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Activity Recognition of Wheelchair Users Based on Sequence Feature in Time-series

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***Abstract*—Mobility impaired individuals need the wheelchair to support their independent life, so monitor activities performed on the wheelchair can provide significant insights on their general health status. Activity recognition related to healthy people is a well established research area; however, only few works addressed this problem for wheelchair users. This paper proposes a novel approach based on dynamic Bayesian networks to recognize physical activities performed on a wheelchair. We equipped the wheelchair seat with a pressure detection unit and attached two inertial measurement units on the user's wrists. We focus on common basic activities and specifically, to experimentally evaluate our method, we defined four dynamic activities (moving forward, moving backward, moving left-circle, moving right-circle) and two static activities (left-right swing, forward-backward swing). Data is collected using a smart wheelchair system we developed in previous research. Firstly, we generate the posture sequence from the pressure signals and detect the raw acceleration data from inertial measurement units; then, we fuse the posture sequence and inertial features to detect the postural-based activities. Results shows that our proposed method can achieve an overall classification accuracy of 91.88%.**

***Index Terms*—Activity Recognition, Smart Wheelchair, Posture Transition Sequence, Sequence Feature, Dynamic Bayesian Network**

I. Introduction

Sedentary lifestyle has been identified as a major cause of physical illnesses [1] specifically related to heart disease, hypertension, high blood pressure, and obesity [2]. In particular, mobility impaired individuals, more commonly conducting physically inactive periods, will be more likely to face these risks. In this paper, we focus on mobility impaired individuals which therefore need the support of wheelchairs to perform daily life activities; in particular, we are interested in detecting common basic activities performed on the wheelchair.

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Upper limb activity is of fundamental importance for mobility impaired individuals. So monitor upper limb motion is very useful to gather information related to the activities being performed on the wheelchair. We developed a wheelchair system using Body Area Networks (BANs) [3] [4], heterogeneous sensor fusion [5], wireless communication, and embedded systems [6]. It is composed of a pressure detection unit embedded in a cushion and two inertial measurement units (IMUs) attached to the user's wrists. Extracted features related to posture and upper limb motion are fused to detect six different activities.

The contributions of this paper are twofold:

1) a novel approach is proposed to process the sequence features that are used to recognize postural-based activities; the approach is generalized in such a way that even very complex sequences could be recognized;
2) feature-level fusion is proposed to jointly process pressure sensor data obtained by the smart cushion with the inertial signals from the wrist-worn IMUs.

The remainder of the paper is organized as follows. Section II discusses the related work about posture and activity recognition in wheelchair systems. Section III describes the instrumentation of the sensing system, the experimental protocol, the feature vector extraction and selection, and the proposed dynamic Bayesian networks (DBNs) classifier algorithm for activity recognition. Section IV discusses the experiment results and provides an empirical evaluation of the system. Finally, Section V concludes the paper with a brief summary of contributions and planned future work.

II. Related work

In this section, we discuss posture and activity recognition in wheelchair systems. Hiremath et al. [7] focused on physical activity monitoring system to detect wheelchair-based activities, using gyroscopes for capturing wheelchair overturn and an accelerometer worn on the upper arm to monitor user activity. It can assist the wheelchair users to track regular physical activity, with the aim of leading to a healthier and more active lifestyle. Popp et al. [8] 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 effective mobility behavior of wheelchair users. Sonenblum et al. [9] designed a method based on accelerometer data to measure manual wheelchair movements. Different types of mobility-related wheelchair activities such as start, stop and steady state propulsion were recognized. Grillon et al. [10] proposed a method using two inertial sensors attached on the wheelchair's bottom and left wheel to detect accelerometer and gyroscope data, and a smartwatch to detect accelerometer and heart rate data attached on a wrist; several activities with different intensity levels of wheelchair users can be recognized.

IMUs are portable and benefit of low-power consumption; therefore, they play an important role in the area of user activity and wheelchair status monitoring. Thanks to their unobtrusiveness, pressure sensors are typically embedded in the seat cushion (i) to detect the postures in many sedentary sitting conditions [11], (ii) for body activity recognition [12], (iii) for activity level assessment [13], and (iv) for long-time sitting fatigue detection [14].

Benocci et al. [15] proposed a method based on five pressure sensors to classify six different postures using a k-Nearest Neighbor (kNN) classifier. Bao et al. [16] also selected five pressure sensors to recognize several sitting posture on wheelchairs, using density-based clustering methods to establish the evaluation model. Fu et al. [17] 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; the posture information is fed into two classifiers, one for back posture and the other for leg posture recognition. A Hidden Markov Model (HMM) approach was used to establish the activity model from sitting posture sequences. Kumar et al. [18] have designed Care-Chair with just four pressure sensors on the backrest of a chair. Equipped with intelligent data analysis, their system can classify 19 kinds of complex user sedentary activities and it can also detect user functional activities and emotion based activities.

The IMUs can provide information on user's upper limb activity and the pressure cushion can be used to detect sitting postures; therefore, in contrast with previous literature, we propose a method for fusing IMUs data and posture transition features in order to more accurately analyze the wheelchair user activities.

III. Methods

In this section, we present the instrumentation of the sensing system, the experiment protocol, the feature vector extraction and selection, and the DBNs classifier algorithm for activity recognition. Currently, all the data is processed off-line.

A) Posture Detection Unit in the smart cushion **B) Shimmer Motion Sensor attach on each wrist**

Fig. 1. Instrumentation of the sensing system.

A. Instrumentation of the sensing system

Two types of sensors are used: a pressure detection unit to recognize sitting postures and two IMUs attached on wrists to detect the activities of the upper limb. Figure 1 depicts the instrumentation of the wheelchair system.

1) Pressure Detection Unit: With respect to our former research [13] [19], in this work we propose a different deployment of the sensors in the cushion. In this work, we deploy all pressure sensors on the seat as shown in Figure 1. 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 recognized. Raw pressure sensor data is acquired by an Arduino-based processing module at a sampling frequency of 10 Hz; classified postures are organized to form posture sequences.

2) Inertial Measurement Unit: Shimmer Motion Sensor [20] offers high data quality with integrated 9 DoF (Degree of Freedom) inertial sensing via accelerometer, gyro, and magnetic sensors. Shimmers have been widely used in BANs and particularly in the field of activity recognition. In this work, we attach Shimmer nodes on the wheelchair user's wrists and we collect the accelerometer data at a sampling frequency of 10 Hz in order to synchronize with the pressure signals. By processing the accelerometer data, we can calculate the Signal Magnitude Vector (SMV) value on each wrist (see Section III-D1).

B. Experiment protocol

This study included four male and four female volunteers with mean age of 26 years (range: 22-30) and mean weight of 65 Kg. A smart cushion was used to measure pressure signals. Accelerometer signals were measured using two Shimmer motion sensors attached on each wrist. Then, subjects were asked to perform activities (see Table I) according to the protocols defined as follows:

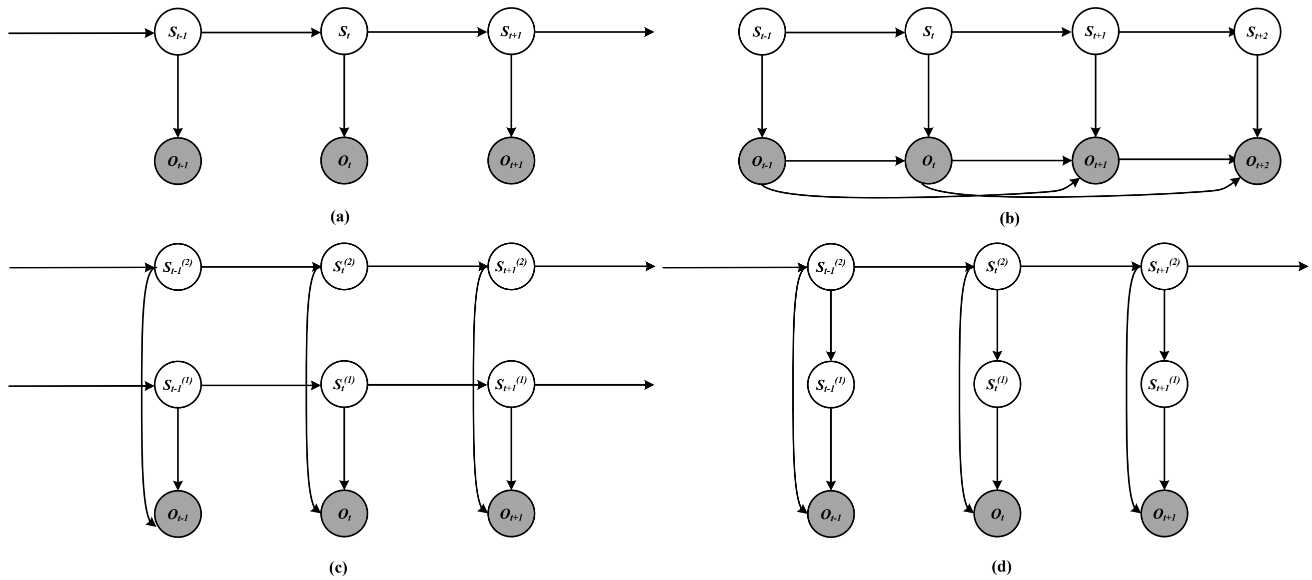

Fig. 2. a. HMMs with Gaussian output. b. Auto Regressive HMMs. c. Factorial HMMs with $\sigma = 2$. d. HMMs with mixture of Gaussian output.

- *Protocol for dynamic activities* - Subjects were asked to sit on the wheelchair and propel it at about 2 km/h. They were required to perform each dynamic activity (moving forward (MF), moving backward (MB), moving left-circle (MLC) and moving right-circle (MRC)) ten times.
- *Protocol for static activities* - Subjects were asked to sit on the wheelchair and perform the pressure relief activities (left-right swing (LRS) and forward-backward swing (FBS)) for five minutes. Each activity has to be repeated twice.

TABLE I
ACTIVITIES PERFORMED ON WHEELCHAIR

Activity	Abbr.	Type	Time duration(s)
Moving Forward	MF	dynamic	1-1.5
Moving Backward	MB	dynamic	1-1.5
Moving Left-Circle	MLC	dynamic	3-3.5
Moving Right-Circle	MRC	dynamic	3-3.5
Left-Right Swing	LRS	static	0.5-1
Forward-Backward Swing	FBS	static	0.5-1

C. Algorithm description

HMM is one of the most popular probabilistic method for modeling human activities [21]. HMM is a special case of DBNs and several variants of this model exist [22], including Auto Regressive-HMMs, Hierarchical-HMMs, and Factorial-HMMs, as shown in Figure 2. In this paper, we proposed to use Factorial-HMMs to classify wheelchair users' activities.

1) Model derivation: Here, we generate our DBNs model by using a set of discrete hidden state variables $\{S_t^\jmath \mid \jmath \in \mathbb{N}, 1 \leq \jmath \leq \sigma\}$ to represent the hidden states, where $t \in \{1, 2, \ldots, n\}$, n is the number of samples, and σ represents the number of discrete states.

Therefore, the joint probability of observations states $\{O_1, O_2, \ldots, O_n\}$ and hidden states $\{S_1, S_2, \ldots, S_n\}$ can be defined as shown in Formula 1.

$$P(S_{1:n}^1, \ldots, S_{1:n}^\sigma, O_{1:n}) = \prod_{\phi=1}^{\sigma} [P(S_1^\phi) \prod_{\tau=2}^{n} P(S_\tau^\phi \mid S_{\tau-1}^\phi)] \times \prod_{\tau=1}^{n} P(O_\tau \mid S_\tau^1, \ldots, S_\tau^\phi) \tag{1}$$

For each state set, S_t^σ is irrelevant (i.e. at time t, the hidden state can be expressed as $S_t = \mathrm{C} S_t^1 S_t^2 \cdots S_t^\sigma$, where C is constant). Meanwhile, $S = \{S_t \mid t \in \mathbb{N}, 1 \leq t \leq n\}$ can be used to represent the whole hidden states, and the solution of joint probability is the same as in general DBNs. The joint probability, therefore, can be simplified as in Formula 2.

$$P(S_{1:n}, O_{1:n}) = P(S_1)P(O_1 \mid S_1) \times \prod_{\tau=2}^{n} P(S_\tau \mid S_{\tau-1}) P(O_\tau \mid S_\tau) \tag{2}$$

In Formula 2, the hidden state probability $P(S_\tau \mid S_{\tau-1})$ is composed of a deterministic and a stochastic part [21] and it can be described in State-Space models [23]. When the transition and the output functions are linear and time-invariant, with Gaussian hidden state and observation noise variables [21], the function can be represented as in Formula 3, where Φ is a hidden state transition matrix and w_τ is a vector of random noise with zero-mean. Similarly, the observation probability $P(O_\tau \mid S_\tau)$ can be decomposed as in Formula 4, where Ψ is the observation matrix.

TABLE II
POSTURE TRANSITION MATRIX

Φ_i \ Φ_j	PS	LL	LR	LF	LB
PS	Φ_{11}	Φ_{12}	Φ_{13}	Φ_{14}	Φ_{15}
LL	Φ_{21}	Φ_{22}	Φ_{23}	Φ_{24}	Φ_{25}
LR	Φ_{31}	Φ_{32}	Φ_{33}	Φ_{34}	Φ_{35}
LF	Φ_{41}	Φ_{42}	Φ_{43}	Φ_{44}	Φ_{45}
LB	Φ_{51}	Φ_{52}	Φ_{53}	Φ_{54}	Φ_{55}

$$S_\tau = \Phi S_{\tau-1} + w_\tau \quad (3)$$

$$O_\tau = \Psi S_\tau + v_\tau \quad (4)$$

2) Maximum likelihood learning: In this paper, we propose the use of Expectation-Maximization (EM) [24] or other clustering method to transform the posture transitions and the upper limb activity transitions from real $\Re^N$ domain to discrete set. Thus, the activity model is given by a probability vector which can be used to detect the activity (see Formula 5).

$$I = \{M_1, \ldots, M_n\} \quad (5)$$

Then, we calculate log probability of $P(O, S \mid \theta)$ to obtain the maximum likelihood $L(\theta)$ as shown in Formula 6, where we use the notations S and O to represent hidden state and observation, while θ is the estimation parameter.

$$L(\theta) = \log \sum_S P(O, S \mid \theta) \quad (6)$$

Finally, in order to obtain the estimation parameter θ, we execute the iteration from θ_k to θ_{k+1} as shown in Formula 7, until $\|\theta_{k+1} - \theta_k\|$ is less than a given threshold.

$$\theta_{k+1} \leftarrow \arg\max_\theta \sum_S P(S \mid O, \theta_k) \log P(S, O \mid \theta) \quad (7)$$

3) Dynamic activity recognition: Given a set of DBNs model $\eta = \{\eta_1, \ldots, \eta_m\}$, obtained from last step, where m is the number of models, then we can recognize the activity as shown in Formula 8.

$$c = \arg\max_\mu P(O_{1:n}, S_{1:n} \mid \eta_\mu) P(\eta_\mu) \quad (8)$$

D. Processing workflow

In this subsection, we describe in detail the system processing workflow, depicted in Figure 3.

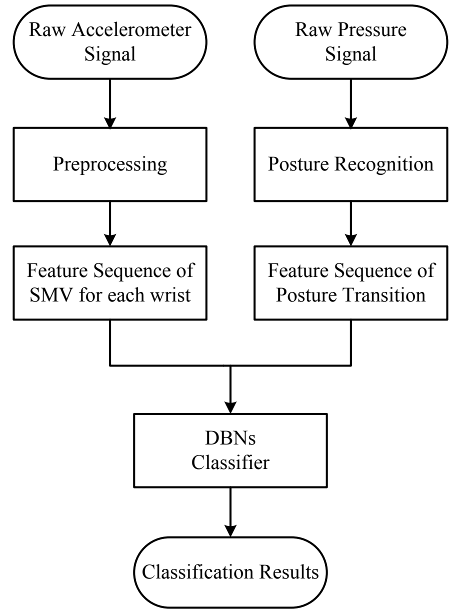

Fig. 3. An overview of the processing workflow.

1) Data pre-processing: The first step of the workflow involves data pre-processing to obtain two types of data as follows:

- *Posture sequence* - In posture recognition step [11], raw pressure signals are fed into an Arduino board and several postures (proper sitting (PS), leaning left (LL), leaning right (LR), leaning forward (LF) and leaning back (LB)) are recognized in real time. Using the recognized results, we can generate a posture sequence vector.
- *Signal Magnitude Vector (SMV) of IMUs* - SMV provides a measure of the degree of body movement intensity [25]; it can be calculated over the tri-axial acceleration values using Formula 9.

$$a = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2} \quad (9)$$

In particular, we obtain two features, $a_l^{(h)}$ and $a_r^{(h)}$ that represent the SMV value of left and right wrist; h is sample number in the time period.

2) Sequence feature extraction: With the algorithm described in Section III-C2, we obtain the posture transition sequence and upper limb transition sequence as follows:

a) Posture transition sequence: After posture recognition (see Section III-D1), we obtain a posture sequence vector. In order to clearly express the model, we denote Proper Sitting (PS), Lean Left (LL), Lean Right (LR), Lean Forward (LF), and Lean Backward (LB) respectively with 1, 2, 3, 4, and 5. Then, the posture transition model can be easily interpreted in Table II. Φ_{ij} represents the posture transition from Φ_i to Φ_j, while $i, j \in \{1,2,3,4,5\}$.

In this model, we only focus on the change of first and last posture of 1 second windows. Here, we use $S_{1:n}^1$ to represent the posture transition sequence in a time slide window. The notation S_1^1, ..., S_n^1 is represented as $S_{1:n}^1$ and $S_t^1 \in \Phi_{ij}$, where t is a generic sample. The probability of $S_{1:n}^1$ depends on posture transition sequence as shown in Formula 10.

$$P(S_{1:n}^1) = P(S_1^1)P(S_2^1 \mid S_1^1)\cdots P(S_n^1 \mid S_{n-1}^1) \qquad (10)$$

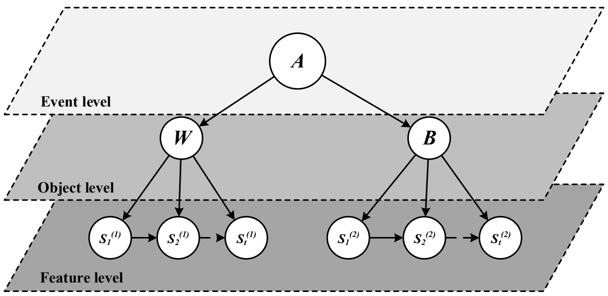

Fig. 4. Hierarchical model of the sequence feature and activity representation.

b) Upper limb activity transition: We define a function $f(l, r, h)$ to express the status of upper limb in sample k. Formula 11 shows the relationship between the function $f(l, r, h)$ and SMV values $a_l^{(h)}$ and $a_r^{(h)}$, the notations $\hat{\delta}$ and $\hat{\zeta}$ are used to represent two different unit vectors.

$$f(l, r, h) = a_l^{(h)}\hat{\delta} + a_r^{(h)}\hat{\zeta} \qquad (11)$$

Using $f(l, r, h)$, we obtain a vector to represent the transition of the IMUs signals. Similarly to the posture transition sequence process, we obtain the probability of upper limb activity transition sequence in a time slide window as shown in Formula 12.

$$P(S_{1:n}^2) = P(S_1^2)P(S_2^2 \mid S_1^2)\cdots P(S_n^2 \mid S_{n-1}^2) \qquad (12)$$

3) Classification: Figure 4 shows our hierarchical model, where the notation A represents an activity; W and B represent Wrist and Body posture. In this model, we use posture transition sequence and upper limb activity transition sequence as hidden states; activities can be recognized through the approach described in Section III-C.

IV. RESULTS AND DISCUSSION

In this section, we describe the results of our proposed method obtained by experimental evaluation. Firstly, we separate the raw data into several activity-defined windows, each of which is composed of 35 samples with 50% overlap. We set the window length considering the time duration of the longest activity (i.e. 3.5 s, see Table I) and the sensor sampling rate, that is fixed at 10 Hz (i.e. 10 samples per second, see Section III-A2). Then, we obtain the sequence features of Posture Transition Sequence and Upper Limb Activity in each time slide window.

In Figure 5, the x_axis represents the data sample and the y_axis represents the posture transition state Φ_{ij} (for example, in the first sample of MRC activity, posture transition status is 15, which means the sitting posture change from PS to LB - see Table II and Section III-D2a); each plot shows 70 posture transition states occurred during ten executions of the same activity. As shown in Figure 5, the postures change randomly for MF, MB, MLC and MRC activities, which is an indication that we can not just use the smart cushion to recognize the activities when the wheelchair is moving. In contrast, the posture states related to FBS and LRS activities change following a regular pattern.

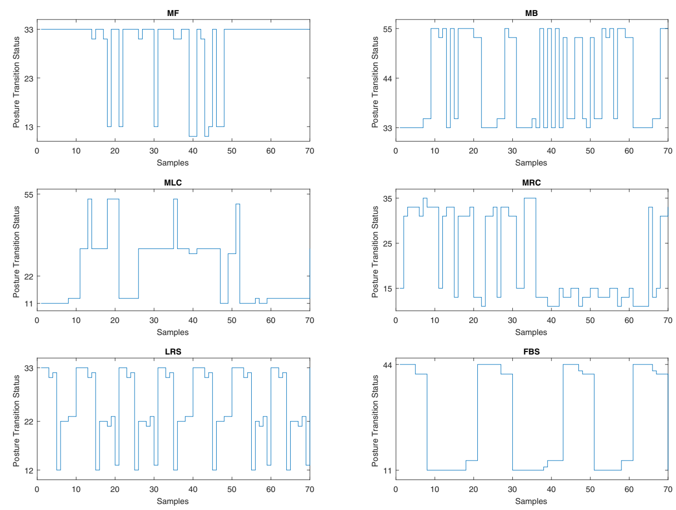

Fig. 5. Posture transition sequence of activity.

In Figure 6, we compare, for each activity, the difference between SMV in both wrists. When the user wants to propel the wheelchair forward (MF) or backward (MB), both hands need to move simultaneously, applying the same force to the wheels. The plots related to MF and MB indeed show that the SMV of each wrist is almost the same. During LRS and FBS activities, the wheelchair is stationary and the user's wrists swing following body swings, so the related SMV plots show a regular pattern, as illustrated in the figure. In MLC and MRC activities, the user intends to make a turn, therefore one hand has to spin the wheels stronger than the other, so the SMV value on that wrist is higher than the other.

To evaluate our proposed approach, we use MATLAB to analyze the two sequence features Φ_{ij} and $f(l, r, h)$. We calculated accuracy, precision, and F-Measure for each activity; results are reported in Table III. Overall, we obtained a weighted average accuracy of 91.88%.

V. CONCLUSION AND FUTURE WORKS

In this paper, we proposed an effective approach to recognize wheelchair users' activities. Our method is based on the analysis of sequence features derived from sitting postures (using a pressure detection unit) and upper limb activities (using wrist-worn accelerometers). Feature-level fusion is applied to process the sequence features. Activities are finally recognized using our DBNs models that are trained using a segmented set

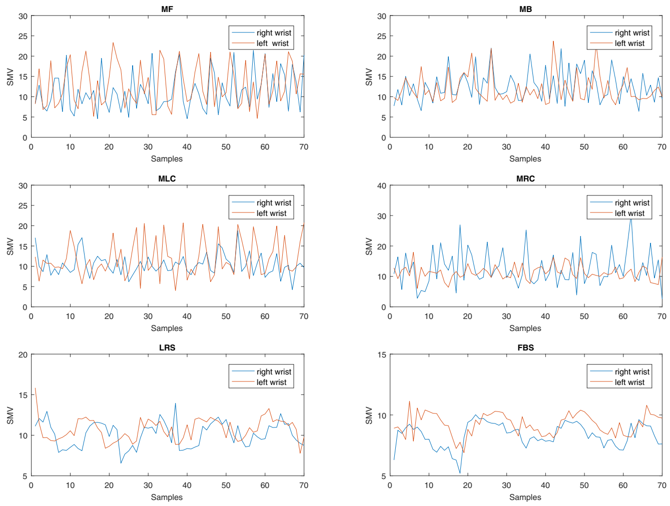

Fig. 6. SMV of left and right wrists acceleration.

TABLE III
PERFORMANCE RESULTS FOR EACH ACTIVITY

Activity	Accuracy	Precision	F-Measure
Moving Forward	90%	90%	90%
Moving Backward	100%	69%	82%
Moving Left-Circle	85%	97%	90%
Moving Right-Circle	93%	97%	95%
Left-Right Swing	95%	100%	97%
Forward-Backward Swing	95%	100%	98%

of posture transition attribute vectors and upper limb activity transition attribute vectors. Experiments showed the proposed approach can achieve high recognition accuracy (91.88%).

As future works, we are planning to recognize more complex wheelchair activities as well as to improve our method with adaptive segmented windows that are dynamically adjusted according to the activity.

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