Smart Chair: What Can Simple Pressure Sensors under the Chairs' Legs Tell Us about User Activity?

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***Abstract*—In this paper, we investigate how much information about user activity can be extracted from simple pressure sensors mounted under the legs of a chair. We show that it is possible to detect not only different postures (0.826 accuracy for 5 subjects and 7 classes), but also subtle hand and head related actions like typing and nodding (0.880 accuracy for 5 subjects and 5 classes). Combining features related to postures and such simple actions, we can detect high-level activities such as working on a PC, watching a movie or eating in a continuous, real-life data stream. In a dataset of 105.6 hours recorded from 4 subjects, we achieved 0.783 accuracy for 7 classes.**

***Keywords*—ubiquitous computing; smart chair; resistive pressure sensor; activity recognition**

I. INTRODUCTION

In general, people spend a lot of time sitting: when working in the office, in a meeting, in the theater, when having a meal, when playing games or watching TV. In [1], it has been shown that on average, people with sedentary jobs sit 9.95 hours at working days and 8.07 hours when not working. From the above, instrumented chairs may seem like an obvious approach to activity recognition. On the other hand, there is the question that how much information can be extracted from chair-mounted sensors. Per definition, when sitting, people tend to engage in activities that involve little motion of the body trunk and are mostly determined by hand actions and cognitive processes. At the same time, the body trunk is the main physical interface between the chair and the user, and thus the main potential source of information. As a consequence, the vast majority of work on chair based activity monitoring has focused on posture analysis and the measurement of physiological parameters that can be extracted from the trunk by electrodes integrated in the seat (see related work section). Such work has so far relied on sensors integrated in the seat itself or the backrest (often using smart textiles), which implies significant effort in terms of unobtrusive instrumentation in every day environments.

A. Paper Contribution

Building on such work, the core ideas that this paper explores, are two fold:

1) Many shoulder, arm, hand and head related actions leave a subtle but characteristic signature in terms of weight distribution changes on the chair. Such signatures can be combined with the correlation between posture and activity for the recognition of complex activities, which are not directly related to trunk motions.
2) The weight distribution and posture changes can be detected using simple, cheap pressure sensors mounted under the chair, without the need to instrument the seating surface or the backrest. This means that existing chairs can be easily retrofitted, allowing for the instrumentation of entire offices, meeting rooms, or theaters.

From the above ideas, the paper makes the following concrete contributions:

- We describe the measurement system, which is based on our own resistive foam sensor, which is simple and cheap; while at the same time providing the required resolution and measurement range.
- We validate the hypothesis that posture changes can be detected using pressure sensors integrated under the chairs' legs (as opposed to pressure sensors matrices on the seat itself as investigated by related work). This is done in experiments with 5 subjects and 7 postures (e.g. sit straight, lean left / right / forward / backward, raise one hand, cross one leg over the other knee), giving a recognition rate of 0.826 on average.
- We validate the assumption that actions related to arm, hand and head motion produce detectable signatures in the pressure signals. This is done in experiments with 5 subjects and 5 actions (e.g. typing keyboard, clicking mouse, nodding, clapping hands and sitting still), giving a recognition rate of 0.880 on average.
- We demonstrate that such information can be used to discriminate high-level activities such as playing a computer game, working on the computer and eating a snack. From 4 test subjects, 105.6 hours of data recording, we are able to divide high-level activities into 7 classes and achieve an overall accuracy of 0.783.

B. Related Work

As early as 1997, Tan, etc. studied the possibility of using a chair as a control interface [2], the idea led to a series of papers with on-chair sensor matrix, used for real-time posture tracking or game interface [3]. By using a near-optimal sensor placement strategy, Multu, etc. managed to reduce the sensor number to 19 while still having 78% accuracy from 10 postures [4]. Beside posture, pressure matrix can also recognize who is sitting on a car seat [5]. There are already

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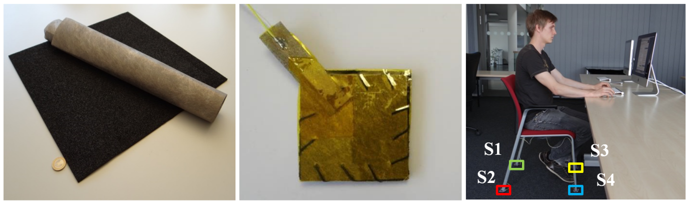

(a) (b) (c)

Fig. 1. System Design; a) raw materials for the pressure sensor; b) a sensor prototype; c) a chair equipped with sensors

a wide range of pressure sensors/matrices commercially available with different shapes, sizes, pressure ranges [6].

Another approach has been to use the contact area between the torso and the chair to measure various physiological parameters. Examples are the measurement of vital signs in aircraft seats [7], car seats [8] and regular chairs [9].

C. Paper Structure

In this paper, we first introduced the system setup in Section II. Then the evaluation in Section III is done by recognizing postures, minor activities and daily activities from experiment results. At last, current work is concluded, and future plans proposed.

II. System Design

Our prototype is composed of a normal office chair with 4 pressure pads, one under each leg. The hardware is completely hidden under the chair (as shown in Fig. 1). With a 5500mAh battery, the system runs continuously for 36 hours.

A. Physical background

The above system provides two types of information: (1) the total weight (vertical force component) applied to the chair; (2) the distribution of the weight/force applied to the four legs. Obviously, different body postures lead to different weight distributions (sitting straight or leaning aside). Thus, the low frequency ”baseline” of the signal is essentially determined by posture and posture changes. On top of this baseline, there are higher frequency fluctuations related to the fact that body parts do not move in isolation. Instead, the human body is a coupled mechanical system where even a subtle movement of one part influences many others. For example, nodding is not only the head moving up and down, but a complex action concerning the whole vertebral column, the buttocks and sometimes the feet. Even subtle limb motions can propagate all the way to the chair’s legs. As a consequence, many activities, that one may not obviously associate with weight distribution changes (e.g. typing), have a weak but characteristic signature in the high frequency signals from pressure sensors in the chair’s legs. In addition, different high-level activities are associated with certain posture types (e.g. leaning forward when typing).

B. System Design

The core requirements resulting from the above considerations are high dynamic range and high precision. In our sensor, the baseline weight of a person sitting in a chair produces a signal $\sim 2V$ while the smallest labeled signal for ”typing”, is in the range of single mV. At the same time, since we aim to eventually be able to easily retrofit whole meeting rooms or theaters, a simple, low cost system is needed.

Our solution is based on polyethylene foam that changes its resistance as a function of mechanical pressure. The resistance of a single 3mm layer varies from several hundred $k\Omega$ to several $M\Omega$. Preliminary tests indicated that the force from an occupied chair is large enough to saturate a single layer. As a consequent state, to improve the stiffness of the whole sensor pad, we have compressed 4 layers of $1 \times 1cm^2$ PE foam into the thickness of one layer and embedded it into the center of a single layer $4 \times 4cm^2$ pad using normal thread. Two electrodes made of metal textile are then secured by normal thread and isolating tape, which turns the whole pad into a resistive pressure sensor.

Each sensor is connected in series to a resistor; a low noise 2.5V DC voltage is applied across the two, converting resistance change to voltage change, which is then fed into a 4 channel 24-bit ADC sampling at 25Hz. The overall noise level of the analog circuit is $\sim 0.22mV(RMS)$.

To enable the user to freely move the chair and to isolate the noise from mains power, we use a battery to power the system and a 2.4GHz Zigbee module to transfer data.

III. Evaluation Strategy and Results

We evaluate the system in two steps. First we demonstrate the ability of our system to recognize a set of predefined postures and simple actions in controlled lab experiments. We then proceed to investigate the usefulness of our concept for the discrimination of more complex, high-level activities in real life data streams.

A. Predefined Postures and Minor Activities

The subject is seated on the chair in front of a desk with a computer and asked to perform the activity displayed on the screen, in total 12 postures and actions $\times$ 20 times each. The postures are sitting straight, leaning forward / backward / left / right, sitting with one leg cross the other knee, and sitting with one hand raised in the air. The actions are, nodding, clapping hands, typing on the keyboard, moving and clicking the mouse. We also include the class ”vacant chair’ in the experiment. Each activity lasts for 15 seconds, followed by a small pause, where the subject returns to the default posture (sitting straight). The activities’ order is randomized in each round except ”vacant chair”, which is always at the round’s end so that the test subject seat him/herself differently in the next round.

Overall 5 healthy subjects (1 female, 4 males, aged 23-34 years) participated in the data recording.

The first and last 2 seconds of each activity are left out, where the subject reacts to the instructions or returns

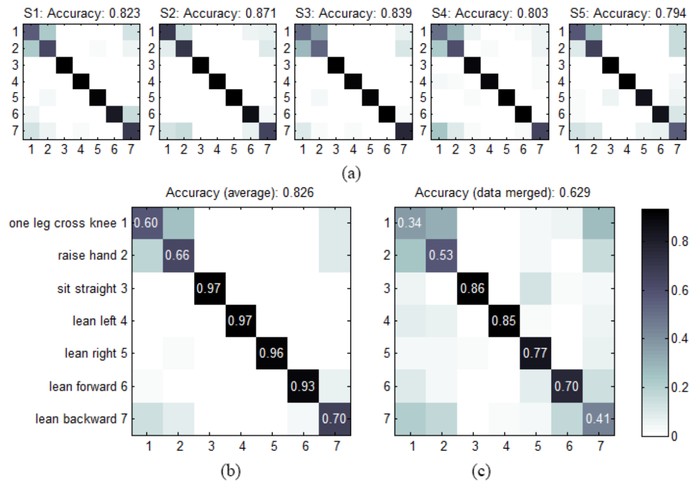

Fig. 2. Confusion matrix of predefined postures: a) each test subject b) average of all subjects c) when merged into a single dataset

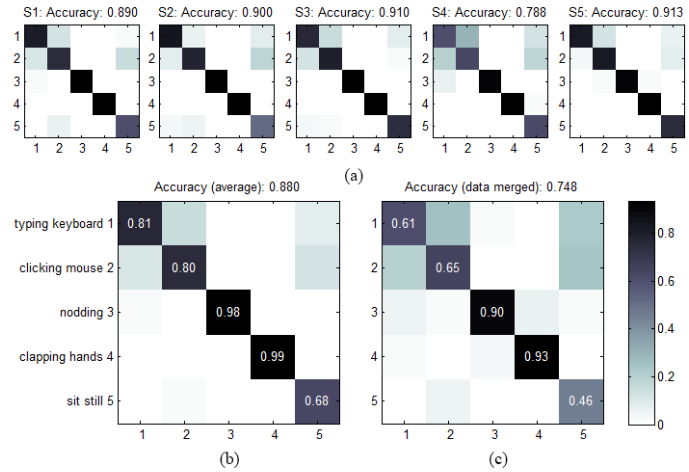

Fig. 3. Confusion matrix of predefined activities: a) each test subject b) average of all subjects c) when merged into a single dataset

to the default posture. The following features are used for classification:

1) Cross-channel features (8 total):

- Mean and RMS of 4 sensors combined.
- Center of weight in two directions: calculated as the differences between sensors on the left and right side of the chair, and between the sensors on the front and back side of the chair, both divided by the sum of all 4 sensors.
- Activity level features: calculated as mean, median of the summed 1st derivative's absolute values in time domain of 4 sensors.
- Median and mean of absolute values sum of 4 sensors after removing DC using a high-pass filter (f_c = 0.5Hz).

2) Single channel features (7× 4 total):

- The mean magnitude, the central frequency, and the magnitude of the central frequency in 5 uniform frequency bands between 0 and 12.5Hz.

We first evaluate 7 sitting postures. The classification is performed using stratified 10-fold cross-validation with an LDA classifier [10]. The average accuracy with subject dependent training is 0.826 (e.g. if the chair knows who is sitting on it, balanced F-score in Fig. 2 b). If data from all subjects is merged into one (e.g. the chair doesn't know the user), then the accuracy drops to 0.629 (Fig. 2 c)).

We then evaluated the 4 simple actions of the hands and the head: typing on the keyboard, clicking the mouse, clapping hands and nodding. The first two are tiny activities with hand and little arm movement; in the latter two, the vertebral column also moves a little. A 5th class is added as sitting still, where we randomly pick 20 out of 100 postures without movement (viz. sitting straight and leaning aside). The average accuracy is 0.880 for the user independent and 0.748 for the across all users case (details in Fig. 3).

B. High-level Daily Activities

Next we consider 7 high-level activities that are routinely performed while sitting: working on PC, eating, playing video games, watching movie, talking with others, browsing the Internet and vacant seat. We record data from 4 healthy subjects (1 female, 3 males, aged 24–34 years). Thus, the subjects are asked to sit on the equipped chair and perform their normal work routine (which mostly takes place in front of a computer in the student room) for at least 8 hours × 3 days. They are also asked to play games and watch movies (which we assume is not part of a daily work routine). For privacy and practicability issues, the experiment is not video recorded and not precisely labeled. Instead, the subjects keep a log of their major activities throughout the day in an experience sampling like approach. Overall, the data encompasses 105.6 hours, out of which 79.2 hours the chair was occupied (details in Table. I).

One key feature for distinguishing the above high-level activities is the ”activity level”, defined as mean and median of the 1st derivative' absolute value in time domain. It increases starting ”watch movies”, through ”play games”,”browse the Internet”,”work on PC”,”eat”,”talk with others”. Even though the exact way of performing the specific high-level activities differs across subjects, their activity levels are still comparable.

Another important feature is the weight center, which is related to the attention on the PC screen for certain activities. It is further in the back when watching movie and browsing website where overview of the whole screen is important. When talking or eating, no screen is needed, so occupants tend to sit comfortably in the middle; while when it comes to computer work and game, where close attention needs to be paid to the screen and frequent keyboard/mouse operation is required, the weight center is pushed forward.

In a 5 min window jumping in steps of 30 sec over the daily data stream, the same set of features were calculated as in Section III-A. When the windows covers multiple high level activities,a majority decision is made. Classification is performed using 10-fold cross-validation method with an LDA classifier. The confusion matrix is given in Fig. 4.

The accuracy is 0.783 for the user dependent case and 0.645

TABLE I
STATUS AND DURATION FOR EACH SUBJECT (HOURS)

Status	Center of weight	Typical activities	S1(F)	S2(M)	S3(M)	S4(M)	Sum hours
watch movie	back/middle	seldom any movement	3.7	2.4	2.8	1.6	10.5
play game	front/middle	frequent mouse movement, seldom body movement	4.4	1.6	4.8	1.6	12.4
browsing the Internet	/	some mouse and body movement	0.4	1.9	2.4	0.5	5.2
computer work	much in the front	frequent typing on keyboard, some mouse and body movement	12.5	9.9	8.9	10.5	42
eat	front/middle	some arm/body movement	0.5	0.1	1.7	0.4	2.7
talk with others	middle/back/aside	bursting arm/head/body movement	0.8	2.7	1.5	1.4	6.4
nobody on chair	/	much less pressure, no movement	10.2	6.7	1.5	8.5	26.4
Sum hours			32.6	25.3	23.7	24.0	105.6

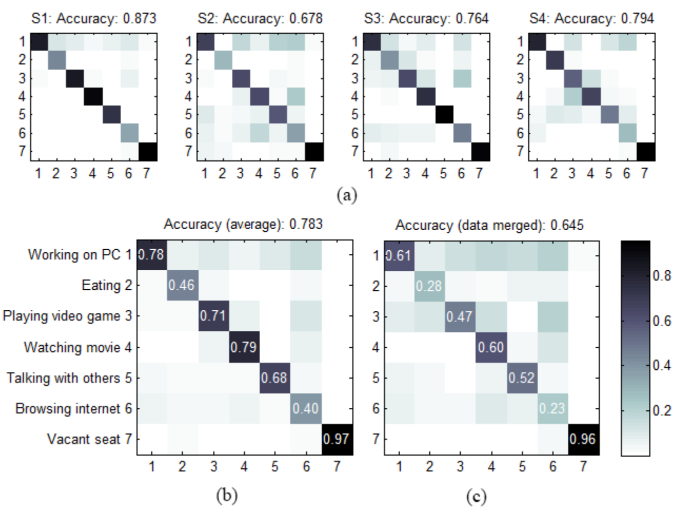

Fig. 4. Confusion matrix of high-level daily activities: a) each test subject b) average of all subjects c) when merged into a single dataset

accross all users. This is far from perfect, but also far above random, making it possible for anonymous implementations. Note that errors are not only due to misclassification, but also related to labeling inaccuracies and the complexity of the activities. For example, working on computer might well include browsing the Internet for a short while (to seek for information). Some subject ate snacks when watching movie, or browsed the Internet while having main meal.

IV. CONCLUSION

While the classification results shown in the previous section are far from perfect; they are also far above random. Overall, we believe that the fact that such results can be achieved using signals from just four simple pressure sensors mounted under the chairs legs is surprising and relevant for a wide range of applications. In particular the ability to easily retrofit large rooms (e.g. a conference room, theater) opens up the interesting research opportunities in the area of social interaction. Another possibility is to equip other furniture (table, bed, couch and etc.) for more complex activity recognition at home or in public spaces; yet the physical sensors need to be improved to support larger force. We will also investigate the possibilities of putting the sensors under furniture with different support, such as castors. In such an approach, visual and audio information is not required, therefore implementation could be anonymous, protecting the occupants' privacy. Finally, we will investigate the combination of furniture integrated sensors with information from users' smart-phones as a way of tying activities to specific persons.

Note that although our validation is done in the office and based on office activities; the aim of the paper is not to develop a practical system for the tracking of office activities and/or related applications. Instead, the main contribution is to show that high-level activities not necessarily related to body torso trunk motions can be detected from simple, easily retrofitted sensors integrated under the chairs' legs and the office activities are merely an easily obtainable dataset.

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