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Emotion-relevant activity recognition based on smart cushion using multi-sensor fusion

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ABSTRACT

More and more common activities are leading to a sedentary lifestyle forcing us to sit several hours every day. In-seat actions contain significant hidden information, which not only reflects the current physical health status but also can report mental states. Considering this, we design a system, based on body-worn inertial sensors (attached to user's wrists) combined with a pressure detection module (deployed on the seat), to recognise and monitor in-seat activities through sensor- and feature-level fusion techniques. Specifically, we focus on four common basic emotion-relevant activities (i.e. interest-, frustration-, sadness- and happiness-related). Our results show that the proposed method, by fusion of time- and frequency-domain feature sets from all the different deployed sensors, can achieve high accuracy in recognising the considered activities.

1. Introduction

In recent years, a vast majority of the worldwide population, including office workers, commuters, long-distance drivers and mobility impaired individuals, is spending several hours per day in performing sedentary activities (e.g. at work, at home, at school, in car [1], and in public transportation). So it is significant to analyse in-seat actions as they can reveal potentially precious information concerning people's daily activities and behavioural patterns. Moreover, this analysis can also support, to a certain extent, emotion recognition methods as an additional source of information, as shown in Fig. 1.

Emotion, as a complex reaction of an organism to significant objects or events [2] with subjective, behavioural, physiological elements, is an indispensable part of daily human life. Recently, psychologists and engineers adopt physiological signals, facial expressions, voice, and gestures to identify human emotions. Moreover, additional important inputs are made available to recognise emotions more accurately [3]; in fact, thanks to the development of wearable sensing [4] and cognitive computing [5], the automatic recognition of postures and body movements [6] can support the analysis of the so-called *kinesics* [7] (also known as *body language*), thus attracting further research interest to this topic.

Therefore, to more comprehensively understand users' current status and possibly provide personalised advices [8], our research is focused on designing a method and data analysis based equipment to recognise users' emotion-relevant activities from their daily in-seat actions.

In particular, we are interested in detecting ordinary fundamental seated activities (concerning the composition of postures and gestures) that might be relevant in the context of emotion recognition.

Since trunk and upper-limb actions usually compose an in-seat activity, we developed a cost-effective and straightforward smart sensing system using body area networks (BANs) [9], heterogeneous sensor fusion [10], wireless communication [11], and an embedded platform [12]. The system is composed of a pressure detection module embedded in a cushion to detect postures and two inertial measurement units (IMUs) attached to the user's wrists to recognise gestures.

The contributions of this paper are twofold:

1. a generalised sequence feature-based technique to recognise postural activities;
2. sensor- and feature-level fusion to jointly process pressure sensor data obtained by a smart cushion with inertial data from wrist-worn IMU devices.

The remainder of the paper is organised as follows. Section 2 discusses the related work on posture and activity recognition. Section 3 describes the system platform and the instrumentation for data acquisition. Section 4 presents the methodology of this work. Section 5 discusses the experiment protocol and provides an empirical evaluation of

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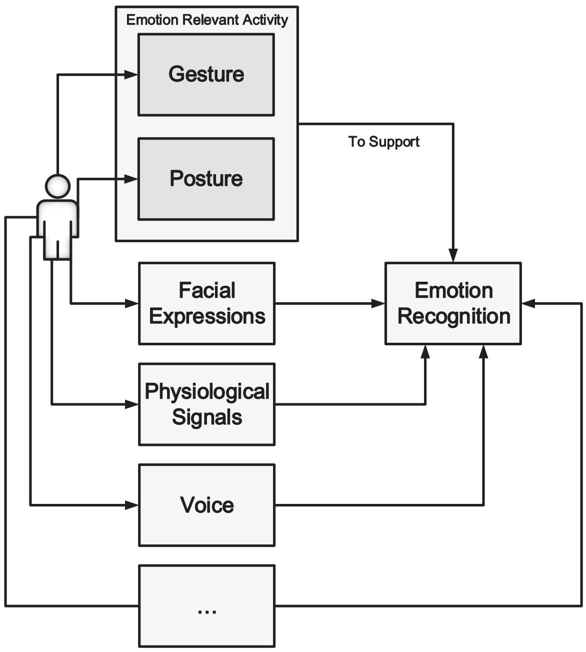

Fig. 1. Block-diagram of an emotion-relevant activity recognition system to support emotion recognition.

the system. Finally, Section 6 concludes the paper and outlines planned future work.

2. Related work

Recently, more and more researchers in various disciplines [6,13,14] have shown that body movement and posture convey emotion-specific information. Therefore, activity recognition can not only reveal human physical state [15] but also support, to a certain extent, the identification of emotions.

2.1. Physical activity recognition

In recent years, researchers have adopted inertial sensors, pressure sensors, and computer vision to monitor and recognise individual's physical activity. In the following, we summarise related work on activity recognition, respectively based on inertial and pressure sensors.

2.1.1. Inertial-based recognition

Thanks to their portability, low energy consumption and cost, inertial sensors play an essential role in the area of human activity recognition and health status monitoring. Wang et al. [16] applied four wireless inertial sensor nodes to recognise 14 types of badminton strokes using 2-layer HMMs. In [17], the authors exploited six IMU sensors located on user's right ankle, left thigh, right thigh, waist, right arm, and right forearm to detect 23 different body movements. Popp et al. [18] proposed a method to distinguish self- and attendant-propulsion for wheelchair users. IMUs were used to monitor wheel kinematics and the type of wheelchair propulsion. The results obtained by this approach can give better insights into the practical mobility behaviour of wheelchair users. Thomaz et al. [19] used a smart-watch embedded with a 3-axis accelerometer to collect and process data to identify different eating activities. Grillon et al. [20] proposed a method using two inertial sensors attached on the wheelchair's bottom and left wheel to detect accelerometer and gyroscope data, and a smart-watch to detect accelerometer and heart rate data attached on a wrist; several wheelchair activities were recognised at different intensity levels. In [21], the authors presented a robust smartphone inertial sensors-based approach for identifying human activity with a deep belief network.

2.1.2. Pressure-based recognition

Pressure sensors are typically non-intrusive; for example, they can easily be embedded in a cushion (i) to detect the postures in many sedentary sitting conditions [22], (ii) for body activity recognition [12], (iii) for activity level assessment [23], and (iv) for long-time sitting fatigue detection [24]. Thanks to their unobtrusiveness, these sensors are widely used nowadays. Di Rosa et al. [25] proposed a wireless sensor insole system based on 14 thin-film resistive pressure sensors to detect postures for estimating fall risk. Cheng et al. [26] have designed a Smart-surface system using large textile pressure sensors arrays. Several activities engaged on the contact surface were recognised. Ma et al. [23] proposed a robust, low-cost, sensor-based smart cushion system for recognising sitting postures and activities. The smart cushion combines pressure sensor unit with inertial sensors, and it can be used to assess user's activity levels and identify the action from the information hidden in sitting postures. Lin et al. [27] used a triboelectric nanogenerator array as a pressure sensor for monitoring sleeping activities and evaluate in real time the sleep behaviour and quality.

2.2. Emotion-relevant activity recognition

Emotion-relevant activity recognition is often realised by using a camera to analyse facial expressions and gestures, or using physiological signals such as electrocardiogram, brain waves, and galvanic skin response. Besides, some studies adopted pressure or inertial sensors to recognise gestures and to understand which emotion-relevant activities are performed.

Kumar et al. [28] designed a Care-Chair which equipped an intelligent data analysis system. Only four pressure sensors were deployed on the backrest of the chair, and 19 kinds of (functional and emotion-based) activities were classified. Shibata et al. [29] suggested that sitting postures have the same structure as facial expressions for emotions by using pressure sensors and accelerometers. Dael et al. [6] adopted a body action and posture (BAP) coding system to examine 12 emotional activities employed by ten professional actors. Encouraging results showed that body movement and posture convey emotion-specific information.

Table 1 summarizes a comparison of our proposed method with some relevant related works. In [28], pressure sensors are used to recognise activities such as crying and laughing that are actually emotion-relevant; however the authors did not investigate this aspect. In [29] the authors used pressure sensor combined with accelerometer to recognise emotion-relevant activities; however, they mainly focused on instantaneous posture and upper-limb recognition while a better understanding of emotion-relevant activities need analysing posture sequences. In [6], authors used a camera to capture user postures and activities, leading to privacy intrusion implications and assuming the subject to be in the view field of the camera [30]. Computer vision methods based on RGB cameras are often sensitive to light conditions, while depth cameras have non-colour information and are sensitive to materials with different reflection properties.

Therefore, in contrast with previous literature, we propose a sensor fusion-based method which combines information on users gesture with posture sequences in order to more accurately analyse users emotion-relevant activities.

3. System architecture

The proposed system includes a pressure detection module (deployed on the seat), two wearable inertial measurement devices (worn at the user's wrists), as shown in Fig. 2, and a personal computer whose details are reported in Table 2. Data is collected from the wearable inertial measurement devices and pressure detection module, and transmitted via Bluetooth to the PC for offline analysis

The system is used to collect pressure and motion signals and to recognise the emotion-relevant activities.

Table 1
Emotion-relevant activity recognition.

	Sensor	Detected Activity	Emotional States
Kumar et al. [28]	Pressure sensors	*Emotion based activities* (e.g. crying, laughing, shouting, weeping, yawning, yelling)	N/A
Shibata et al. [29]	Pressure Sensors, Accelerometers	*Sitting postures with different leg, arm and neck part condition* (e.g., Body leans to the back, Neck leans forward or backward, Body and neck stand upright, Crossed legs)	Arousal, Pleasantness, Dominance (awake, sleepy, exited, calm, satisfied, happy, irritated, angry, tense, afraid)
Dael et al. [6]	Cameras	*Emotional activities* (e.g. Arms resting at side with trunk leaning to the front, asymmetrical one arm action, body leaning backward or movement with upward gaze and lateral trunk lean, Forward whole body movement, Repetitive head action with touching arm actions)	Arousal, Valence (interest, irritation, despair, anxiety, panic fear, anger, joy, pride, pleasure, sadness, relief, amusement)
Proposed Method	Pressure and Inertial Sensors	*Emotion-relevant activities* (e.g. proper sitting, leaning left/right, leaning forward/backward, arms crossed, arms raised, arms straight down, hands hold the head)	related to Interest, Frustration, Sadness, Happiness

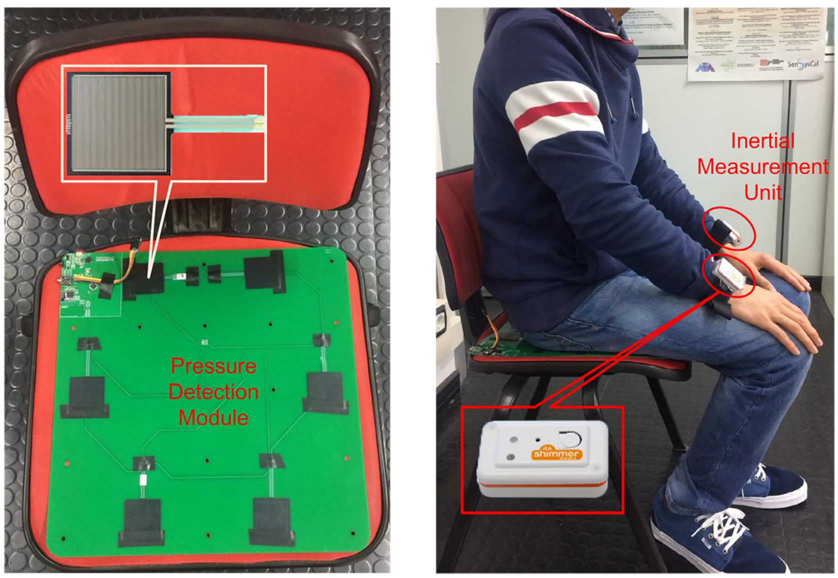

Fig. 2. Instrumentation of the sensing system.

Table 2
Configuration of the Computer.

HW/SW Characteristic	
Central processing unit (CPU)	Intel Core i7-4720HQ
Random access memory (RAM)	16 GB
Operating system (OS)	Windows 10

3.1. Pressure detection module

We use a smart cushion, which has been developed in our previous research [31], to analyse users posture. Pressure sensors are all deployed on the board as shown in Fig. 3. Specifically, we used the force sensing resistor 406 (FSR - 406), whose specifications are reported in Table 3), that is a kind of pressure sensor patch produced by Interlink Electronics. While force is applied to the FSR sensing area, the resistance value will be correspondingly altered. Thanks to its characteristics, the pressure data can be easily measured by the voltage value.

Using the cushion, five different sitting postures (proper sitting (PS), lean left (LL), lean right (LR), lean forward (LF) and lean backward (LB)) can be very accurately recognised [31]. Raw pressure sensor data is acquired by an Arduino-based acquisition module at a sampling frequency of 100 *Hz*; data is classified into postures using an embedded classification algorithm; the classified postures are organised to form posture sequences.

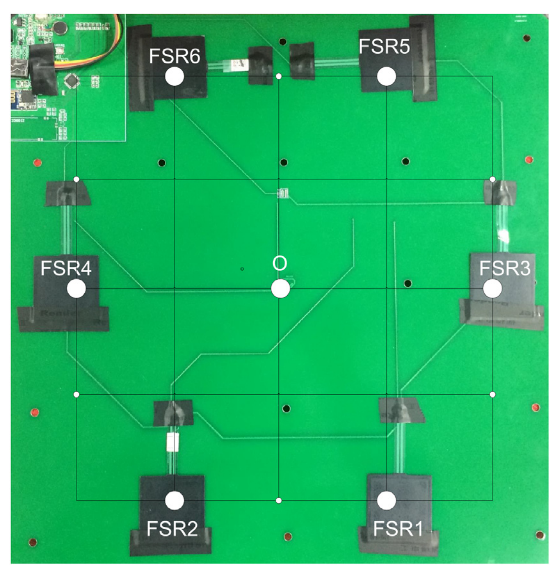

Fig. 3. Sensor deployment of the pressure detection module.

3.2. Inertial measurement unit

Shimmer Motion Sensor (rev. 2R) [32] offers high data quality with integrated 9 DoF (Degree of Freedom) inertial sensing via

Table 3
FSR-406 technical specifications.

Feature	Value
Actuation force	0.1 N
Force sensitivity range	0.1–10.02 N
Size	43.69 × 43.69 mm
Thickness range	0.2–1.25 mm
Non-actuated resistance	10 MW

accelerometer, gyro, and magnetic sensors. Shimmer devices have been widely used in BANs and particularly in the field of activity recognition [33,34]. Specifically, we attach two Shimmer nodes to the user's wrists and collect accelerometer and gyroscope data at a sampling frequency of 100 *Hz*.

4. Proposed method

In this section, we present the system processing workflow (see Fig. 4) that involves three steps, each discussed in detail in the following subsections:

1a. *Posture synthesis*. It consists of the recognised posture with its features;
1b. *Gesture synthesis*. It consists of the recognised gesture with its features;
2. *Data synchronisation and normalisation*. Posture and gesture data is synchronised and normalised to generalise feature set for emotion-relevant activity recognition;
3. *Feature fusion and classification*. Feature subsets are fused to derive new feature sets for classification.

Currently, all the data is processed off-line.

4.1. Posture synthesis

At this step, we use the Smart Cushion to detect and process the data, as discussed in Section 3.1, that will be normalised to extract the features. The feature set includes mean, root mean square, standard deviation, and Centre of Pressure (CoP) [35], principal component analysis (PCA) of raw data, and DC component of fast Fourier transform (FFT). The CoP is a parameter, weighted by the pressure of each sensor, for measuring the centre point. It is defined as the point location of the vertical seat reaction force vector. The sensor deployment in the

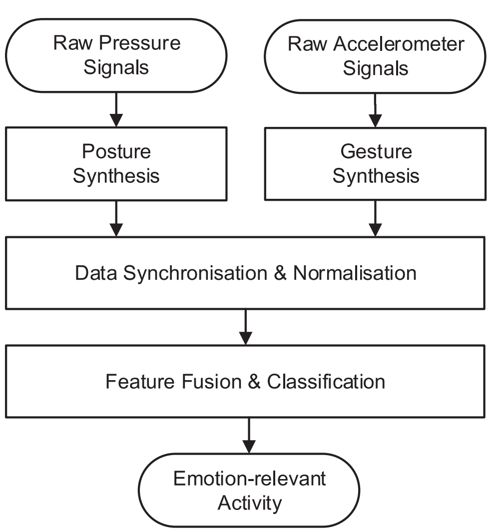

Fig. 4. An overview of the processing workflow.

Table 4
Location of the pressure sensors in the cushion.

Sensor	Location (x,y)
FSR1	1, − 2
FSR2	− 1, −2
FSR3	2, 0
FSR4	− 2, 0
FSR5	1, 2
FSR6	− 1, 2

FSR*i* - force sensing resistor *i*

cushion has been discussed in our former research [23]. Here, in Fig. 3, the central point is assumed as the origin of our coordinate system *O*(0, 0), and each FSR sensor has its location as shown in Table 4. The CoP can be easily identified by its coordinates with Formula 1 and Formula 2, where f_i is the pressure value of each FSR sensor, and (x_i, y_i) represents the location, $i \in \{1, 2, 3, 4, 5, 6\}$.

$$CoP_x = \frac{\sum f_i * x_i}{\sum f_i} \tag{1}$$

$$CoP_y = \frac{\sum f_i * y_i}{\sum f_i} \tag{2}$$

The classification algorithm is embedded on an Arduino Mini Pro-board to process the raw pressure signals; five static postures (proper sitting (PS), leaning left (LL), leaning right (LR), leaning forward (LF) and leaning back (LB)) can be recognised in real time (see Section 3.1). Using the identified results, we generate a posture sequence vector, and the posture transition sequence can be easily obtained.

4.2. Gesture synthesis

For gesture recognition, to get rid of the noise due to a natural shaking of the users' hands, a discrete wavelet transform is applied to inertial sensor signals as a low-pass filter to smooth the data, as shown in Fig. 5.

After denoising, the data will be normalised in the range [0, 1]. A sliding window segmentation method is adopted to split acceleration signal into multiple windows with a fixed length l_1 and 50% overlap between two adjacent windows. When a peak value of acceleration in one window is larger than a threshold T, it can be regarded as an activity transition point. When the difference between two adjacent activity transition points is less than a threshold l_2, the smaller peak value corresponding to the adjacent activity transition points need to be removed. In fact, the activity transition is usually fast; therefore the time slide window can be defined by the activity transition as shown in Table 5. Here, we selected the threshold $T = 1.2g$ (g means Gravitational Acceleration) and the time slide windows are $l_1 = 1.5s$ with $l_2 = 1s$. Similarly, the gyroscope data can be divided into windows corresponding to the segmentation of acceleration data Fig. 6.

In this paper, sequence features are used to classify upper-limb activities performed in sitting condition. We extract features both in time- and frequency-domain. The time-domain features we selected are mean, root mean square, standard deviation, movement angle, signal magnitude vector (SMV), and PCA of raw data; in the frequency-domain, we selected DC component of FFT.

SMV provides a measure of the degree of movement intensity; it can be calculated from the tri-axial acceleration values using Formula (3).

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{3}$$

In particular, two features (a_l^h and a_r^h) are obtained, where a_l^h and a_r^h represent the SMV value of left and right wrist; h is sample number in the time period.

FFT is a quick way to calculate discrete Fourier transform (DFT),

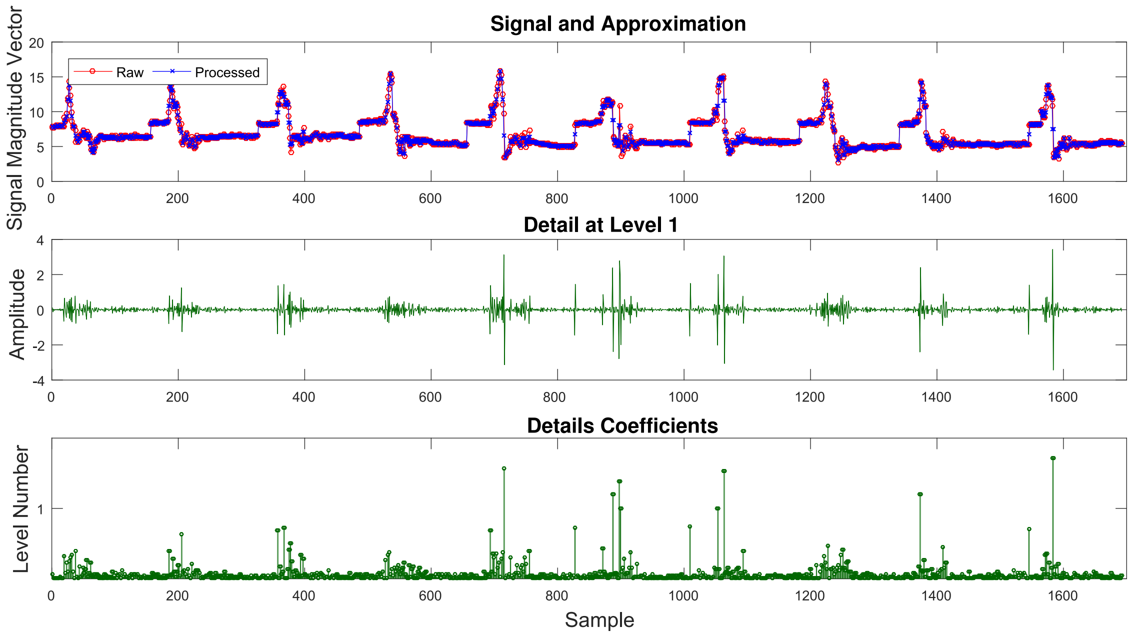

Fig. 5. 1-D Haar wavelet transform with 1-level analysis.

Table 5
Time duration of gesture transition examples.

Activity	Time duration (s)
Arms crossed in front	1.5–2
Arms raised and held on head	1.5–2
Arms straight down	1.5–2
Arms straight raised up	1.5–2

which is an algorithm that can be used to convert a finite sequence of equally-spaced samples from time-domain to a frequency domain, and it can describe the energy of motion signal. DC component, which is a time-independent constant, represents the average of the signal. We calculate the DC component of FFT for generating the feature.

PCA [36] is a statistical procedure, and it uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. By using this method, we can use the linearly uncorrelated variables called principal components as a feature.

4.3. Data synchronisation and normalisation

Currently, the data is synchronised by means of manually marked labels in the signals. The posture-based sequences will have the same length of gesture-based sequences, and altogether will be used to classify the emotion-relevant activity. After synchronisation, a further processing required to normalise the data; normalisation adjusts values measured on different scales to a notionally standard scale such as the range between 0 and 1.

4.4. Feature fusion & classification for emotion-Relevant activities

Feature extraction and selection are crucial in a machine learning process; here, we include the features discussed in Section 3.2 as well as the postures and gesture sequences themselves. We form several feature sets by combining different features to find an appropriate feature set as shown in Table 6.

Once these feature subsets are obtained from the original data, we can derive new feature sets based on the selected subsets for the activity

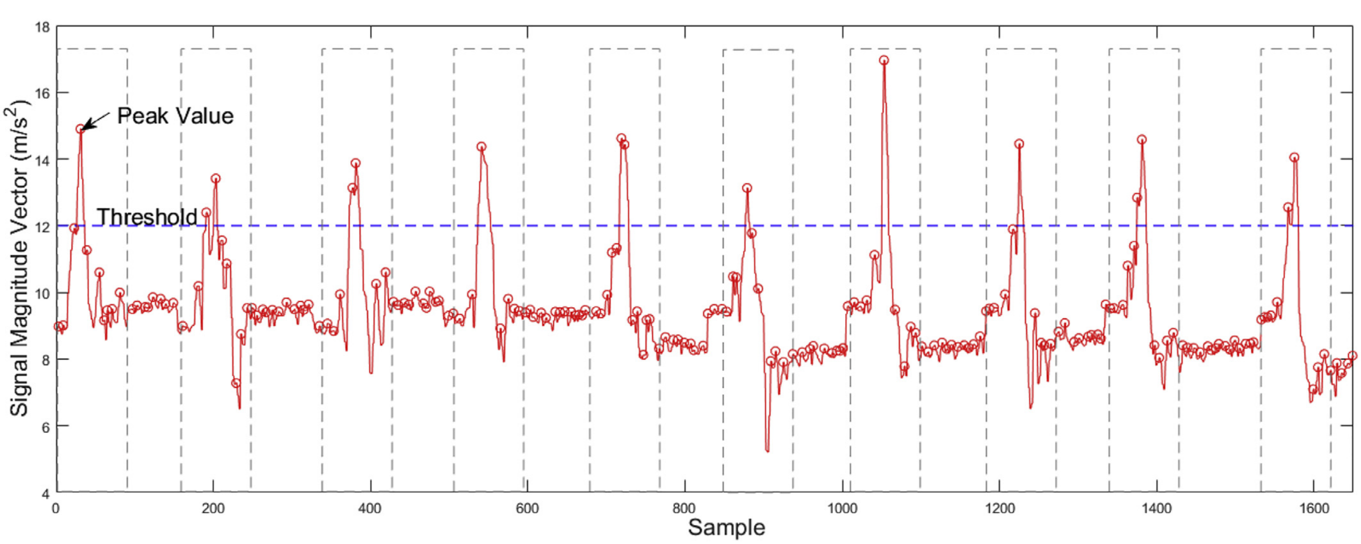

Fig. 6. Time slide window selection.

Table 6
Feature sets and attributes.

Sequence feature set	Abbreviation	Attribute
Raw	FEA_1	Pressure, Acceleration and Gyroscope Data, Posture, Gesture
Time domain	FEA_2	Mean, Root Mean Square, Standard Deviation, CoP, SMV, Movement Angle, PCA
Frequency domain	FEA_3	FFT of Raw Feature

classification. These new features may improve the accuracy of activity recognition to a certain extent. Therefore, in the following Section 5.3.2, we fused two or more feature subsets into new feature sets (see Table 8).

In order to recognise an activity performed in sitting condition, we use hidden Markov model (HMM), which is one of the most popular probabilistic methods for modelling human activities [37], to train and test the data. HMM is very suitable for modelling the time series sequence and has a robust capability of pattern classification. It allows us to model state transitions using time-dependent features in an elegant and formal manner. Furthermore, with preliminary studies, we found out an HMM approach would be promising in achieving better performance than other algorithms (which has been confirmed by performance evaluation shown in Section 5.4).

In our HMM, a continuous activity can be represented by a finite number of states. Each state consists of transition probabilities to other states as well as observation probabilities of all the discrete symbols from every state. Fig. 7 shows the hierarchical model of the sequence feature and activity representation. In this model, each kind of activity represents a trained HMM. Thus, when we obtain a discrete observations sequence $\{O_1, O_2, ..., O_n\}$, the appropriate HMM can be found through the maximum likelihood [31] and the recognised activity can be obtained by Formula (4).

$$c = \arg\max_{\mu} P(O_{1:n}, S_{1:n}|\lambda_\mu)P(\lambda_\mu) \tag{4}$$

5. Experiment and results

5.1. Experiment protocol

The experiment conducted in this study included four male and four female volunteers with a mean age of 26 years (range: 22–30) and an average weight of 65 Kg (range: 50–78).

Table 7
Emotion-relevant activities performed on a seat during the experiment.

Activity	Type	Potentially related emotion
Proper sitting	Posture	Interest [38], Happiness [39]
Leaning right	Posture	Interest, Disgust [38]
Leaning left	Posture	Interest, Disgust [38]
Leaning forward	Posture	Sadness, Frustration [40]
Leaning backwards	Posture	Disgust, Surprise, Terror [38]
Arms crossed in front	Gesture	Disgust, Pride [40], Interest [38]
Arms raised	Gesture	Happiness [41]
Arms straight down	Gesture	Sadness [39]
Arms hold head	Gesture	Frustration [38]

Table 8
Recognition accuracy (%) using different feature sets.

Sequence Feature Set	Interest	Frustration	Sadness	Happiness	*Average*
FEA_1	100.0	93.0	70.0	80.0	85.8
FEA_2	99.0	79.0	73.0	61.0	78.0
FEA_3	98.0	82.0	86.0	72.0	84.5
fusion FEA_1_2	93.8	95.7	97.8	81.8	94.7
fusion FEA_1_3	87.0	82.0	97.0	81.0	86.8
fusion FEA_2_3	**98.0**	**100.0**	**100.0**	**98.0**	**99.0**
fusion FEA_1_2_3	92.3	93.5	93.2	92.9	93.0

According to the protocol defined in the following, subjects were asked to perform the activities reported in Table 7 and depicted in Fig. 8.

In particular, the experiment aims to perform the following activities that, under certain circumstances, can be assumed due to an undergoing emotion (see Table 7):

- *Interest related* - Subjects are asked to sit on the chair performing backwards sitting with two hands on their knees. Then, they are required to perform an interest related activity by proper sitting with arms crossed in front.
- *Frustration related* - Subjects are asked to sit on the chair performing backwards sitting with two hands on their knees. Then, they are required to perform a frustration related activity by leaning forward with arms hold on the head.
- *Sadness related* - Subjects are asked to sit on the chair performing backwards sitting with two hands on their knees. Then, they are required to perform a sadness related activity by leaning forward with arms straight down.
- *Happiness related* - Subjects are asked to sit on the chair performing

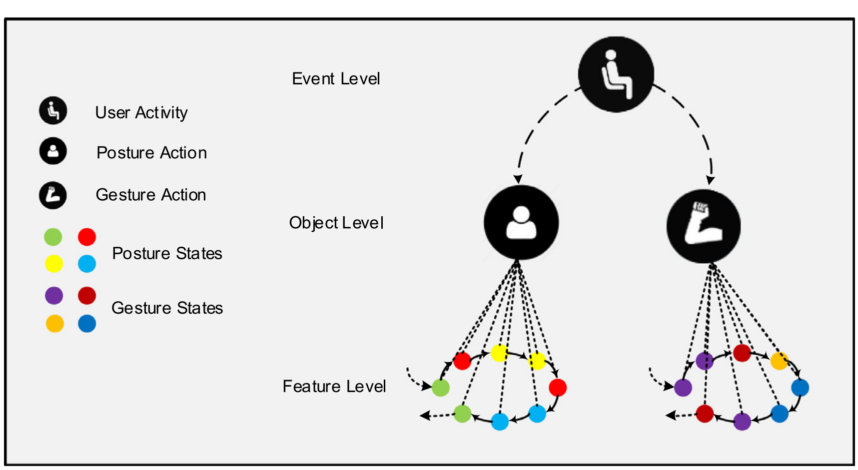

Fig. 7. Hierarchical model of the sequence feature and activity representation.

Fig. 8. Experiment protocol.

backwards sitting with two hands on their knees. Then, they are required to perform a happiness related activity by proper sitting with arms raised up.

Clearly, without contextual information is not possible to infer the emotion from the activity. For instance, leaning of the chair can represent an indication of either disgust or interest, depending if the subject is leaning towards or away a significant external event. It is worth reminding the scope of this work is not to identify emotions but to recognise emotion-relevant activities.

Each activity is kept for $2.5 - 3.5$ seconds and repeated ten times. All the experiment sessions are video recorded, with the written consent of each participant, and visually annotated to have an accurate ground truth against which compare the output of our activity recognition algorithm.

5.2. Prototype implementation considerations on user comfort and acceptance

The proposed system, as presented earlier, is based on a smart cushion and a wrist-worn inertial sensing device. To envision real-life application, both require proper ergonomics and form factors design choices to reach user acceptance. The smart cushion should not give any discomfort: if noticed when the user is seated, there is the risk to alter the natural sitting posture. The current version of our prototype board is not very flexible and even if it was embedded on the bottom of

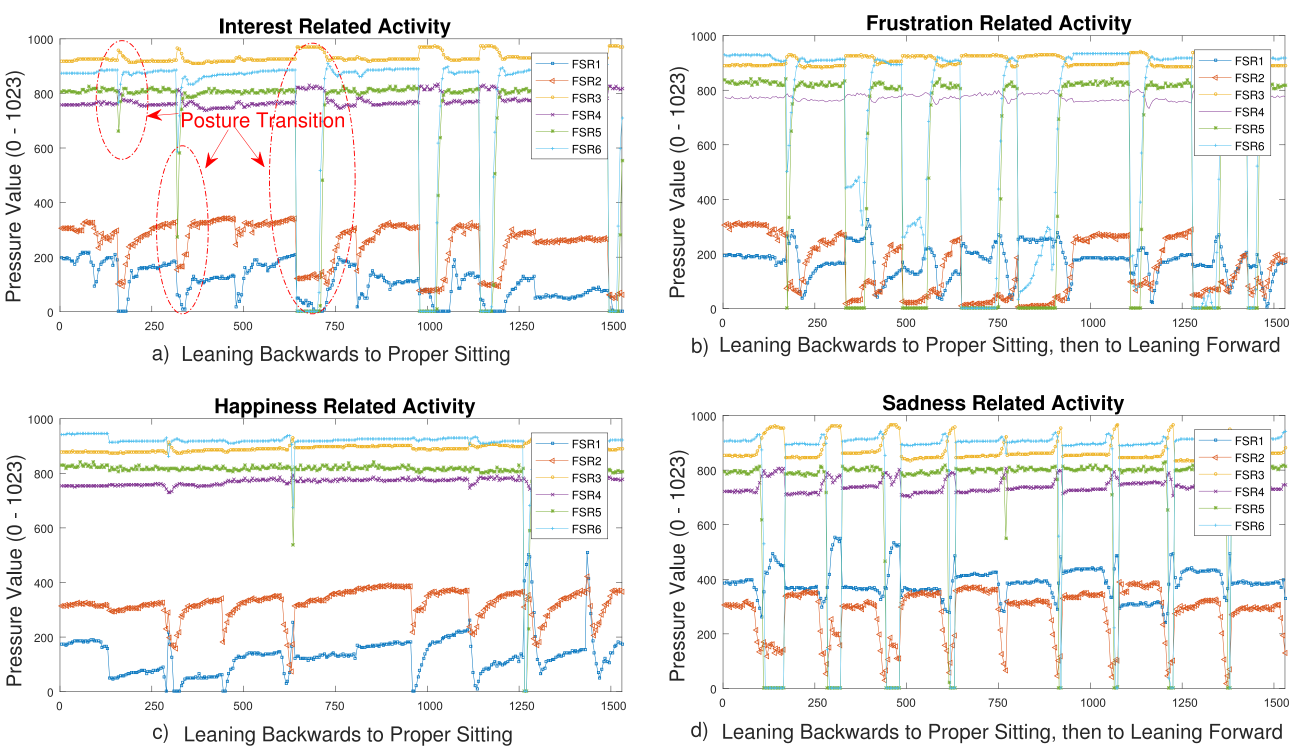

Fig. 9. Pressure data of emotion-relevant activities.

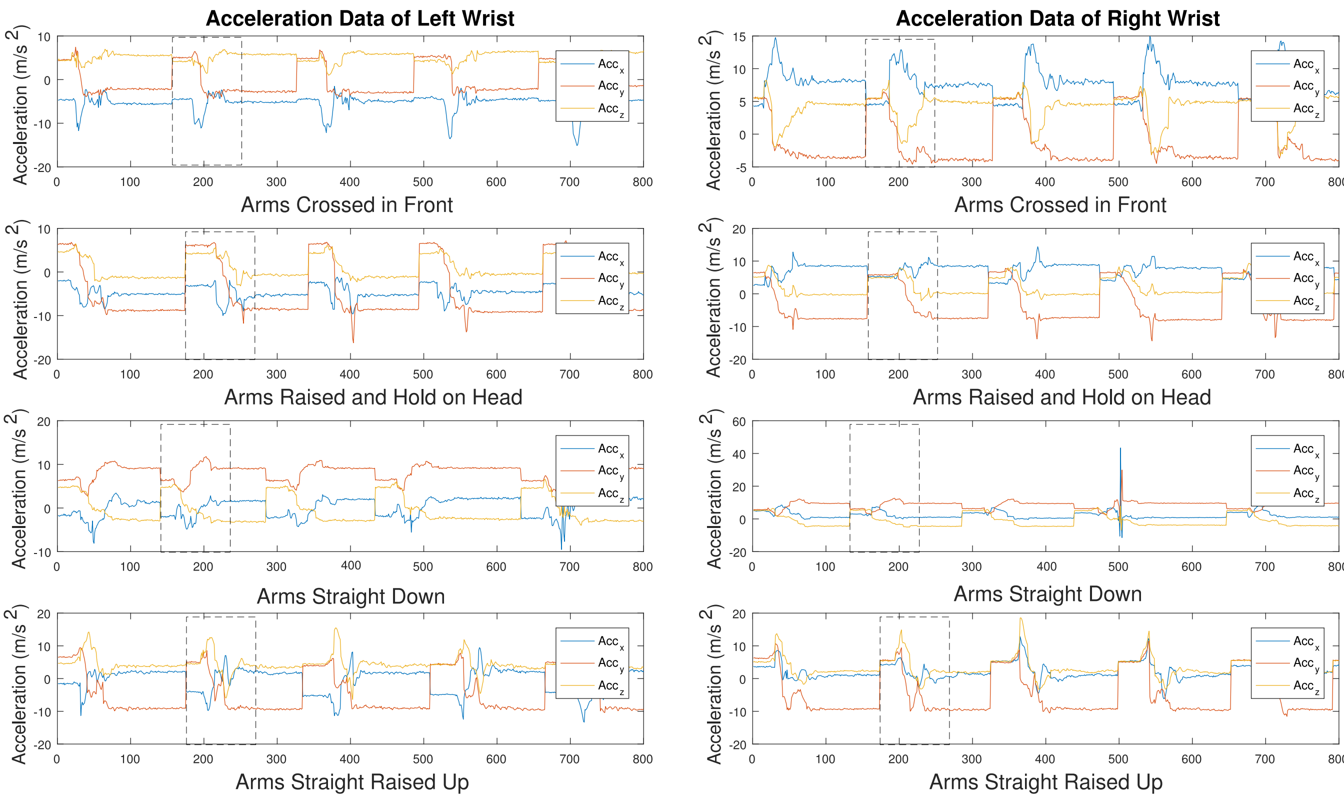

Fig. 10. Acceleration data of emotion-relevant activities.

the cushion (under the foam), participants to the experiments reported to slightly feel the board, so a semi-rigid structure supporting the pressure sensors should be designed. The wrist-worn device presents fewer comfort implications since a conventional smart watch/bracelet could be adopted without negatively affecting user acceptance.

5.3. Recognition performance

5.3.1. Raw data analysis

Figs. 9–11 show the raw data of pressure, accelerometer and gyroscope sensors, respectively.

In Fig. 9, we can note that the changes in the signals due to the *Interest related Activity* and the *Happiness related Activity* are relatively less marked than the *Frustration related Activity* and the *Sadness related Activity*. As is shown in Fig. 9, sometimes when the subject show interest or is happy for something, the body will not only assume a proper sitting posture but also will lean forward (see the annotation with dash and dot lines in Fig. 9 to point out the transition among the postures).

In Figs. 10 and 11, the rectangle with dash line are adapted to highlight an activity or a posture transition. From the figures, each activity is approximate with their neighbour activities and follow a regular pattern.

5.3.2. Comparison of different feature sets

In this section, we compared the activity recognition accuracy of the proposed method with different feature sets. As shown in Table 8, fusion feature sets can obtain higher accuracy than non-fusion feature sets; the most accurate result (99% average accuracy) is obtained with the feature set *FEA_2_3* which is fused from *FEA_2* and *FEA_3*.

It means when we combine time- with frequency-domain data, higher results can be achieved. In addition, as shown in Table 8, by adding raw data as a feature, the accuracy will be reduced because *FEA_1* set is more affected by noise interference.

5.3.3. Comparison of all the possible sensor combinations

Table 9 summarises a comparison of the different combinations of all the possible sensors to identify the most significant combination that allows for the highest recognition accuracy. Here, we applied the proposed method on the feature set *FEA_2* to evaluate the accuracy of multiple sensor combinations. The results show that the highest accuracy can be obtained when fusing data from all three different deployed sensors.

5.4. Comparison of multiple classification algorithms

To carry out an objective evaluation, we compared the proposed algorithm with other literature methods using WEKA data-mining toolkit. In particular, J48 [42], Naive Bayes classifier (NB) [43], support vector machine (SVM) [44], Random Forest (RF) [45], are applied to recognise the four types of emotion-relevant activities considered in this study and compared against our HMM-based method. Results in Tables 10 and 11 have been obtained using feature set *FEA_2* starting from the same raw data in every classifier; the highest accuracy (91.8%) is achieved with our proposed method. Although the average recognition accuracy (91.6%) of J48 is a bit lower (just 0.2%) than our proposed method, its model build time is nearly four times longer than with the proposed method. Therefore, as shown in Table 10, we can conclude that the proposed algorithm can achieve the best performance regarding recognition accuracy and model build time.

6. Conclusion and future works

In this paper, we proposed an effective approach to recognise users' emotion-relevant activities in sitting condition. The recognised activities can be used as an additional source of information in emotion recognition systems. Our method is based on the analysis of sequence features derived from sitting postures (using a pressure detection module) and upper limb gestures (using wrist-worn inertial sensors). Sensor- and feature-level fusion are applied to process the sequence

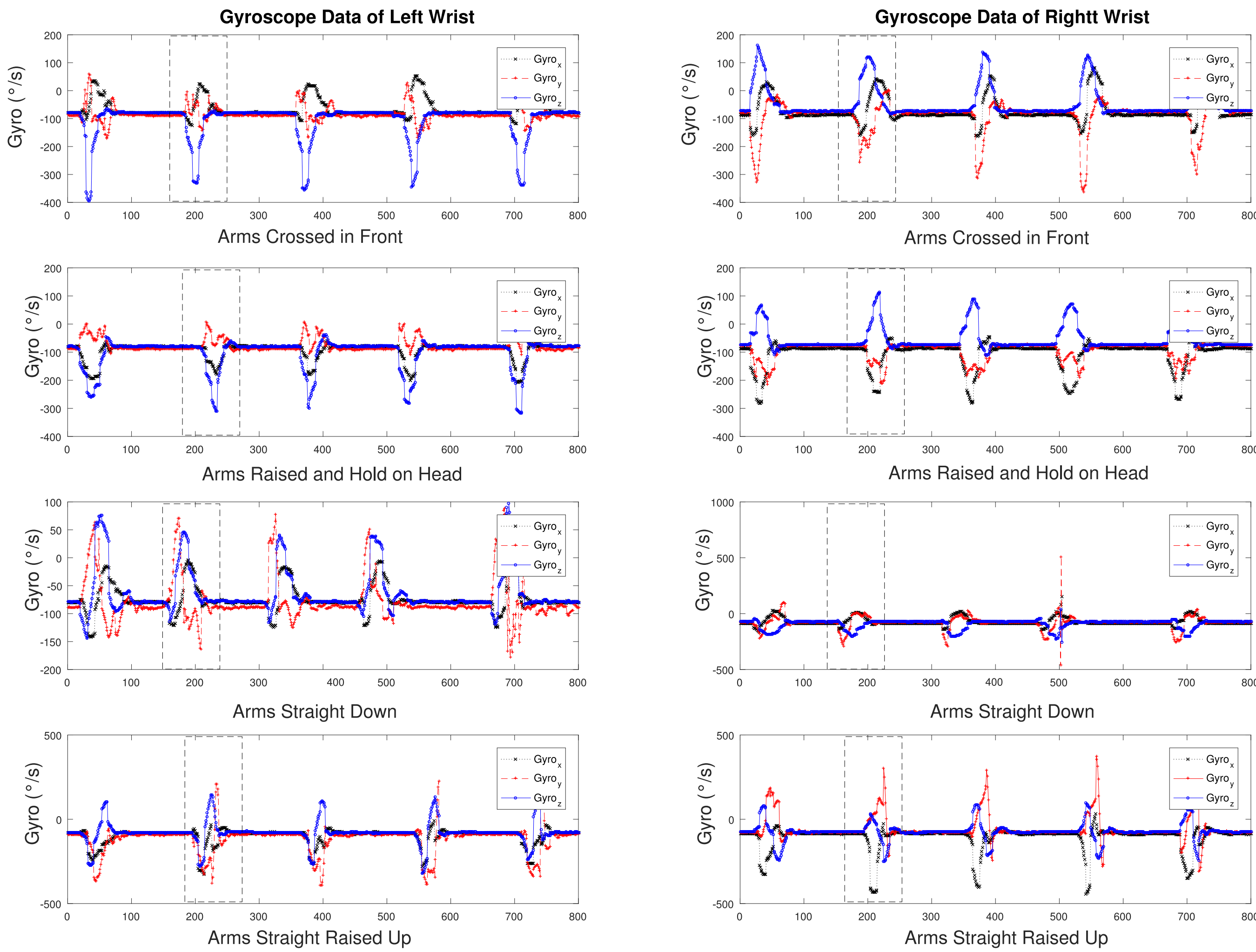

Fig. 11. Gyroscope data of emotion-relevant activities.

Table 9
Recognition accuracy (%) using different sensor combinations.

Sensor	Interest	Frustration	Sadness	Happiness	*Average*
PSA	96.0	76.0	87.0	81.0	85.0
SSL	77.0	80.0	82.0	79.0	79.5
SSR	72.0	65.0	90.0	62.0	72.3
PSA + SSL	92.0	78.0	88.0	82.0	85.0
PSA + SSR	91.0	76.0	86.0	76.0	82.3
SSL + SSR	85.0	83.0	95.0	82.0	86.3
PSA + SSL + SSR	**91.0**	**86.0**	**98.0**	**92.0**	**91.8**

Pressure sensor array (PSA), Shimmer sensor - left wrist (SSL), Shimmer sensor - right wrist (SSR)

Table 10
Classification accuracy (%) of different emotion-relevant activity recognition algorithms.

Algorithm	Interest	Frustration	Sadness	Happiness	*Average*
J48	100.0	82.6	81.5	85.1	87.2
NB	93.3	69.8	84.7	30.2	69.4
SVM	91.8	10.3	64.1	4.8	42.4
RF	99.1	87.5	88.3	91.8	91.6
Proposed Method	**91.0**	**86.0**	**98.0**	**92.0**	**91.8**

J48 - an open source Java implementation of the C4.5 decision tree algorithm, NB - Naive Bayes classifier , SVM - support vector machine, RF - random forest.

Table 11
Model build time and average accuracy of different emotion-relevant activity recognition algorithms.

Algorithm	Time (s)	Accuracy (%)
J48	0.18	87.2
NB	0.03	69.4
SVM	1.33	42.4
RF	0.88	91.6
Proposed Method	**0.24**	**91.8**

features. Activities are finally recognised using HMM models. Experiments showed the proposed approach can achieve high recognition accuracy by involving time- and frequency-domain fused feature set from all the different deployed sensors. Future works will be devoted to perform further experiments involving a bigger sample of participants and including more complex activities; the availability of an increased dataset will also allow us to investigate the use of deep learning methods. We plan an improvement of the proposed method with adaptive segmentation and synchronisation of data windows that can be dynamically adjusted according to the action. Finally, we need further analysis of the features compared with the emotion-relevant activity identified using physiological signals.

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