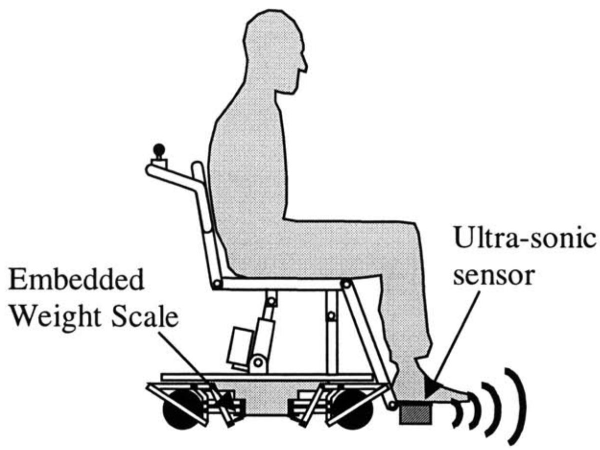


Figure 33. Additional Sensors for *i*PASS

Patient Transfer: Position clamp to bed frame is needed to secure the chair to a bed, when transferring a patient between the bed and the chair.

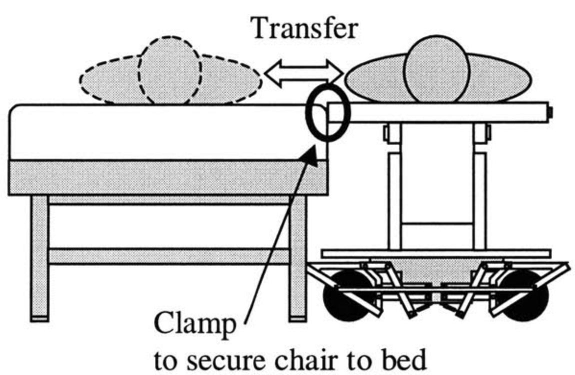
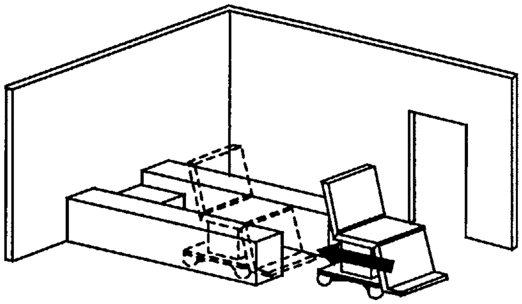
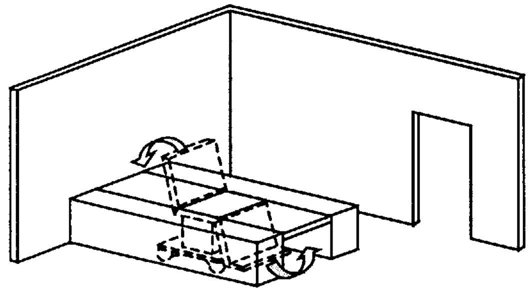


Figure 34. Clamp between iPASS and Bed

Docking Station to Bed: In some cases, caregivers require additional space to care for particular patient needs such as changing their clothes. By having the compact, narrow chair reconfigure and slide into a docked station beside the traditional bed, additional surface area is temporarily provided for special patient care. Some nurses prefer the concept of a temporary docking station with special facilities for patient handling.



Docking to Station



Reconfigured to Bed

Figure 35. Docking Station

3.7 SUMMARY OF DIMENSIONS AT THE BEDFORD VAMC

To make a successful design of iPASS for practical implementation, it is important to find how much space is available in the facility. Table 1 shows some dimensions at the Bedford VAMC.

Table 1. Dimensions at the Bedford VAMC

Description	*Dimensions (inch)*
Toilette height	**16.5**
Handicapped toilette height	**19**
(clearance from bottom of bowl to floor)	**7**
(width from wall to edge of bowl)	**10**
Stall width	**35**
Stall width (entrance)	**24**
Door width (main entrance)	**40**
Door width (bed room)	**34 – 45**
Width Between beds	**50**
Bed height	**25 – 37**

3.8 IMPROVED DESIGN OF *i*PASS

The previous section describes the redesign issues which need to be incorporated: chair height, maximum load, folding arm rests, adjustable foot rest, wheelchair speed, controller position, support handle, seat belt, sensors.

Our primary goal of the redesign of *i*PASS is making it usable and acceptable for demented patients and caregivers at the Bedford VAMC. For this purpose, three functions are to be included in *i*PASS: wheelchair, reclining chair including bed configuration, and standing-up assistance. As mentioned above, some patients at the Bedford VAMC require assistance in walking and could benefit from the walker function. However, exclusion of the walker function could make the development of *i*PASS simple and shorten the development period. Since this function is not necessary for all the patients at Bedford VAMC, it could be left over for the next phase. The system also can be made compact by eliminating the walker function from *i*PASS.

<u>Additional Features of *i*PASS:</u>

1. Head rest.
2. Foldable arm rests.
3. Support bars for standing-up assistance.
4. Height adjustable foot rests.
5. Wheelchair controller on the back of the chair.

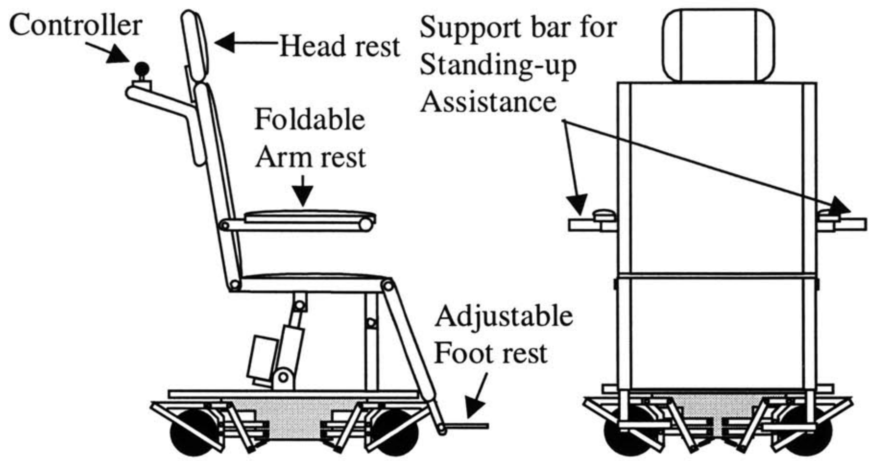


Figure 36. Projected iPASS System

Figure 35 summarizes the necessary modifications for a successful *i*PASS system implementation at the Bedford VAMC facility.

4 CONCLUSIONS

The method for recognizing a human intention through a human action was developed for assisting a patient in operating a physical assist device such as *i*PASS. Since *i*PASS is operated mainly by elderly people, patients with physical impairment, and caregivers, it needs high standards of safety in operations. To avoid serious accidents due to ignorance of human intentions in operations, it is crucial to monitor human actions and to understand intention of the actions. The patterns of the pressure distribution on the seat surface were modeled statistically. The pressure distribution pattern was differentiated with the Bayes classifier, and a certain human action was detected through the pressure distribution pattern. This method was applied to the stand-up assist of *i*PASS.

In this method, it was assumed that there is some correlation between a human action and a human intention. When the patient has an intention or a desire stimulated by physical interaction with *i*PASS, the intention or desire comes out as a muscular exertion. The muscular exertion changes the patient's posture and the exerted force to the seat surface, and finally the pressure distribution pattern changes. Therefor, a pressure distribution pattern can be associated with a muscular exertion and finally associated with a human intention or desire. The experiment verified that a human intention comes out as a muscular exertion and it results in a human action.

This thesis also described the assessment of *i*PASS for practical implementation. The functions of the first *i*PASS prototype were reviewed by the project group at MIT and researchers and clinical staff at the Bedford VAMC. Our focus is on the redesign of *i*PASS to enable practical use of the system at the Bedford VAMC. First, the necessity of each function at the Bedford VAMC was evaluated based on feedback from nurses, occupational therapists and physicians at the Bedford VAMC. The basic concept of *i*PASS was widely considered useful and helpful to support bedridden patients, but some modifications and additions were needed for practical implementation. To make each function acceptable to patients and caregivers at the Bedford VAMC, additional functions and requirements were clarified. Although the modifications were small, the realization of these additional requirements was necessary for practical use. These modifications and additions were illustrated in this thesis, and an improved design of *i*PASS was proposed.

APPENDIX A. SOFTWARE IMPLEMENTATION

The control and pattern recognition software was implemented on the PC with Real-time Linux (RTLinux). RTLinux enable special tasks to run in real-time. In addition to it, standard tasks on Linux can co-exist with the real-time tasks. The real-time task can be used for critical hardware control as well as data acquisition. The standard task can used to implement tasks which don't require real-timeness, such as graphical user interface, data logging, and network interface. These two tasks can communicate with each other by using the shared memory. This provides a flexible programming environment. Figure 36 illustrates the software Architecture of RTLinux [10].

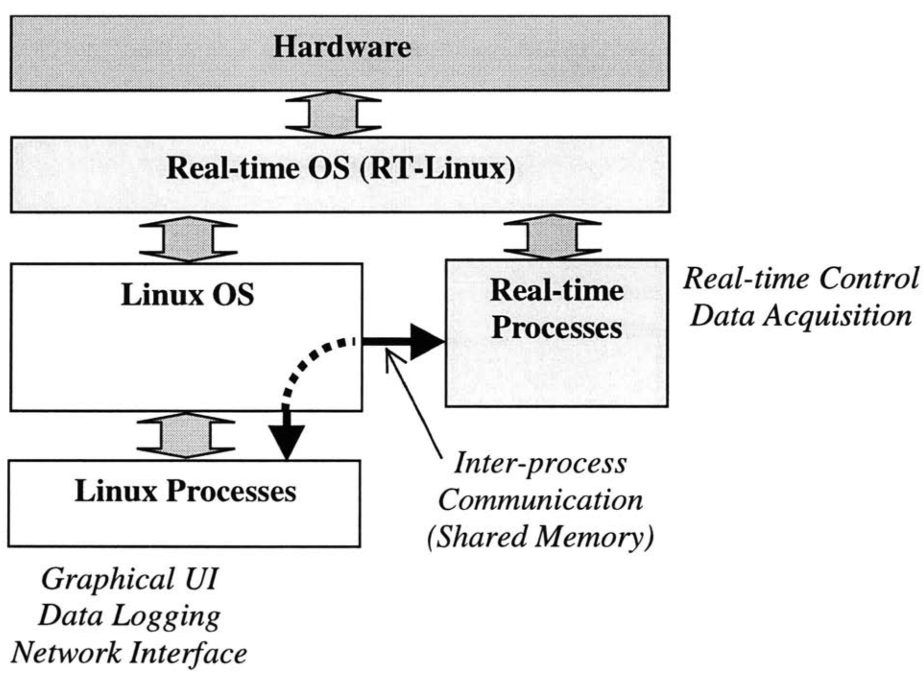


Figure 37. Software Architecture

Two real-time tasks are implemented to control *i*PASS and to acquire the data from the pressure sensors respectively. The control task runs periodically with the interval of 5msec, and the data acquisition task runs periodically with the interval of 100 msec. The control task reads the command from the user interface on the shared memory, and writes the status of *i*PASS to the shared memory. The data acquisition task writes the data from pressure sensor array to the shared memory.

The graphical user interface is implemented by using a standard Linux process. It communicates with the real-time tasks via the shared memory. The graphical user interface shows the status of *i*PASS and the data from the pressure sensor array. In addition it includes the Bayes classifier and shows the status of the patient detected by the classifier. It also provides the operation switches for *i*PASS. Figure 37 shows the implemented graphical user interface.

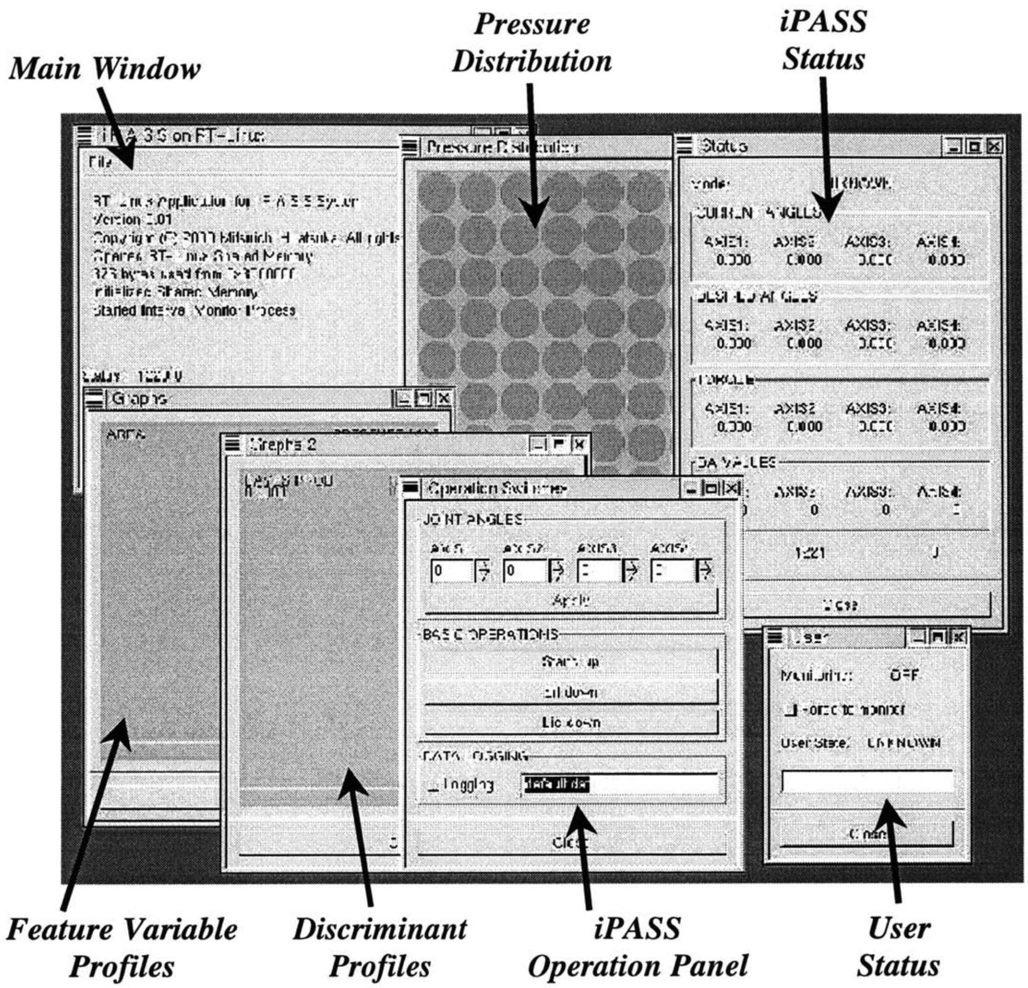


Figure 38. Graphical User Interface

REFERENCES

[1] T. Sato, Y. Nishida, J. Ichikawa, Y. Hatamura, and H. Mizoguchi, "Active Understanding of Human Intention by a Robot through Monitoring of Human Behavior," *Proc. of IROS '94*, Vol. 1, pp.405-414, 1994.

[2] Y. Nishida, M. Takeda, T. Mori, H. Mizoguchi, and T. Sato, "Monitoring Patient Respiration and Posture Using Human Symbiosis System," *Proc. of International Conference on Intelligent Robots and Systems*, Vol. 2, pp.632-639, 1997.

[3] J. Yang, Y. Xu, and C. S. Chen, "Human Action Learning via Hidden Markov Model," *IEEE Trans. Syst. Man and Cybern. (Part A: Systems and Humans)*, vol.27, no.1, pp.34-44, 1997.

[4] R. Sharma, and J. Molineros, "Computer Vision-Based Augmented Reality for Guiding Manual Assembly," *Presence*, vol.6, no.3, pp.292-317, 1997.

[5] J. S. Spano, "Design and Control of a Reconfigurable Bed/Chair System with Body Pressure Sensing," *S.M. Thesis*, Massachusetts Institute of Technology, 1997.

[6] M. Wada, and H. H. Asada, "Design and Control of a Variable Footprint Mechanism for Holonomic Omnidirectional Vehicle and its Application to Wheelchair," *IEEE Trans. on Robotics and Automation*, Vol. 15, No. 6, pp.978-989, 1999.

[7] J. S. Walter, P. G. Sola, J. Sacks, Y. Lucero, E. Langbein, and F. Walter, "Indication for a Home Standing Program for Individuals with Spinal Cord Injury," *J. Spinal Cord Med.*, 22(3), pp.152-158, 1999.

[8] R. O. Duda, and P. E. Hart, *Pattern Classification and Scene Analysis*, New York Wiley, 1973.

[9] T. B. Sheridan, and W. R. Ferrell, *Man-Machine Systems: Information, Control, and Decision Models of Human Performance*, MIT Press, 1974.

[10] V. Yodaiken, *The RTLinux Manifesto*, http://www.rtlinux.org