IntelliChair: An Approach for Activity Detection and Prediction via Posture Analysis

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***Abstract*—This paper proposes a robust, low-cost, sensor based system that is capable of recognising sitting postures and placing them in correspondence with sitting activities. This system is also capable of predicting subsequent activities for individual users. Force Sensing Resistors are mounted on the seat and back of a chair to gather the haptic (i.e., touch-based) posture information. Subsequently, posture information is fed into two classifiers, one for back posture and the other one for leg posture. A hidden Markov model approach is used to establish the activity model from sitting posture sequences. Furthermore, by implementing a context awareness prediction algorithm (e.g. Active-Lezi), the system discovers patterns and predicts subsequent activities. The system will lead to many potential applications such as the analysis of sitting or lying subjects, motion tracking for rehabilitation, interaction assistance, and the detection of anomalous activities.**

***Index Terms*—Intelligent Environment, Machine Learning, FSR, Hidden Markov Model, Pattern Recognition.**

I. Introduction

Existing intelligent environment research, such as the CASAS project [1], [2] focuses on the interpretation of a subject's behaviour at the activity level by logging the Activity of Daily Living (ADL) such as eating, grooming, cooking, drinking, and taking medicine. In general, the sensors employed (e.g. PIR sensors, contact sensors) provide low-resolution information. Combined with the measurements of room temperature, humidity and other indoor environment information, intelligent environment systems are able to provide valuable functions like remote health monitoring and intervention. Meanwhile, the expansion of wearable computing allows researchers to attempt to improve human behaviour analysis by gathering additional information.

Compared with the activity detection method in [2], motion tracking technology including the IntelliChair, provides more detail about human biomechanical movements and this additional information makes the system to detect activities more easily. The IntelliChair is proposed as an approach, which combines accuracy with more detailed record of activity. The goal of the system is to track the naturally occurring sitting postures of a user through the use of non-intrusive, low cost, chair surface-mounted sensors and establish the correspondences between sitting postures and sitting activities such as reading, typing, relaxing, watching TV, etc. A behaviour pattern is a sequence of ordered activities that frequently occur together. Those behaviour patterns can be used to provide personalised service based on individual sitting habits. Imagine a scenario that in a room environment with both IntelliChair and CASAS integrated, a user has a sitting habit that there will be approximately one hour reading before watching TV when he sits on a couch. When the user is sitting on the IntelliChair mounted couch, the IntelliChair system could determine whether this user is reading based on the detected sitting postures. And based on this user's sitting habit, the system will send request to the CASAS system to cooperate when one hour is reached, and ask CASAS to switch on the TV. This scenario shows IntelliChair is able to assist the users to shift their activities naturally based on their individual sitting habits. In order to do this, it is crucial that the system is able to discover users' common behaviours and predict future activity from past behaviours. This system is also expected to deal with unconstrained real data to be able to analyse multiple subjects' behaviours. It will lead to many potential applications such as sitting behavioural analysis, motion tracking for rehabilitation, the detection of anomalous sitting activities.

There are many motion sensing techniques for sitting posture recognition. Vision is currently widely used in motion detection but there are many drawbacks: privacy issues, the effect of background conditions, the subject's appearance and position, so that vision based motion detection is not particularly useful. Therefore, other approaches like the utilisation of inertial sensors integrated in clothing [3], conductive fabric [4], pressure sensor mats [5] and Force Sensing Resistors (FSR) [6] are often adopted. Among those sensor techniques, an inertial sensor suit could perform accurate detection but it is rather intrusive; conductive fabric in [4] only detects the presence of the subject but is of low cost; pressure sensor mats in [5] generate accurate contact surface pressure images, but the price for such system is many thousands of dollars. IntelliChair utilises the FSR for its low-cost and acceptable force sensing performance.

II. Data Collection and System Hardware

Product FSR 406 from Interlink Electronics [7] is chosen as the pressure sensor and eight FSRs are mounted on the

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chair. Four units on the horizontal surface and the rest are on the vertical surface. This type of sensor exhibits a decrease in resistance with an increase in the force applied to the active sensor surface. Each FSR is incorporated in a potential divider circuit and its resulting voltage is digitised as a 10-bit value representing pressure.

Values from all eight FSRs are collected at the same time, and they are stored in an array. This eight element array indicates the pressure information at a specific time stamp. Then raw data set is constructed by a set of time ordered arrays that combine with the time stamp information, so this data set represents the pressure information within a time interval.

The instrumented chair and the FSR positions are shown in figure one. Figure two shows a simple visualisation of the pressure distribution from the FSRs when a subject sits on the chair.

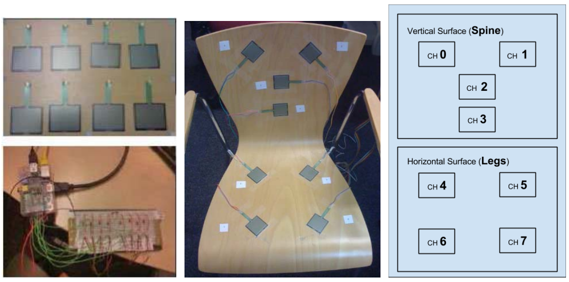

Fig. 1. Left: FSR 406 (top) and middleware of Raspberry Pi with support circuit (bottom). Middle: Chair with FSR mounted and sensor positions. Right: FSRs are represented by channel numbers correspond with middle.

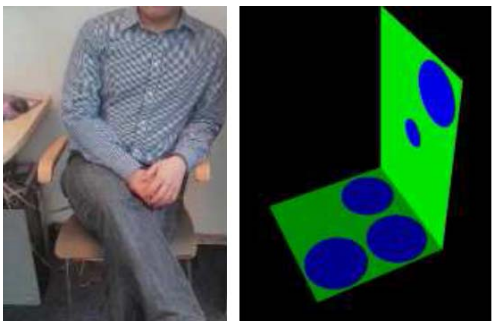

Fig. 2. Demonstration of IntelliChair. Right is the real time display of the force Information, the radius length of blue cycle indicates the pressure.

The Raspberry Pi [8] is a low-cost, credit card sized single board computer, and it is chosen to be middleware of IntelliChair system. Python [9] is selected for the software development because it is capable of hardware access, is cross-platform and has support for scientific and numeric computing.

Because of its limited computation capability, the software on the Raspberry Pi will undertake basic tasks like raw data storage, data processing and transmission as well as some advanced, but less computationally intensive, functions like posture classification, activity recognition and prediction based on the trained model. However, a more powerful computer system is required to undertake the tasks like model training, estimation and optimisation. The use of the dedicated computers (e.g. Raspberry Pi), makes IntelliChair system relatively independent and more flexible compare with other existing chair systems [4]–[6].

III. DATA ANALYSIS METHOD

The system is capable of recognising three things: a static sitting posture, an activity based on the input posture sequence and a behaviour pattern within the activity sequence.

A. Recognition of static sitting posture

First, the incoming pressure data at one time stamp is required to be recognised as a static sitting posture. Classification algorithms (e.g. decision tree, support vector machine, etc.) are employed for this recognition task, in order to sort the input data into one of the pre-defined sitting posture classes. And through experiment, decision tree is used because it has relatively better performance in classification accuracy. According to [5] and our early experience while using IntelliChair, it is useful to divide the data set into spine posture data and leg posture data as follows: four spine posture classes and five leg posture classes.

In order to simplify the classification computation, the posture classes are labelled with numbers as follow:

- Spine labels: {0: Body Leaning Right, 1: Leaning Back,2: Body Leaning Left, 3: No Contact}.
- Leg labels: {0: Sitting upright, 1: Crossing right leg on left leg, 2: Crossing left leg on right leg, 3: Sitting forward, 4: No Contact}.

By combining the two classification results, a complete whole body posture at a time stamp could be determined.

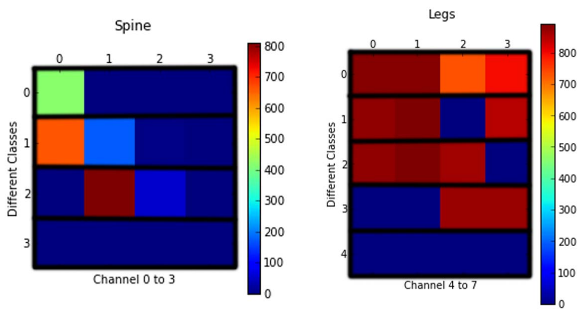

Fig. 3. Colorscale image of spine and leg posture classes. Left: Plot of Spine class difference. Right: Plot of Legs class difference, the number 0 to 3 on X axis is the index of array, it actually represents channel 4 to 7.

As figure one illustrated, the spine data is collected from channel 0 to 3 while leg data is collected from channel 4 to 7. Figure three shows the correspondence of posture classes (Y axis), channel numbers (X axis) and pressure strength information (colorscale value), each row in the plot represents a posture class and it contains four channel values. Figure three also shows the feature of differences between posture classes, for example, in the left plot, class 0 (the body leaning right posture) had a high pressure value at channel 0 while class 2 (the body leaning left posture) had a high pressure value at channel 1. Refer to the channel position in figure one, this data set separation method indicates the difference between posture classes and it also improved the accuracy of classification.

B. Recognition the activities

The second stage is to recognise the activity based on the generated posture sequence. Hidden Markov Models (HMM) [10] are utilised in this stage, and the strategy of HMM implementation is to firstly train a set of independent HMMs that each HMM corresponds to a given activity (reading, typing, relaxing, etc). This HMM set will be used to discovery temporal patterns among posture sequences in order to determine activities.

In the recognition stage, each HMM in the trained model set takes a sequence of postures obtained from the previous classifier as discrete inputs. Then, system computes the probabilities for the input posture sequence across the set of HMMs generating an array of probabilities for corresponding activities. Also, because the input is time-ordered posture sequence, the time factor is also included in this modelling process. The reason for the inclusion of time factor is because some similar activities may be hard to distinguish if the posture is the only basis (e.g. reading and typing).

Through this modelling process, the posture sequence is abstracted into an activity sequence, and the relationship between posture and activity is established.

C. Recognition of behaviours

We define behaviour patterns as a variable range of ordered activity sequences that frequently occur together. Because of differences in individual sitting styles, it is crucial that the system is able to learn users' common behaviours and predict future activity from past behaviours in order to provide personalised services. This is a well researched field in the area of intelligent environment and there are many options for the prediction algorithm.

The Active-Lezi algorithm [11] was chosen because it not only predicts future activity but also parses the activity sequence into phrases and stores them in the dictionary. Those phrases could be considered as behaviour patterns, and the algorithm also provides statistical information which is helpful in significant behaviour pattern discovery. Furthermore, the performance of the Active-Lezi algorithm improves as the data set increases.

When the system detects a previously unknown behaviour or a behaviour that is known to be indication of a problem (e.g. an epileptic fit), this information can be useful to alert a caregiver or ambulance to increase the chance of rescue.

IV. FUTURE WORK

The next stage of research is to test the system using a wide range of subjects and ensure that activities and behaviours can be identified independently of the physical characteristics (e.g. weight, height) of the subjects.

IntelliChair is a relatively independent system for sitting posture tracking and sitting activity modelling. It would be relatively easy to add audio input or output to the Raspberry Pi to provide feedback to users in a natural way.

It is also compatible with many existing overall smart environment systems such as CASAS. From the hardware aspect, the usage of wireless network technology enables IntelliChair as a subsystem within a sensor network. From a software aspect, it is autonomous which reduces the computation burden of the overall system. Refer to the previous example scenario, IntelliChair could make existing overall systems more sensitive, adaptive and responsive to resident's habits and needs which is an important contribution in an assisted living environment.

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