Activity Level Assessment of Wheelchair Users Using Smart Cushion

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ABSTRACT

A large majority of worldwide population, such as office workers and long journey vehicle drivers, spends lot of time everyday in sedentary activities. In this paper, we specifically focus on the assessment of different levels of wheelchair users' activity. The postures that wheelchair users assume during daily activities hide valuable information that can reveal their wellness and general health condition.

Aiming at mining such underlying information, we propose a hamming weight based algorithm to assess the activity level from sitting posture sequences. Using a smart cushion placed on the wheelchair, we can monitor users' postures. Postures sequence is transformed into binary value vector segments in order to reduce the computation load. The algorithm can detect three levels of activity (stationary, moderate or hyperactivity) with high accuracy. The proposed method could be embedded into several potential applications such as health estimation of sitting subjects, activity statistics, and detection of abnormal activities.

Keywords

Activity Level Assessment; Smart Cushion; Wheelchair Users; Posture Sequences; Hamming Weight

1. INTRODUCTION

In the context of Body Area Networks (BANs) [11], multi sensor fusion [18], wireless communication and embedded systems [13], many assist devices have been developed to enhance our daily lifestyle. As the elder population and the number of disabled persons is continuously raising, there is a strong need for better wheelchairs that are able to assist more independent life. As a consequence, several user-centric applications [20] such as smart home [8] and smart chair [26] are being developed.

People using wheelchairs spend long time in sitting posture and it is easier to incur in neck and back pain or pressure ulcer [1]. On the one hand, keeping the same posture for a long time is bad for health; on the other, very frequent posture transitions [17] might also represent evidence of discomfort. Posture transitions underly useful information. In this paper, we present an approach to monitor seating postures and assess users' activity level from posture sequences, so to provide users with reminders to correct posture adoption and therefore to minimize the health risk as well as to let caregivers take timely necessary interventions.

Our aim is to develop a fast, robust and highly accurate method for continuous activity level assessment. Specifically, the contributions of this paper are twofold. Firstly, we propose a hamming weight based algorithm to recognize three activity levels (i.e. stationary, moderate or hyperactivity); secondly, to reduce computational load, we propose to transform the posture sequences to binary value vector segments.

The reminder of the paper is organized as follows: Section 2 introduces the pressure sensing technology and knowledge discovery from postures; Section 3 describes in detail the proposed method and system design; Section 4 discusses experiments and obtained results. Finally, in Section 5 some conclusions and future works are drawn.

2. RELATED WORK

Posture/activity recognition and abnormalities detection

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have been hot topics in many research areas, such as pervasive and mobile computing, context-aware computing, and ambient assisted living. As pressure sensor based smart cushion is unobtrusive, several related works adopted it to recognize physical activity [12], to measure comfort and wellness [2], posture and fatigue [23] of users sitting on normal chairs and wheelchairs. In the following paragraph, we introduce the related works of pressure sensing based posture recognition and discovery from posture analysis.

2.1 Pressure sensing for posture recognition

Tan et al. [32] used a commercially available pressure distribution sensor called body pressure measurement system (BPMS). Using principal components analysis to analyze pressure distribution map as a gray scale image, sitting posture classification was successfully achieved. Meyer et al. [27] presented their own capacitive textile pressure sensor array cushion to measure pressure distribution of the human body. They used a Naive Bayes classifier to identify 16 different sitting postures on the chair, with similar results to Tan. Multu et al. [29] proposed a robust low-cost non-intrusive seat; compared to the commercially-available Tekscan ConforMat system (2048 sensors) used in [32, 27], they managed to reduce the number of sensors, and an optimal sensor deployment with 19 pressure sensors was adopted to recognize sitting postures. Xu et al. [34] presented a textile-based sensing system called Smart Cushion to recognize the sitting postures of human being. Binary pressure distribution data were collected and the data model could be interpreted to binary representation of a gray scale image. They used dynamic time warping to analyze the pressure distributions and recognize postures. Kamiya et al. [21] used a 8×8 pressure sensor matrix embedded in a cushion of a chair to identify sitting postures. They used a radial basis function with default SVM to classify the postures. Fard et al. [9] presented a system that involves a 8×8 pressure sensor matrix for continuous monitoring of surface pressure. Pressure map was generated to recognize different postures with the aim of preventing pressure ulcer using a MATLAB application.

In contrast with using e-textile sensor arrays, recent research focused on using fewer, independent sensors. Benocci et al. [5] proposed a method using 5 pressure sensors and k-Nearest Neighbor (kNN) was used to classify 6 different postures. Bao et al. [3] also used 5 pressure sensors to recognize the sitting posture on wheelchairs, using density-based clustering methods to establish the evaluation model. Barba et al. [4] used 16 pressure sensors and an Arduino board to develop an on-line posture recognition system to monitor users' affective states, such as boredom, attention and nervousness, during learning scenarios. Min et al. [28] proposed a real-time sitting posture monitoring system based on measuring pressure distribution of the human body sitting on the chair. A decision tree is used to recognize 5 sitting postures; when the user deviates from the correct posture, an alarm function is activated. Our former research [24] used 3 pressure sensors (two on the seat and one on the backrest) to detect user's postures sittin on a smart wheelchair. Six different postures were recognized and experimental results showed high classification accuracy.

Posture recognition is important, but how we can uncover valuable knowledge from postures is probably yet more relevant. In the following, we discuss the state-of-the-art on knowledge discovery from postures.

2.2 Knowledge discovery from postures

Chica et al. [7] focused on the movement intentions of patients restricted to a medical bed, developing a recognition system using pressure map sequences to monitor even slight movements. Artificial neural networks were used to analyze the pressure map in real time. Cheng et al. [6] investigated on user activity detected from simple pressure sensors mounted under the legs of a chair. Results showed that it is possible to detect not only different postures, but also subtle hand and head related actions like typing and nodding. Fu et al. [14] proposed a robust, low-cost, sensor based system that is capable of recognizing sitting postures and activities. Eight force sensing resistors (FSRs) were placed on chair backrest and seat, and a Hidden Markov Model approach was used to establish the activity model from sitting posture sequences. Kumar et al. [22] have designed Care-Chair with just 4 pressure sensors on the backrest of a chair. Equipped with intelligent data analytics, their system can classify 19 kinds of complex user sedentary activities and it can also detect user functional activities and emotion based activities. Furugori et al. [15] used seated posture information to detect mental fatigue. It was found that changes in the center of mass represented the change of driver's posture, so authors claimed it is a good index to fatigue estimation.

In the following, we briefly present our sitting posture recognition method and we propose a hamming weight based algorithm to detect the activity level. Compared with former research, we transform the posture sequence to binary vector, with significant computation load reduction.

3. METHOD

3.1 Static sitting posture recognition

With respect to our former research [24, 25], we propose an improvement of the sensors deployment on the cushion. In order to better fit individual weight and anatomic differences, our new sensing device contains 6 pressure sensors (4 pressure sensors placed on the seat and 2 other pressure sensors placed on the backrest), as shown in Figure 1.

Figure 1: Cushion based wheelchair system.

Using the cushion based wheelchair system, we are able to recognize 5 different sitting postures [24] (Proper Sitting

(PS), Lean Left (LL), Lean Right (LR), Lean Forward (LF) and Lean Backward (LB)). Instance vectors are generated from the pressure sensors signals. In particular, raw data are acquired by the Arduino-based processing module at a sampling frequency of $2Hz$, so to reduce energy consumption. As demonstrated in our previous research, the aforementioned postures can be efficiently recognized with a J48 decision tree [30]. This classification algorithm is also easy to be implemented on embedded devices such as our Arduino platform. At time t, the posture can be represented as $P(t)$.

3.2 Activity level assessment

Kumar [22] defined several kinds of sedentary activities such as static activities, movement based activities, user functional activities and user emotion based activities. In [33], the authors proposed a method to detect three levels of activities (high-level, middle-level, and low-level intensity) using acceleration signal.

It has been reported that moderate exercise can reduce the risk of metabolic syndrome and better improve the health condition of the sedentary individuals [16].

Under this perspective, in this work we are not interested in the specific activities performed by wheelchair users, while we need to consider the activity level/intensity, as summarized in Table 1. The table also reports examples of activities that can fall under a specific activity level performed by the wheelchair users, defined as follows:

- Stationary Activity (sit still for a long time),
- Moderate Activity, and
- Hyperactivity (posture transition frequently in a short period)

Table 1: Categorization of different activity levels of wheelchair users

Activity Level	Description	Examples
Stationary	User is static sitting for a long time.	Napping, Reading, Watching TV
Moderate	User performs common daily life activities.	Reading, Watching TV, Desk working, Conversation, Doing exercise
Hyperactivity	User is excited, nervous or uncomfortable.	Watching TV, Conversation, Doing exercise, Feeling nervous, Uncomfortable

As described in Table 1, some activities can belong to different levels. To exemplify, if the user is watching a TV documentary, he/she might behave stationary, while if the user is watching a football match of his/her favorite team, he/she might behave hyperactivity.

Using the postures recognized in Section 3.1, we propose a novel algorithm to assess wheelchair user' activity level. In the following, we describe the posture sequence representation and our hamming weight based algorithm activity assessment method.

Let be the posture transition represented as Hi. We assume the initial state of H_0 is 1. Then, if two consecutive postures in the sequence change, we mark Hi as 1, otherwise we mark it as 0, as depicted in the code below.

```
if P(i) = P(i-1)
        Hi = 0
else
        Hi = 1
```

Thus, this process converts the posture sequence into a binary vector that is used for further processing. There are two advantages of transforming posture sequence to binary values: firstly, it can clearly indicate posture transitions and, secondly, it can reduce computation load.

Hamming weight is used in several disciplines including digital signal processing, image and data processing, encoding and error correction, cryptography, combinatorial search, and DNA computing [31]. The Hamming weight $\omega(A)$ of a binary vector A is the number of one bits in the vector. The flow chart of the algorithm is shown in Figure 2.

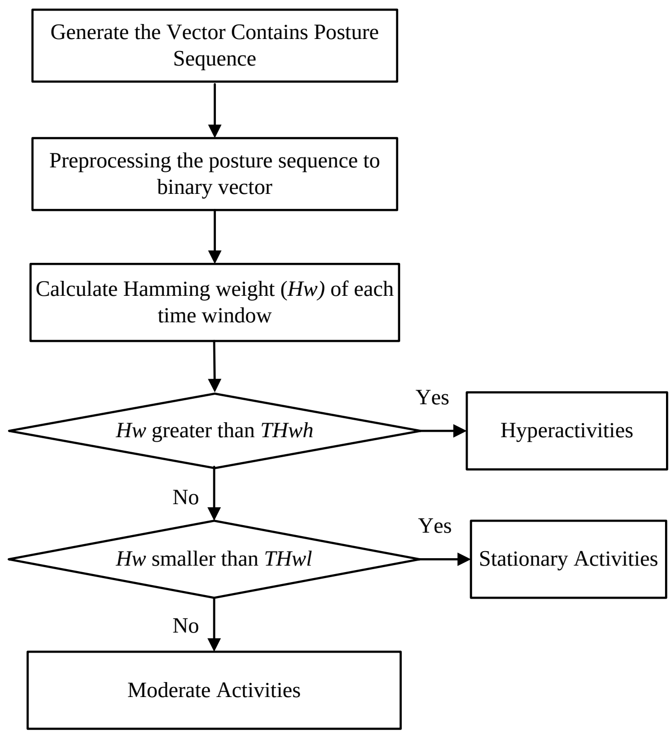


Figure 2: Algorithm of activity assessment.

The algorithm consists of the following three steps:

1. Posture sequence vector is generated. We detect the postures using the method described in Section 3.1, then we generate a vector containing postures represented as: $Pt = \{P1, P2, P3, P4, P5, P6, \ldots Pn\}$.

2. Sequence vector is transformed into binary vector representation. The complete posture sequence is transformed in terms of binary transition series as:
$Ht = \{H1, H2, H3, H4, H5, H6, \ldots Hn\}$.

3. Decision making is executed. We calculate *hamming*

weight (Hw) of each frame, then wheelchair users' activity level is assessed using the Algorithm 1.

Based on preliminary tests performed in lab settings, a fixed time window of 1 minute is used to distinguish between different levels of activity. We performed experiments with time windows varying from 5s to 30s and we observed little changes of the activity levels. So we choose a longer time frame. Empirical tests showed little difference between 30s and 60s time windows, but 1 minute window can better capture peculiarities of hyperactivities.

One minute time frame contains 120 posture samples (remind that postures are recognized at $2Hz$ rate). We calculate the Hw of each frame. We defined two thresholds, $THwl$ and $THwh$, that are determined by the data we collected during our experiments. Using the two thresholds, we can determine if an activity belongs to stationary, moderate or hyperactivity.

Algorithm 1 Activity level assessment

Require: Ht (posture vector)
if $Hw > THwh$ **then**
  Return Hyperactivity
else if $Hw < THwl$ **then**
  Return Stationary Activity
else
  Return Moderate Activity
end if

3.3 System Design

The architecture of the proposed system is depicted in Figure 3.

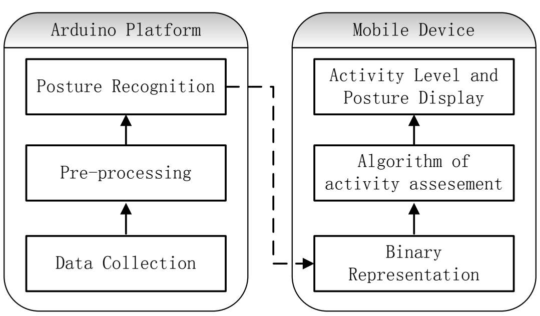


Figure 3: Architecture of the proposed system.

It is composed of two main parts:

- a wheelchair equipped with Arduino-based smart cushion to detect the postures,
- a mobile device (e.g. smartphone) to assess the activity level and give a friendly interface to interact with wheelchair users and to alert caregivers in case of abnormal states.

The data sensing module is equipped with pressure sensors produced by Interlink Electronics. As force is applied on the sensing areas, the resistance value of the pressure sensor will be correspondingly altered. As it is thin and flexible, it is suitable to be embedded into the chair textile or foam filling.

The data processing module is an Arduino DUE board. It features low energy consumption, high sampling rate and high processing speed, so it can be effectively used for sensor data acquisition and industrial automation.

The Arduino DUE has 12 analog inputs, allowing for a uniform distribution of sensors in the seat and the back of the cushion. The electrical diagram of the system is shown in Figure 4.

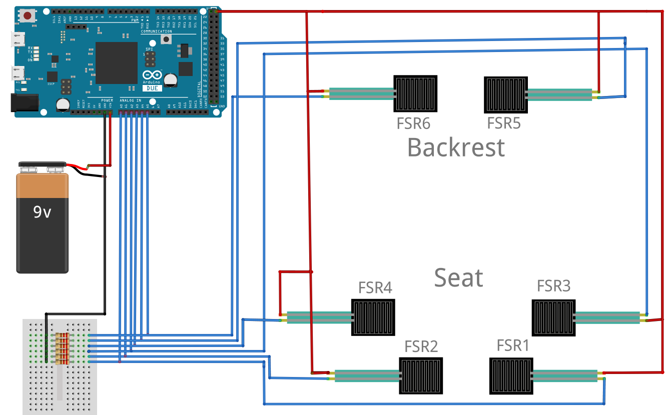


Figure 4: Circuit of the system.

Sensors data is collected and processed; then, posture recognition results are sent to the smartphone through wireless communication. We used Bluetooth technology as it is widely supported in the field of smart mobile devices.

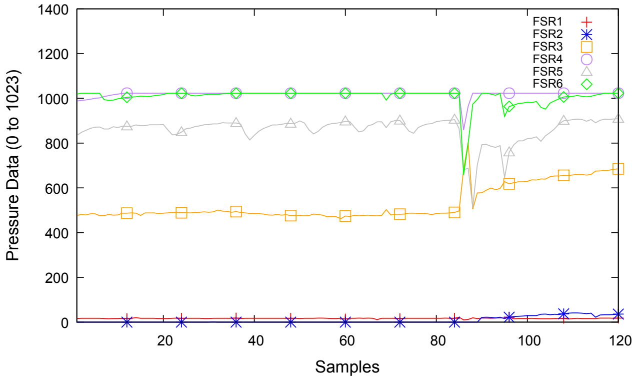
4. EXPERIMENTS AND RESULTS

In this section, we describe the initial experimental testing of our system which aims at providing reminders - and alarms, when necessary - to users and caregivers. To maintain good health condition, long-term wheelchair users should avoid to keep the same posture for long time; conversely, hyperactivity on the wheelchair can be also the symptom of abnormal events that worth to be put to caregivers' attention.

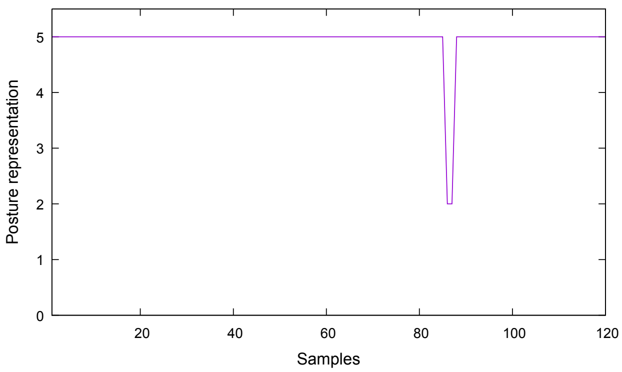
4.1 Experiments

We recruited eight subjects that participated in this study: 5 males and 3 females (hereafter called S1 to S8), with age in the range of [22, 36] and BMI (Body Mass Index) in the range of [16, 34], in order to cover different body types such as thin, fit and fat. Experiments were conducted during two weeks. All the participants were informed of the purpose and procedure of the study and, after signing an informed consent, they filled a form including questions on gender, ethnicity, age, height, and weight.

During the experiment, they were free to choose the time period for the test session and they were asked to perform common activities on wheelchair among (1) Napping, (2) Reading a book, (3) Watching TV, (4) Working at a computer, (5) Having a conversation, (6) Doing physical exercise such as lifting a dumbbell. On average, experiment sessions lasted about 2 hours and each participant had to perform 6 sessions in the two weeks. All the experiment sessions have been video recorded so to manually label the samples of each performed activity with one of the three defined levels. It is worth noting that during the experiments we occasionally observed frequent posture transitions that, by inspecting the

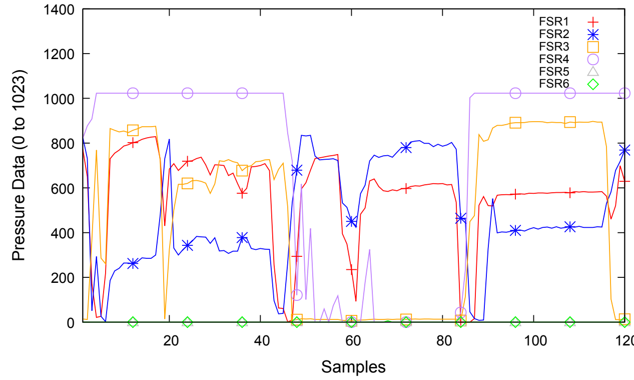


(a) Pressure sensor data of napping activity.

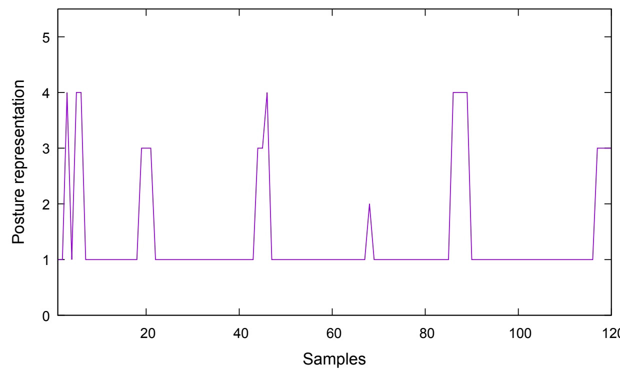


(b) Posture sequence of napping activity.

Figure 5: Data samples and posture sequence of napping activity.



(a) Pressure sensor data during desk working.



(b) Posture sequence during desk working.

Figure 6: Data samples and posture sequence during desk working.

video records, were found to be caused by short term excitement and discomfort (e.g. (i) S3 was watching a soccer match of the team he supports, (ii) S7 had a lively argument with another person, (iii) S8 was uncomfortable because not used to the provided wheelchair).

4.2 Results

To provide an exemplification, we show pressure sensor data and posture sequences corresponding to napping activity in Figure 5. Sensor data are obtained from each of the analog inputs of the Arduino DUE. For graphical clarity, we used 1, 2, 3, 4, 5 in the figures to represent Proper Sitting (PS), Lean Right (LR), Lean Left (LL), Lean Forward (LF) and Lean Backward (LB), respectively. As it can be noted in Figure 5, the pressure sensor data rarely changes and the posture only changes a little. The most common posture is LB (5) and occasionally changes to LR (2). By inspecting the video record, we found that the wheelchair user was napping slightly leaning against the right armrest. To provide another example, in Figure 6, we show plots corresponding to desk working (which belongs to moderate activity). As we can see, the most common posture is PS (1). In addition, in Figure 7 we show plots corresponding to a physical exercise activity (lifting the dumbbell with the left hand). As we can see, the most common postures are PS (1) and LL (3). Intuitively, when the wheelchair user is doing exercises, postures change more frequently.

With the data collected during the experiments (see Section 4.1) we generated a training set, then hamming weight of each one minute time window was calculated. Results are summarized in Table 2. The table shows that the napping activity has the lowest value while hyperactivities definitely lead to the highest hamming weight value.

As it can be noted in Table 2, there is a gap between two levels (e.g. max Hw value for stationary activity is 4 while min Hw value for moderate activity is 13). To address this issue, we propose to determine the $THwl$ and $THwh$ thresholds with the following formulas:

$$THwl = \frac{TH_{max}(Stationary) + TH_{min}(Moderate)}{2}$$

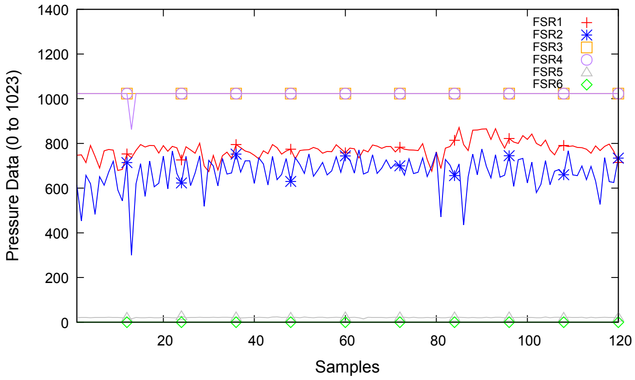
$$THwh = \frac{TH_{max}(Moderate) + TH_{min}(Hyperactivity)}{2}$$

Therefore, $THwl$ and $THwh$ are set as follows:

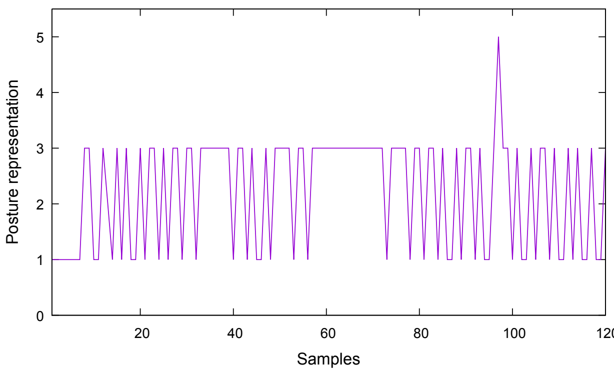
$$THwl = 8.5$$

$$THwh = 30$$

An initial performance evaluation has been carried out. In particular, we asked the eight participants to behave normally in their living space, without any restriction, for multiple sessions of 2 hours in which we also took video recordings. Collected data has been used to generate an independent test set.



(a) Pressure sensor data during physical exercise.



(b) Posture sequence during physical exercise.

Figure 7: Data samples and posture sequence during physical exercise (lift the dumbbell with left hand).

Table 2: Hamming weight of each activity level

Activity level	**Min**	**Max**
Stationary Activity	2	4
Moderate Activity	13	28
Hyperactivity	32	66

From these preliminary results, we obtained activity assessment precision of 100%, 96.6%, 93.7% for stationary, moderate, and hyperactivity, respectively. Specifically, we run the algorithm on the test set and we compared its output against our ground truth, which is the activity level labels that were manually annotated from the video recordings.

When wheelchair users are napping, or they are concentrated in reading or watching TV, they rarely change postures; we can indeed detect the stationary level very precisely. Sometimes, however, while the subjects e.g. watch TV (such as a football match) or have lively conversations, there might move the upper limb vigorously; in this case, even if we labeled the corresponding level as hyperactivity, our system has (erroneously) classified it as moderate. Conversely, in some cases, moderate activities have been recognized as stationary when they involve more upper limb movements rather than trunk or total body movements.

5. CONCLUSION

Stationary activity assessment of wheelchair users is an important factor in the evaluation of general health status and early prediction or prevention of severe pathologies such as pressure ulcers. In this paper, we proposed an efficient algorithm for fast and robust wheelchair users' activity level classification that is based on posture sequences analysis. It is suitable for monitoring the wheelchair users anywhere, anytime in mobility as it can be easily implemented with low-cost embedded devices.

Future works will be devoted to improve our Wheelchair Assist System so to provide remote real-time monitoring and 24/7 data access of mobility-impaired individuals to the caregivers. We are also investigating the integration of physiological sensor data [19, 10] to get more comprehensive health information. Furthermore, we will include the monitoring of upper limb movements using inertial wearable sensors to provide total body activity analysis and of waist movements to provide a quantitative metric of activity level. Finally, we plan to improve the accuracy of the method, specifically to recognize abnormal hyperactivities for the detection of user physical and mental discomfort.

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