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A SENSING CHAIR

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ABSTRACT

This paper is concerned with how objects in an environment can be made aware of people via haptic sensing. It was motivated by the desire to make our environment "smarter" by providing it with sensory systems similar to our own. The work reported here focuses on an object that is involved in virtually all human-computer interactions, yet has remained sensory-deprived — the chair. A real-time sitting posture classification system has been developed using surface-mounted pressure sensors placed on the seatpan and backrest of a chair. The ultimate goal of this work is to build a robust multi-user sitting-posture tracking system that will have many applications including ergonomics and automatic control of airbag deployment in a car. Challenges for reaching the goal and plans of future work are discussed.

1. INTRODUCTION

This work was motivated by the desire to make the environment we occupy "smarter" by providing it with sensory systems similar to our own. In recent years, several "smart" environments have been developed that enable computers to identify people and interpret their actions and speech in real time (e.g., Torrance, 1995; Pentland, 1996). These systems enable computers to see and hear through various imaging and acoustic sensors. This work investigates how to enable a computer to "feel" its environment via haptic sensors. In a typical setup where a haptic human-machine interface is placed between a human and a computer, information flows in four pathways (see Fig. 1). The focus of this paper is a haptic perceptual user interface. Here we are mainly concerned with how a computer can derive haptic information about its user.

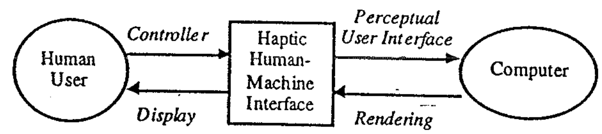

Figure 1. The four pathways of information flow for a haptic human-machine interface.

The office chair was chosen as the sensing object because it is involved in virtually all human-computer interactions, but has so far remained sensory-deprived. Surface-mounted pressure distribution sensors were selected for several reasons. First, they function similarly as the skin — the largest organ on a human body. They provide the chair with a layer of "artificial skin". Second, chairs are less mobile than the person. By attaching sensors to the chair, the human user need not be tethered. Third, data collected from pressure sensors are essentially two-dimensional digital arrays that resemble gray-level images. Thus they lend themselves very well to computer vision algorithms.

2. THE BODY PRESSURE MEASUREMENT SYSTEM

The sensing system used by our sitting-posture classification system is the Body Pressure Measurement System (BPMS) manufactured by Tekscan, Inc. in South Boston, Massachusetts. It consists of two identical surface-mounted pressure-sensitive transducer sheets, their interface electronics, and a PC interface board. The two sensor sheets are mounted on the seat pan and the back rest of an office chair. Each ultra-thin sheet is printed with an array of 42-by-48 sensing units and measures 0.10 mm in thickness. The sensing units are uniformly spaced with a 10 mm inter-element distance. Therefore, each sensor sheet has an active area of 41-by-47 cm. Each sensing unit acts as a variable resistor in an electrical circuit. When the unit is unloaded, its resistance is very high; when a force is applied to the unit, its resistance decreases. This output resistance is then converted to an 8-bit digital value. The sensors can be calibrated to display pressure readings in digital units, PSI, or mmHg. For the purpose of sitting-posture classification, only the relative pressure distribution information is needed. Therefore the raw 8-bit digital values are used.

The pressure maps from the two sensor sheets are spliced to form an 84-by-48 grayscale image which lends itself very nicely to image modeling and classification algorithms. Two typical pressure-map images for the sitting postures of "seated upright" and "left leg crossed" are shown in Fig. 2. To understand the orientation of these pressure maps, imagine standing in front of the chair and viewing the pressure maps from the backrest (tops) and the seatpan (bottoms). Therefore, the left and right sides of the pressure maps in Fig. 2 correspond to the right and left sides of the person sitting in the chair, respectively. Notice that the pressure readings from the seatpan are usually higher than those from the backrest. Notice also that the pressure maps for the two postures are quite distinctive, especially the bottom halves corresponding to the pressure distributions in the seatpan.

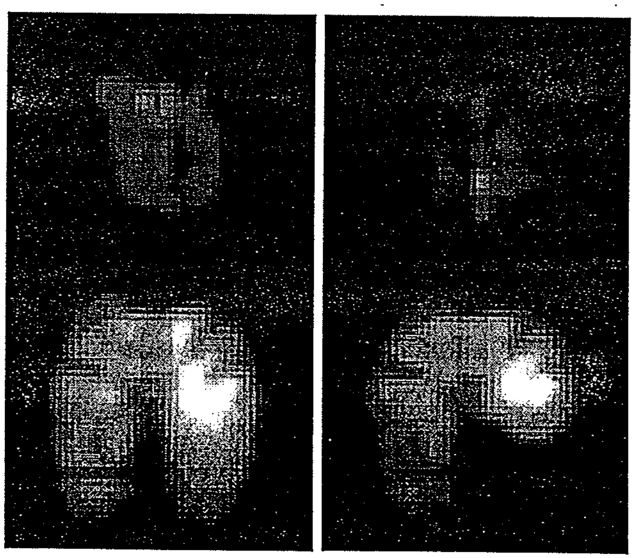

Figure 2. Pressure maps for "seated upright" (left) and "left leg crossed " (right) postures. Darker pixels correspond to lower pressure readings. See text for details.

3. POSTURE-BASED EIGENSPACES FOR POSTURE CLASSIFICATION

Our eigenspace-based approach to sitting-posture classification is based on a well-known algorithm in computer vision called "eigenfaces for recognition" (Turk & Pentland, 1991; Pentland, Moghaddam, & Starner, 1994). This approach extracts the relevant information in a pressure-distribution map by finding the principal components of the distribution of such maps, or the eigenvectors of the covariance matrix of the set of pressure maps. Let a pressure map $P(x,y)$ be a two-dimensional 84 by 48 array of 8-bit digitized values. Such a map may also be considered as a vector of dimension 4032, so that each pressure map becomes a point or a vector in a 4,032-dimensional space. An ensemble of pressure-map vectors then maps to a collection of points in this huge space. The locations of the pressure-map vectors, however, are not uniformly distributed in this space. In fact, points corresponding to the same posture collected from the same person should form a cluster and can be described by a relatively low dimensional subspace. The eigenvectors that describe this low dimensional subspace are called Eigen Pressure Maps (EPMs) in this paper.

Calculation of EPMs for a Single Posture

Let $\mathbf{P}_1$, $\mathbf{P}_2$, ... $\mathbf{P}_M$ (size 4032×1) be the set of M training data corresponding to one posture. The average pressure-map vector for this posture can then be computed as:

$$\overline{\mathbf{P}} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{P}_i$$

Each training pressure-map vector differs from the average by the vector:

$$\Phi_i = \mathbf{P}_i - \overline{\mathbf{P}}$$

The covariance matrix for Φ_i is then:

$$\mathbf{C} = \frac{1}{M}\sum_{i=1}^{M}\Phi_i\Phi_i^{\mathrm{T}} = \frac{1}{M}\mathbf{A}\mathbf{A}^{\mathrm{T}}$$

where $\mathbf{A} = [\Phi_1 \quad \Phi_2 \quad \ldots \quad \Phi_M]$ is a matrix of the size $4032\times M$.

The computation of the eigenvectors of the covariance matrix $\mathbf{C}$ is computationally prohibitive, since the size of $\mathbf{C}$ is 4032×4032. Luckily, given M training data ($M = 10 << 4032$ was used in this study), only M eigenvalues are nonzero. Furthermore, the eigenvectors of the 4032×4032 covariance matrix $\frac{1}{M}\mathbf{A}\mathbf{A}^{\mathrm{T}}$ and an

$M \times M$ matrix $\frac{1}{M}\mathbf{A}^{T}\mathbf{A}$ are related. Let $\mathbf{v}_i$ ($M \times 1$) be the eigenvectors of $\frac{1}{M}\mathbf{A}^{T}\mathbf{A}$, then

$$\left(\frac{1}{M}\mathbf{A}^{T}\mathbf{A}\right)\mathbf{v}_i = \mu_i \mathbf{v}_i$$

where μ_i are the corresponding eigenvalues. Premultiplying both sides by $\mathbf{A}$ gives:

$$\left(\frac{1}{M}\mathbf{A}\mathbf{A}^{T}\right)(\mathbf{A}\mathbf{v}_i) = \mu_i(\mathbf{A}\mathbf{v}_i)$$

In other words, the eigenvalues and the eigenvectors of $\mathbf{C} = \frac{1}{M}\mathbf{A}\mathbf{A}^{T}$ are μ_i and $\mathbf{A}\mathbf{v}_i$, respectively.

Given this analysis, we first construct the $M \times M$ matrix $\mathbf{C}' = \frac{1}{M}\mathbf{A}^{T}\mathbf{A}$ and find the M eigenvectors $\mathbf{v}_i$ of $\mathbf{C}'$. The EPMs $\mathbf{u}_i$ (4032×1) are then determined by the linear combinations of the M training pressure maps as

$$\mathbf{u}_i = \mathbf{A}\mathbf{v}_i = \sum_{j=1}^{M} v_{i,j}\Phi_i$$

where $v_{i,j}$ is the j-th component of $\mathbf{v}_i$, and $i = 1, 2, \ldots M$.

Posture-based EPM Subspaces and Posture Classification

Training data on a total of N=14 sitting postures have been collected. These postures are (1) seated upright, (2) leaning forward, (3) right leg crossed (with knees touching), (4) right foot on left knee, (5) left leg crossed (with knees touching), (6) left foot on right knee, (7) leaning back, (8) left foot on seatpan, (9) right foot on seatpan, (10) slouching, (11) leaning left, (12) leaning left with right leg crossed, (13) leaning right, and (14) leaning right with left leg crossed. EPMs for each posture are computed from the $M = 10$ training pressure maps for that posture. These EPMs form a total of N independent "posture subspaces" in the 4032-dimensional pressure-map vector space.

Given a new pressure-map vector $\mathbf{P}$, its distance from posture space (DFPS) for all N posture subspaces are calculated as follows. The mean-adjusted pressure-map vector $\Phi_k = \mathbf{P} - \overline{\mathbf{P}}_k$, where $\overline{\mathbf{P}}_k$ is the average pressure-map vector for k-th posture, is projected into the k-th posture space to obtain the weights

$$\omega_{k,i} = \mathbf{u}_{k,i}^{T}\Phi_k$$

where $\mathbf{u}_{k,i}$ is the k-th EPM for posture k, $k = 1, 2 \ldots N$, and $i = 1, 2 \ldots M$. The projection of Φ_k into the k-th posture space is simply the linear combination of the EPMs:

$$\Phi_k' = \sum_{i=1}^{M} \omega_{k,i}\mathbf{u}_{k,i}$$

To the extent that the new mean-adjusted pressure-map vector Φ_k is well represented by the EPMs in the k-th posture subspace, Φ_k and Φ_k' would be almost identical. Mathematically, the DFPS ε_k^2 is computed as the squared distance between the two pressure-map vectors

$$\varepsilon_k^2 = \left\|\Phi_k - \Phi_k'\right\|^2$$

and used as a measure of the distance between them. Provided that all ε_k^2 values ($k = 1, 2 \ldots N$) are below a preset threshold, the posture corresponding to the smallest ε_k^2 classifies the new pressure map.

Summary of Posture Classification Algorithm

Based on the above derivation, our sitting posture classification algorithm can be summarized as involving the following steps.

Preprocessing:

1. Collect $M = 10$ samples for $N = 14$ sitting postures. The pressure maps from the backrest and the seatpan are combined as shown in Fig. 2 and converted to a column vector $\mathbf{P}_{k,i}$ ($k = 1, 2 \ldots N$ and $i = 1, 2 \ldots M$) of the size 4032×1.

2. For each posture k, compute the mean pressure-map vector $\overline{\mathbf{P}}_k$. Compute the mean-adjusted pressure-map vectors $\Phi_{k,i} = \mathbf{P}_{k,i} - \overline{\mathbf{P}}_k$ for $i = 1, 2 \ldots M$.

3. For each posture k, first construct the $M \times M$ matrix $\mathbf{C}_k' = \frac{1}{M}\mathbf{A}_k^{T}\mathbf{A}_k$ where $\mathbf{A}_k = [\Phi_{k,1} \;\; \Phi_{k,2} \;\; \ldots \;\; \Phi_{k,M}]$. Compute its eigenvectors $\mathbf{v}_{k,i}$ and sort them in descending eigenvalues.[1]

[1] To reduce the amount of computation further, one might consider using only the first M' ($M'<M$)

4. For each posture k, compute the M nonzero eigenvectors, the EPMs, for the covariance matrix $\mathbf{C}_k = \frac{1}{M}\mathbf{A}_k\mathbf{A}_k^T$ as $\mathbf{u}_{k,i} = \mathbf{A}_k\mathbf{v}_{k,i}$ for $i = 1,2\ldots M$.

5. Repeat steps $2-4$ for $k = 1,2\ldots N$.

The above steps for preprocessing are performed offline in MATLAB.

Online processing:

1. Acquire a new combined pressure map $P(x,y)$ of the size 84×48 and apply local smoothing using its eight neighbors. Convert the result to a pressure-map column vector $\mathbf{P}$.

2. If $\sum_{x=1}^{84}\sum_{y=1}^{48} P(x,y) \le P_{th}$ where P_{th} is a preset threshold on the sum of pressure readings, the new pressure map is classified as from an empty chair. Return to step 1.

3. For the EPM subspace corresponding to posture k, compute the mean-adjusted new pressure-map vector $\Phi_k = \mathbf{P} - \overline{\mathbf{P}}_k$.

4. Compute the projection of Φ_k into the k-th EPM space, $\Phi_k' = \sum_{i=1}^{M}\omega_{k,i}\mathbf{u}_{k,i}$, where $\omega_{k,i} = \mathbf{u}_{k,i}^T\Phi_k$ reflects the weight for each EPM.

5. Compute DFPS $\varepsilon_k^2 = \left\|\Phi_k - \Phi_k'\right\|^2$.

6. Repeat steps $3-5$ for $k = 1,2\ldots N$.

7. Find the value of k, k', that corresponds to $\min_{1\le k\le N}\varepsilon_k^2$.

8. If $\varepsilon_{k'}^2 \le t$ where t is a preset threshold, then the new pressure map is classified as from posture k. Otherwise, it is declared as unknown.

Results

Our algorithm was implemented on a Pentium PC in Windows 3.11 environment (required by the Tekscan hardware driver). As the user moves in the chair, the system continuously reports the classified posture name (including "empty seat" and "unknown") on the computer screen. In static mode (i.e., the user assumes one of the pre-trained sitting postures), the system always correc identifies the posture. It is, however, difficult to gauge the system's overall performance for several reasons. First, the current implementation is designed to *classify*, not to *track*, the user's sitting postures. As the user switches from one posture to the other, the system keeps attempting to classify postures in real time, thereby giving erroneous responses. Second, we lack a general database of pressure distribution patterns for sitting postures that can be used to evaluate the performance of any algorithms. Third, the hardware driver provided by Tekscan Inc. prohibits direct access to data buffers, thereby greatly reducing the efficiency of data acquisition. For that reason, the update time of our algorithm could not be reasonably determined.

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eigenvectors corresponding to the M' largest eigenvalues in subsequent steps.

4. FUTURE WORK

The long-term goal of this work is to build a robust, multi-user sitting-posture tracking system — a "smart chair". Towards this goal, work in the near future will follow these directions: (1) a general pressure map database for chairs, (2) extend the current algorithm to a multi-user sitting posture classification system, (3) modeling of pressure maps from transitional postures, and (4) assessment of minimum resolution required of pressure-distribution sensors.

A general pressure-map database is needed in order to understand the variations in chair surface press distribution due to parameters such as user (age, gende, weight, and size), chair (cushioned vs. hard surface, contoured vs. flat surface, height of the seatpan relative to the user's size), activity (typing on a keyboard, talking on the phone, driving), and obviously, sitting posture. This knowledge can be used to estimate certain features (e.g., the approximate weight of the user) from pressure distribution maps. It can also be used to normalize pressure distribution maps for different people and chairs for the purpose of identifying sitting postures regardless of user's weight or height. Another important function of a general pressure-map database is to evaluate and compare the performance of sitting posture classification algorithms. By annotating each pressure map with salient features such as the person's weight and sitting posture and use them as the "correct answers", the accuracy of a sitting posture classification algorithm can be quantitatively measured.

The current algorithm can be easily extended to a multi-user sitting posture classification system by introducing a new measure called Distance-Inside-Posture-Space (DIPS). Instead of computing EMP subspaces using only the training data from one person for a sitting posture, we will use training data from several users to form the EMP subspace. The pressure-map vectors corresponding to different users are likely to form clusters within this subspace of the 4032-dimensional pressure-map vector space. We will first use DFPS to find the subspace that is closest to a new pressure-map vector, then use DIPS to find the cluster of training data that is closest to the new pressure map. We will then be able to identify both the sitting posture and the individual.

In order to have a posture tracking system that can not only identify the static sitting posture but also track the change from one posture to the other, we need to model the change in pressure maps for transitional postures. Several techniques, including biomechanical modeling of the human body and Hidden Markov Models (HMM) will be investigated.

Finally, the 10 mm inter-element spacing of the Body Pressure Measurement System is probably more than adequate. Pressure maps acquired from the BPMS will be down-sampled and the performance of posture tracking algorithm re-evaluated. The goal is to be able to specify the minimum sensor resolution required in order to achieve a certain performance criterion. A low-cost and low-resolution pressure sensing system can then be developed to facilitate the widespread use of smart chairs.

A smart chair such as the one we are developing can have many important applications. For example, a sensing chair that continuously monitors the pressure distribution on chair surfaces can be a valuable ergonomics tool for people who suffer from lower-back pain due to poor postures. It can also assist furniture designers to assess the long-term, dynamic performance of a new chair. A carseat that can reliably estimate the weight of its occupant can be used to control the force of airbag deployment. Finally, a smart chair that continuously tracks its occupant's movements in the chair can be regarded as a new type of haptic interface. The possibilities for the use of such an interface for human-computer interactions can only be limited by our imagination.

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