31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Unsupervised Monitoring of Sitting Behavior

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Abstract— **In recent years, the monitoring of sitting postures was discovered to be a promising measure of healthy sitting behavior, comfort, physical wellness and emotions. Most state-of-the-art systems for monitoring sitting behavior are based on supervised methods that are limited to a fixed set of classes. We present a method that does not rely on training but distinguishes between different postures autonomously.**

We designed and implemented a system to monitor sitting behavior in an unsupervised manner. Based on the pressure distribution acquired from a pressure mat we generate prototypes of sitting postures. The prototypes are stored in a database and serve as reference for comparing and classifying incoming pressure data. The system relies on only a few, interpretable system parameters and performs in real-time.

We conducted an experiment with a collective of 8 subjects and recorded the data of 16 different postures for each subject. Our proposed method generates on average 15.57 prototypes of postures. This reflects well the 16 postures that actually occurred in the experiment. In 91% of all cases an unambiguous assignment of a posture to exactly one generated prototype was achieved. On the other hand an unambiguous assignment of a prototype to a posture was obtained in 86%.

Keywords: unsupervised monitoring, posture recognition, prototype database, database matching

I. INTRODUCTION

The third European Working Conditions Survey identified the most common work-related health problem as backache reported by 33% of respondents [1]. As a consequence the absence from work or even permanent disabilities result in high economic costs [2]. According to [3], fixed postures and prolonged sitting are risk factors for developing lower back pain. Furthermore, any prolonged posture will lead to static loading of the soft tissues and discomfort. As a prevention strategy fixed postures should be avoided. Motivated by these findings, researchers from different disciplines are working on the automatic monitoring of sitting postures to support healthy sitting behavior.

Nowadays, commercial pressure mats allow for continuous unobtrusive sensing of the pressure distribution on a chair. and a wide range of methods for the automatic detection of sitting postures was developed. In most of these methods pressure data from different postures and users is collected in a first step. In a second step the recorded pressure data is preprocessed, meaningful features are extracted and a supervised classifier is trained to automatically detect the sitting postures under investigation. These supervised classifiers require labeled training data as opposed to unsupervised classifiers. Thus, most state-of-the-art systems are limited to a fixed set of postures that must be specified in advance during the training phase. In contrast, we present an unsupervised approach for monitoring sitting behavior that does not rely on a fixed set of postures but distinguishes between different postures autonomously. A temporal distribution of the detected postures can be derived to identify prolonged static postures and provide a risk assessment of the subject's sitting behavior. Supervised approaches can be beneficial if unhealthy sitting postures are known in advance. The core of our method is a frame-by-frame comparison of pressure data with posture prototypes stored in an autonomously created database. The system relies on only a few, interpretable parameters and performs in real-time.

In section II we present related work on monitoring sitting behavior and prototype databases. In section III we present our method in detail. Section IV contains the description of the performed experiment and in section V we present the achieved results. Finally, we draw conclusions, discuss our results and provide an outlook on our future work in section VI.

II. RELATED WORK

A. Pressure sensing for posture recognition

A wide range of methods exists for automatically detecting postures. Pressure sensor mats have been used to detect sitting postures in a chair [4]–[7]. Pressure mats have also been employed to identify a driver in a car [8], to evaluate a car driver's behavior [9], [10], to measure driver's fatigue based on postural changes [11] and as a measure for comfort [12] and physical wellness [13]. In recent work, the authors of this paper have shown that nervous subjects exhibit higher variance of movements under mental stress and that a person-independent discrimination of stress from cognitive load is feasible when using only pressure data [14].

B. Prototype database

The unsupervised database approach presented in this paper is related to the family of Adaptive Resonance Theory (ART) algorithms [15]. This approach adapts prototypes continuously when instances appear in a defined neighborhood. Therefore, this method is well suited to problems with an evolving database. However, in our application, we need the prototypes to remain fixed to allow a consistent interpretation of recognized postures over time.

III. METHODS

A. System description

The overall system architecture of our method is illustrated in Fig. 1. In the first step the current pressure distribution on

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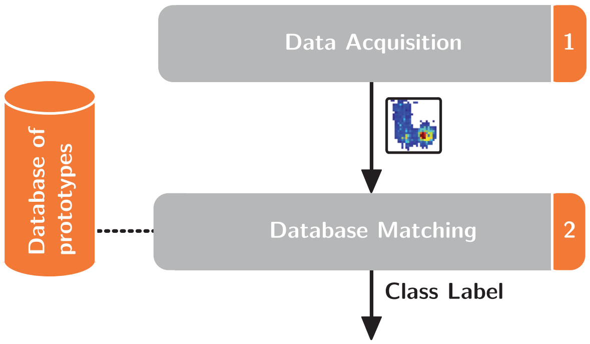

Fig. 1. Overall system architecture: in the first step the current pressure distribution on the seat is acquired from a pressure mat. In the second step the pressure frame is compared to prototypes stored in a database. If a similar prototype is available, this prototype is assigned as class label to the current frame. If there is no similar prototype available, the current pressure frame is added to the initially empty database.

the seat is acquired from a pressure mat. In the second step the pressure frame is compared to prototypes of postures stored in a database. If a similar prototype is available, this prototype is assigned as the class label to the current frame. If there is no similar prototype available, the frame is added to the initially empty database as a prototype representing a steady-state posture as described in section III-A.2. In the following, the two system components are described in more detail.

1) Data acquisition: Input data is acquired from a commercially available pressure mat from *Tekscan* [16]. Each sampled frame comprises pressure data of 1024 sensor elements arranged in a grid. The sampling rate was set to 25 Hz. A frame can be interpreted as an image, illustrating the current pressure distribution. Examples are shown in Fig. 2. The sum over all pixels is normalized to one for each frame.

2) Database matching: The initially empty database is filled with posture prototypes representing the different postures occurring during the measurement session. The current pressure frame is compared to the prototypes in the database and the nearest posture prototype (NPP) is determined. We take the sum of absolute difference (SAD) between the current frame and the prototypes as the similarity measure. The index of the NPP in the database is assigned as the class label to the current frame. A new prototype is added to the database if it meets the following two conditions:

- The posture is *unknown*: a posture is considered as unknown if it is not similar to any existing prototype in the database. The current frame is first compared to each prototype stored in the database based on the SAD and is considered as a new posture prototype if the difference exceeds a threshold T_{mean}. The threshold T_{mean} allows control of the database's granularity: a higher T_{mean} means that fewer prototypes will be generated and the database will be coarser, consisting of only very different prototypes.
- The posture is in a *steady-state*: since we are interested in taking "snapshots" of representative postures into the database, we have to ensure that the new posture is in a steady-state. We consider a new posture as steady-state if the variance of the similarity measure mentioned above is below a threshold T_{var}.

Postures emerging from translation or rotation are handled as different prototypes if they meet the above criteria.

B. Adjustment of system parameters T_{mean} and T_{var}

As mentioned above, a new prototype is added to the database if the posture is unknown and in a steady-state. These two conditions are controlled by the two parameters T_{mean} and T_{var}.

We have evaluated the influence of the two parameters in a systematic way based on the data recorded for a single subject. The similarity measure and its variance were used to find reasonable values for T_{mean} and T_{var}. In a first step a prototype is stored in the database representing a certain posture. Next, the remaining pressure frames of the same posture are presented to the system and the similarity measure to the prototype is calculated. This procedure is repeated for all postures. The mean and the variance of the similarity measure are then used to determine reasonable values for T_{mean} and T_{var}.

Using data of subject 1 exclusively, we obtained 0.16 for the mean and 0.00033 for the variance of the similarity measure on a window of length $W = 3$ s. Note, that the similarity between frames of an identical posture is not perfect due to small movements of the subject as well as noise from the sensor elements. To specify T_{mean} we added three times the standard deviation to the mean calculated above to account for 99.7% of the occurring values. As a result of visual inspection we found that taking twice this value results in a more stable classification. In the following, all results are based on these settings presented in Table I.

IV. Posture Experiment

A posture experiment has been conducted to characterize the classification performance of the system. The pressure mat described in section III-A.1 was calibrated in the range of 0 to 3.3 N/cm^2 with the calibration system from *Tekscan* and was mounted on a wooden swivel chair with a flat surface. The sampling rate was set to 25 Hz. The height of the chair was adapted to the length of the legs of the subjects so that their heels were just touching the floor when sitting upright.

The experiment was conducted with 8 subjects (5 male, 3 female, age 25–58). For each subject 16 static postures including transition phases have been measured and labeled. Examples of patterns for the postures measured by the

TABLE I

Description and values of the main system parameters.

Parameter	Value	Description
T_{mean}	0.44	Threshold for detecting unknown postures
T_{var}	0.00033	Threshold for detecting steady-state postures
W	3	Window length in seconds

pressure mat are depicted in Fig. 2. The dataset also contains very similar postures, e.g. posture 4 and 5. Each posture was maintained by the subject for 30 s. To define the transitions between the postures a default posture was included between each succeeding posture. In the default posture the subjects were sitting upright and maintained the position for 5 s. In total about 4 h of data was recorded during the experiment.

V. RESULTS

In Fig. 3 we provide as an example the classification results for subject 7. The results for the remaining subjects look similar. Each of the 16 ground truth classes is represented by a colored bar. E.g., in the beginning the ground truth class changes from 1 to 2, separated by a transition phase. The classification result is given by the curve showing the prototype assigned by the unsupervised system over time. The overall time frame shown covers 13 minutes.

In the optimal case, all frames of a certain ground truth class would be assigned to one prototype and each prototype would be assigned to one class. However, in practice frames of a certain ground truth class can be assigned to different prototypes. On the other hand, a prototype can serve for several ground truth classes. The latter deviation from the ground truth indicates that two ground truth classes are very similar and should be grouped. Following our example, postures 6 and 8 are both assigned to prototype 5 as it is observable in Fig. 3. Comparing postures 6 and 8 in Fig. 2 reveals that they are indeed similar.

We computed the matching matrices also known as confusion matrices in supervised learning for the subjects 2–8 to quantify the overall performance in mapping prototypes to ground truth classes. Data from subject 1 was not used in the results, because it has already been taken into account for determining the system parameters. In Fig. 4 we present as an example the matching matrix for the data of subject 7. For each matching matrix we calculated the ratio of the maximum occurring value in each row to the total number of elements in this row. The resulting values are averaged over all rows. Analogously we calculate the corresponding ratio for each column. The resulting values are presented in Table II. In the last row we present the mean values for all subjects. On average the assignment of a posture to one prototype was achieved in 91% of cases while an unambiguous assignment of a prototype to a posture was obtained in 86% of cases. In addition, we present the number of prototypes found for each subject in Table II. On average our proposed method discovers 15.57 postures, which is very close to the 16 postures contained in the data.

VI. CONCLUSIONS, DISCUSSION AND OUTLOOK

We designed and implemented a framework for monitoring sitting behavior in an unsupervised manner. Based on the pressure distribution acquired from a pressure mat we generate prototypes of sitting postures. The prototypes are stored in a database and serve as comparison reference for classifying incoming pressure data. The system performs in real-time and relies on only few system parameters, which were adjusted in a preliminary step. To characterize the classification performance of the system, a posture experiment has been conducted. On average our proposed method discovers 15.57 postures for all subjects, which reflect the 16 postures that occurred in the experiment well. On average the assignment of a posture to one prototype was achieved in 91% of cases while an unambiguous assignment of a prototype to a posture was obtained in 86% of cases. These promising results suggest that the presented framework is feasible for monitoring sitting behavior. Possible applications can utilize the captured set of postures and evaluate sitting dynamics over time. In one scenario a feedback could be provided to the user showing the posture prototypes and the amount of time these postures were taken by the user. This would allow the user to quantify the risk for developing lower back pain, i.e. the amount of time a user took fixed postures and prolonged sitting. In another application scenario the sitting dynamics could by investigated by analyzing the amount of posture changes related to working conditions. As a result, the sitting dynamics could indicate comfort, physical

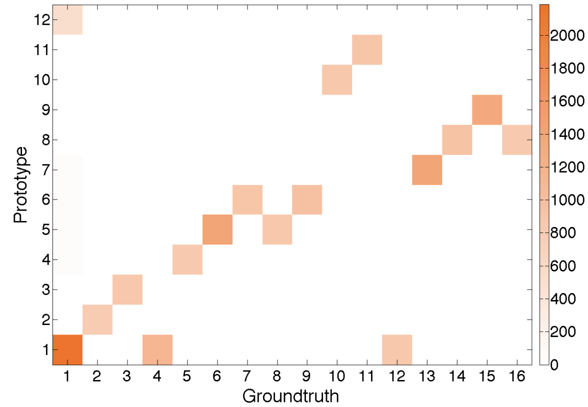

Fig. 4. Matching matrix obtained from the data for subject 7. Comparing for example the confused postures 6 and 8 in Fig. 2 reveals that they are indeed similar.

TABLE II

OVERALL PERFORMANCE IN MAPPING PROTOTYPES TO GROUND TRUTH CLASSES BASED ON THE MATCHING MATRICES FOR THE SUBJECTS 2–8. FOR EACH MATCHING MATRIX WE CALCULATE THE RATIO OF THE MAXIMUM OCCURRING VALUE TO THE TOTAL NUMBER OF ELEMENTS IN THIS ROW (CLASSIFICATION RATIO). ANALOGOUSLY WE CALCULATE THE CORRESPONDING RATIO FOR EACH COLUMN (GROUND TRUTH RATIO). THE LAST COLUMN CONTAINS THE NUMBER OF PROTOTYPES FOUND FOR EACH SUBJECT (#PT).

Subject	Classification Ratio	Ground Truth Ratio	#PT
2	0.93	0.81	14
3	0.89	0.87	16
4	0.87	0.91	18
5	0.91	0.90	17
6	0.88	0.92	17
7	0.95	0.72	12
8	0.95	0.90	15
mean	0.91	0.86	15.57

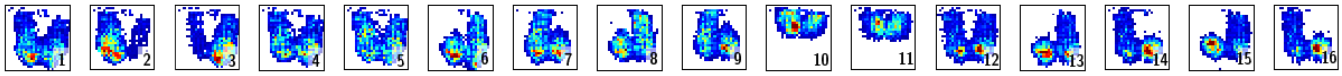

Fig. 2. Examples of pressure patterns for the 16 postures recorded during the posture experiment: Sitting upright, default posture (1), lean left (2), lean right (3), lean back (4), lean front (5), left over right leg, knees touching, upright (6), right over left leg, knees touching, upright (7), left over right leg, knees touching, lean back (8), right over left leg, knees touching, lean back (9), sitting on leading edge (10), lie (11), slouching (12), left over right leg, foot on knee, upright (13), right over left leg, foot on knee, upright (14), left over right leg, foot on knee, lean back (15), right over left leg, foot on knee, lean back (16).

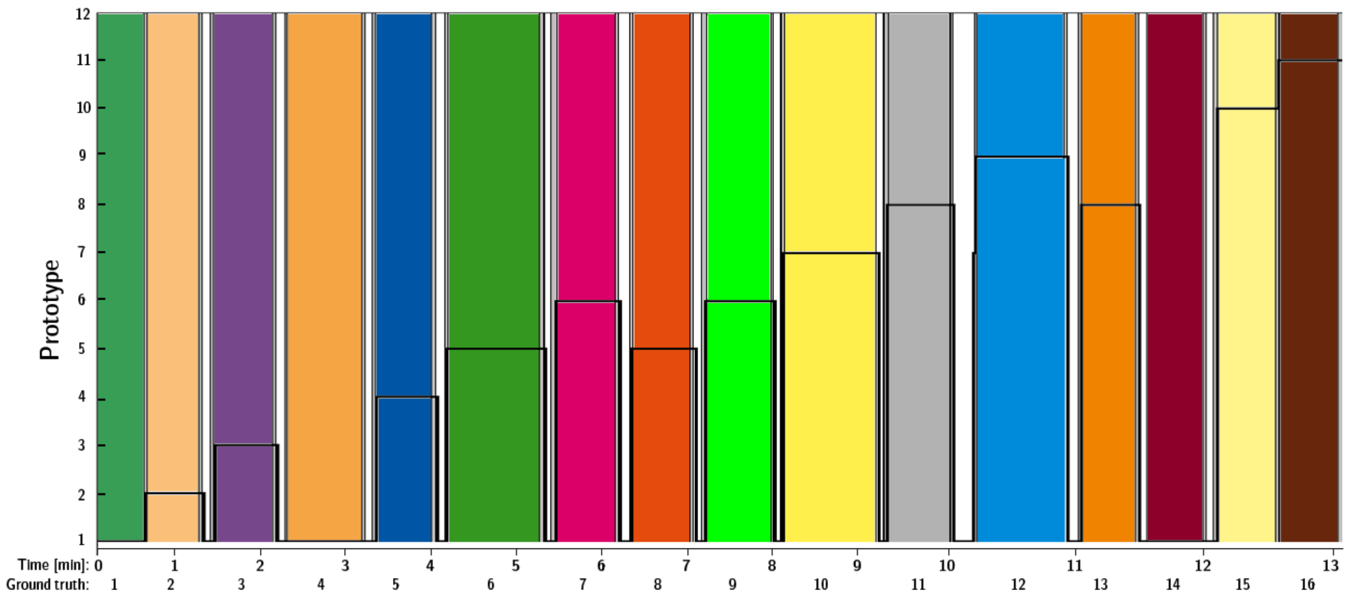

Fig. 3. Classification results for subject 7 as an example: each of the 16 ground truth classes is represented by a colored bar and a corresponding class label shown below the x-axis. E.g., in the beginning the ground truth class changes from 1 to 2, separated by a transition phase. The classification result is given by the curve showing the prototype assigned by the unsupervised system over time.

wellness or even affective states like stress. Both scenarios can help to achieve and maintain a healthy sitting behavior.

In future work we will investigate a real-life office scenario to evaluate the system performance in a more naturalistic setting. The same measurement setup will be used together with a coarse labeling performed by each subject. This will allow to investigate how well the automatically found postures reflect the daily routine of the user related to healthy sitting behavior.

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