PAPER • OPEN ACCESS

A Gait Patterns Recognition Approach Based on Surface Electromyography and Three-axis Acceleration Signals

A Gait Patterns Recognition Approach Based on Surface Electromyography and Three-axis Acceleration Signals

Jinghan Hao, Peng Yang, Lingling Chen and Yanli Geng

School of Artificial Intelligence, Hebei University of Technology, No.8 Guangrong Road, Hongqiao District, Tianjin, China

Email:aq87778@163.com

Abstract. In this paper, an approach based on combining surface electromyography(sEMG) and three-axis acceleration(ACC) signal was proposed to recognize 5 different kinds basis daily gait patterns, including walking on the ground, going up stairs, going down stairs, going up slope and going down slope. Firstly, the gait related sEMG signal and three-axis ACC signal were collected from the lower limbs of subjects. Secondly, the de-noising of sEMG signal was finished and the segmentation of the fusion signal was done. Thirdly, the features of fusion signal were extracted. Finally, a classifier based on 2-stream hidden Markov model (HMM) was built to recognize 5 kinds of basis daily gait patterns. The experiment obtained an average recognition accuracy of 94.32%, which is 4.15% higher than the accuracy by adopting sEMG signal only (Average 90.17%), and 9.60% higher than the accuracy by adopting ACC signal only (Average 84.72%). The result demonstrated that it can improve the recognition accuracy of gait patterns effectively to combine sEMG signal and three-axis ACC signal.

1. Introduction

In recent years, due to the frequent occurrence of accidental injuries such as traffic accidents, work-related injuries and natural disasters, as well as the continuous spread of such chronic diseases as cerebrovascular diseases, diabetes and osteoarthrosis, a considerable number of people have lost the ability to walk, bringing heavy burdens to families and society. Improving the quality of life of such patients and gradually restoring their walking ability have become the focus of social concern and the subject of medical rehabilitation [1].

The electromyography signal (EMG) is the source of the electrical signal that generate muscle force, reflecting the connection between neuromuscular activity and functional state. The electromyography signal is a weak bioelectrical signal from the neuromuscular activity in the process of human movement. It occurs after the intention of the brain movement is generated, and before the muscle actually contracts. It is a signal that is closer to the original intention of human movement [2]. Compared with only gathering dynamic information or image information such as posture and angle, gathering the myoelectric signal to recognize movement intention has obvious advantages. As a signal source, it can guarantee the real-time control [3,4].

Accelerometer(ACC) is a kind of motion sensor, which is wearable. Its analysis algorithm is relatively simple. And the real-time performance of accelerometer is good. The acceleration signal cannot only reflect the velocity information generated by daily behavioral movements over time and the motion

track information in space, but also provide the angular inclination information of daily behavioral movements relative to the direction of gravity acceleration. Therefore, it is widely used in daily behavioral movement detection and fall detection. Time domain features of acceleration signal are often extracted, such as simple threshold value, kurtosis, signal magnitude area (SMA) [5] and instantaneous change value of acceleration. Irene S et al. [6] used acceleration to recognize sitting, standing and walking, and obtained 99% accuracy.

As both sEMG electrodes and ACC sensors have the advantages of low cost, miniaturization and portability, the research results of many scholars[7-9] showed that SEMG and ACC signal fusion technology was superior to single sensor in human movement intention recognition, which benefited from the advantages of sEMG signal in detecting fine movements and ACC signal in detecting large-scale movements and behaviors. Roy et al.[10] used 8 accelerometers and 8-channel surface myoelectric signal to classify 11 recognition tasks and 10 non-recognition tasks, and obtained an average recognition rate of 90%. Zhang et al.[11] and Kosmidou et al.[12] applied SEMG and ACC signal fusion technology to continuous sign language gesture research, and the experimental results showed that the classification accuracy of two types of sensors was significantly improved than that of one type of sensor alone.

However, most of the identified targets of the above research were the gestures recognition based on sEMG signal and ACC signal. There are few researches on human gait recognition.

In this paper, the sEMG signal which can reflect the original intention of the human body and the ACC signal which can reflect the motion track information in space were combined. And a classifier based on 2-stream hidden Markov model (HMM) was built to recognize 5 kinds of human body basis daily gaits, including walking on the ground, going up stairs, going down stairs, going up slope and going down slope.

2. EXPERIMENTAL SETUP

2.1. Experimental Acquisition Equipment
In this experiment, DELSYS Trigno™ Wireless EMG System (Delsys Inc., 20-450Hz band pass filter) was used as data acquisition system, as shown in Figure 1. The device is composed of Trigno charging base station and EMG smart sensors. Every sensor can simultaneously collect sEMG signal and three-axis acceleration signal.

5 typical lower limb gait patterns in human daily movement were selected, including walking on the ground, going up stairs, going down stairs, going up slope and going down slope.

Figure 1. Acquisition of the sEMG singals and ACC signal.

2.2. Experimental Platform
The experimental platform consists of staircase, slope and flat panels, as shown in Figure 2. The staircase has 6 steps. The height of the steps is 150mm, which is widely used. The slope is 15°，which

is the barrier-free access angle. The number of the gait cycle that subjects can complete on the experimental platform relate to personal walking habits, which is generally 3-4.

Figure 2. Experimental Platform.

2.3. Experimental Procedure

5 subjects (3 males and 2 females) who are with an age range from 20 to 27 years participated in this experiment. As Figure 3 shown, five muscle groups were selected to collect signal:

(1) rectus femoris(sensor1);
(2) vastus medialis(sensor2);
(3) vastus lateralis(sensor3) ;
(4) medial gastrocnemius(sensor4) ;
(5) lateral gastrocnemius(sensor5).

Figure 3. Positions of sensors.

3. Data Processing Method

3.1. SEMG Signal De-noising

In the process of signal collection, the sEMG signal was affected by noise, environment and other factors. Analyzing the signal directly will lead to many errors and reduce the recognition rate of gait patterns. So it is necessary to reduce sEMG signal noise.

In this paper, wavelet packet de-noising method was adopted. Sym8 wavelet was selected to decompose the sEMG signal in 4 layers. Then the threshold value of each layer was obtained. Soft threshold method was used to reduce noise of the signal. Figure 4 shows the comparison between the original sEMG signal and the de-noising sEMG signal of vastus medialis when subject was going upstairs.
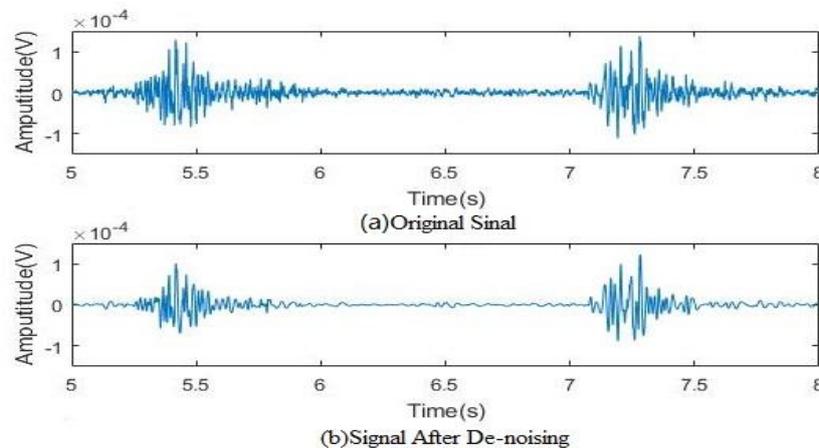

Figure 4. Comparison of SEMG Signal Before and After the Signal De-noising

3.2. Segmentation

This article defined that the movement from the measuring side foot just touching land to the next time measuring side foot just touching land as an active segment. According to the previous research, the general time of an active segment is 1.3s-1.6s. When the fusion signal is used to recognize various gaits directly, sending the fusion signal to the recognition system is too long, which will cause a perceptible delay to the user. Therefore, the active segment was segmented by sliding window method. It is generally believed that the user will not feel the delay if the time interval between the muscle contraction of the lower limb and the corresponding gait by the recognition system is less than 300ms [13]. In the experiment, the sliding window length was set as 128ms. And the window increment was set as 64ms.

3.3. Feature Extraction

Each windowed data was extracted.

3.3.1. sEMG Feature Extraction

5 kinds features were calculated, including the mean absolute value (MAV), standard deviation (STD), zero crossings (ZC), waveform length (WL) and 4-order AR coefficients of sEMG signal of each window for every channel as the features. Then, all the features of 5 channels will combine to form the sEMG feature vector. These features are capable of representing the waveform amplitude, frequency and duration [13-14]. Finally, a 40-dimension sEMG feature vector(named sEMG) was obtained.

The mean value (MEAN) represents the average intensity of a segment of sEMG signal. The calculation formula is as follows:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x(i)| \qquad (1)$$

The standard deviation (STD) reflects the intensity of signal deviating from its average value, and reflects the change range and intensity of sEMG signal during movement. The calculation formula of standard deviation is as follows:

$$STD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(S(i) - \bar{S})^2} \qquad (2)$$

where the calculation formula of $\bar{S}$ is as follows:

$$\bar{S} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}S^2(i)} \qquad (3)$$

The zero crossings (ZC) reflects the change of the intensity of the sEMG signal. The calculation formula is as follows:

$$ZC = \sum_{i=1}^{N-1} sgn(-x(i)x(i+1)) \qquad (4)$$

$$sgn(x) = \begin{cases} 1 & x > 0 \\ 0 & else \end{cases} \qquad (5)$$

The waveform length (WL) is the cumulative value of the waveform over a period of time. The calculation formula is as follows:

$$WL = \sum_{i=1}^{N-1}|x(i+1) - x(i)| \qquad (6)$$

Auto-Regressive(AR) model is widely used for its outstanding performance in time series analysis, which is suitable for short data analysis. The sEMG meets the requirements of this parameter model. In the AR model, sEMG can be seen as the product of a linear system motivated by a white noise $e(i)$ with zero mean [15-16]. Therefore, the feature parameters of AR model can be extracted as the features of gait pattern recognition. The AR model was established as follows:

$$x(i) = \sum_{k=1}^{p} a_k \times x(i - k) + e(i) \qquad (7)$$

where $x(i)$ is the sEMG of ith sample point, a_k is the ith coefficient of AR model, p is the order number of AR model, $e(i)$ is white noise residual, which obeys normal distribution. In this experiment, 4 order AR model empirically, i.e. p=4。

3.3.2. Acceleration Signal Feature Extraction
For a three-axis acceleration sensor, the data collected each time can be represented as a vector $\boldsymbol{a} = (a_x, a_y, a_z)$. Firstly the mean value (MEAN) and the standard deviation (STD) of each window for each axis were caculated. Then a 12-dimension feature vector from acceleration data of both sensors(named ACCa) was extracted. Secondly, the modulus of vector $\boldsymbol{a}$ was calculated:

$$|\boldsymbol{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2} \qquad (8)$$

then, unitize $\boldsymbol{a}$:

$$\boldsymbol{a_e} = \frac{\boldsymbol{a}}{|\boldsymbol{a}|} \qquad (9)$$

The three-axis data of three-axis accelerometer are related to the attitude of the sensors, i.e. the attitude of thighs and calves. Even if the attitude of body cannot be calculated accurately by the ACC signal when the lower limbs is moving, the accelerometer sensor data can be used to get some useful information that can represent the attitude in a certain extent. For an acceleration sensor, an assumption can be made that kinematic acceleration will not significantly influence the direction of resultant acceleration when subjects are moving, which means the magnitude of the acceleration of gravity dominates [17].Then a estimation is made that the direction of gravity is the same as $\boldsymbol{a}$ under five movement patterns[18]. So the modulus of kinematic acceleration is:

$$a_m = |\boldsymbol{a} - g \times \boldsymbol{a_0}| \tag{10}$$

where g is the modulus of the gravitational acceleration.

Although this is not an accurately estimate of motion posture, they can represent posture information in a certain extent. Finally, the MEAN and STD of $\boldsymbol{a_e}$, $|\boldsymbol{a}|$ and a_m in each window of both acceleration sensors was calculated to obtain a 20-dimensional feature vector(named ACCb).

So, by combining ACCa and ACCb to get a 32-dimensional acceleration feature vector (named ACC).

4. Classifier

A 2-stream hidden Markov model (HMM) classifier was selected to recognize the gait patterns. HMM is a statistical analysis model, which was established in the 1970s. It was spread and developed in the 1980s and became an important direction of signal processing. HMM is a dual-random process. On the one hand, it is a kind of Markov chain. Its state cannot be directly observed, but can be reflected through the observation sequence. On the other hand, each observation vector is represented as each state by some probability density distribution, so each observation vector is generated by a state sequence with a specific probability density distribution. HMM can be described by five elements:

$$\lambda = (A, B, \pi, N, M) \tag{11}$$

Where N is the number of hidden states, and M is the number of observations that can certain probability distribution for each state. A, B and π are three different probability matrices. A is the hidden state probability matrix. B is the observation sample probability matrix. And π is the initial probability distribution matrix, which is usually assigned the same value during initialization.

The main steps of training and classification of gait patterns adopting 2-stream HMM[19], are as follows: set sEMG and ACC signal feature sequence as $O = \{O^E, O^A\}$. O^E is sEMG signal observation sequence, O^A is ACC signal observation sequence. For training samples of known gait patterns, $O = \{O^E, O^A\}$, the Baum-Welch algorithm was used to train the classifier. Then a 2-stream HMM was gotten of each gait pattern, i.e. $\lambda_c = \{\lambda_c^E, \lambda_c^A\}$, where c represents a kind of unknown gaits patterns. In this paper, the hidden state number N of HMM was empirically set to 5. And the probability distribution of each observation value was modeled by a 3-order Gaussian mixture model [20].

In the testing phase, for unknown gait patterns, the likelihood probability of the observation sequence was calculated in all the gait pattern HMMs, i.e. $P(O|\lambda_c^E), P(O|\lambda_c^A), 1 \leq c < C$, where C is the number of all the movement patterns. This paper will recognize 5 kinds gait patterns so that C=5. Then the gait pattern was identified as the gait pattern of the 2-stream HMM which produced the maximum sum of likelihood probability, i.e.:

$$c^* = \arg\left(\max_{1 \leq c < C} P(O^E|\lambda_c^E) + P(O^A|\lambda_c^A)\right) \tag{12}$$

5 Result and Discussion

The size of window length was set as 128ms meanwhile the increment size was set as 64ms. Half of the feature vector dataset was used as training sample to train classifier. And the other half was used as testing dataset to test the performance of classifier. For comparing the recognition accuracies of different data sources, the experiment was performed with different datasets from:

(1) sEMG;

(2) ACC;

(3) sEMG+ACC.

The recognition accuracy for 5 kinds of basis daily gait for 3 kinds of datasets was calculated, as shown in Table 1. And Figure 5 is the bar chart form of Table 1.

Table 1. Recognition accuracy of 3 kinds of datasets.

	SEMG ONLY	ACC ONLY	SEMG+ACC
WALK	91.18%	87.27%	94.63%
UP STAIR	89.34%	81.06%	93.36%
DOWN STAIR	89.33%	86.16%	95.33%
UP SLOPE	89.36%	83.16%	94.65%
DOWN SLOPE	91.65%	85.96%	93.65%
AVERGE	90.17%	84.72%	94.32%
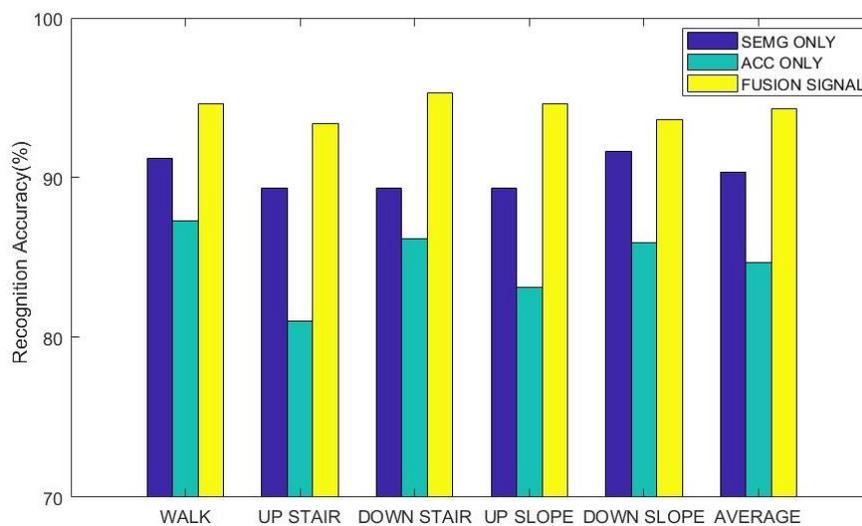
Figure 5. Recognition accuracy bar chart of 3 kinds of datasets.

Figure 5 and Table 1 show that the recognition accuracy by adopting the fusion of sEMG and ACC (Average: 94.32%), is 4.15% higher than that by adopting sEMG only (Average: 90.17%), and 9.60% higher than that by adopting ACC only (Average: 84.72%). This indicates that combining sEMG signal and ACC signal can improve the recognition accuracy compared to only adopting sEMG signal or ACC signal.

Combining sEMG signal and ACC signal is a good choice for lower-limb exoskeleton to identify human gait patterns. But for people with disabilities who need prostheses because of amputation, it is impossible to collect the sEMG signal and ACC signal from calf. Therefore, the signal from thigh only was selected to identify the gait pattern. The recognition accuracy of five motion patterns was obtained, which adopted sEMG and ACC signal of thigh. The result is shown in Table 2. And the results are compared with the results adopting all the signal, as shown in Figure 6.

Table 2. Recognition accuracy of adopting thigh dataset only.

|	WALK	UP STAIR	DOWN STAIR	UP SLOPE	DOWN SLOPE
Accuracy	91.23%	89.27%	87.65%	88.99%	88.29%
Average					89.09%
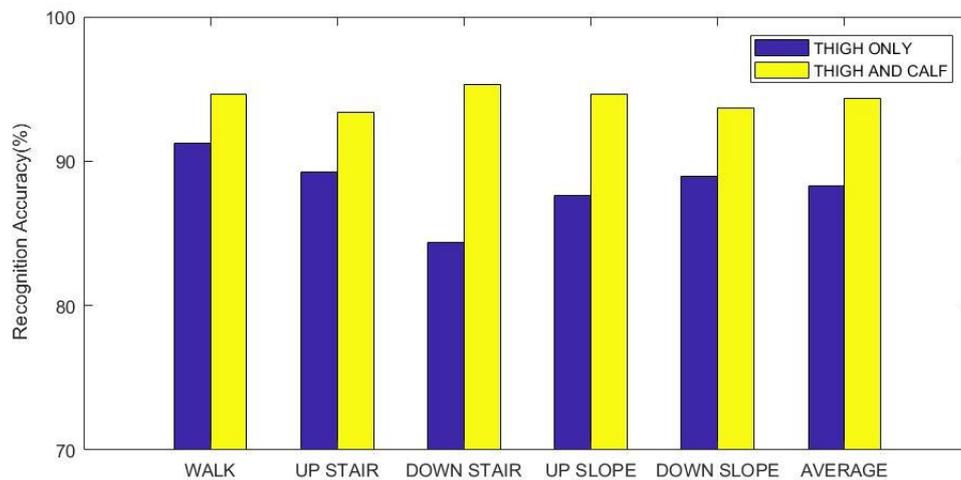
Figure 6. Recognition accuracy bar chart of adopting thigh signal only and adopting all signal.

Only through adopting sEMG signal and ACC signal of thigh, the recognition accuracy obtained is low. This is because the data provided by the three sEMG signal collection points at the thigh and an acceleration sensor at the front of the thigh cannot accurately distinguish the five basic gait patterns. This cannot meet the requirements of active prosthesis for identifying the motion intention of prosthesis wearers. In the future, research will be continued to study how to obtain higher lower-limb intention recognition rate without collecting data information of the calf. The gait patterns recognition rate of prosthetic wearers will be improved by increasing the sEMG signal collection points at the thigh and placing an acceleration sensor at the upper body, etc.

6. Conclusions

Gait patterns recognition has been studied and achieved good recognition results in other previous study. But the selection of sensor signal in those studies usually focused on the sEMG signal. The experiment in this paper showed that more useful movement information could be obtained by combining sEMG signal and ACC signal, which help improve the recognition accuracy.

This paper proposes methods to improve the recognition accuracy of gait pattern by combining sEMG signal and ACC signal. Experimental result shows that this method can successfully improve the recognition accuracy in a statistically significant way. The recognition accuracy by adopting the fusion of sEMG signal and ACC signal (Average: 94.32%), is 4.15% higher than that by adopting sEMG signal only (Average: 90.17%), and 9.60% higher than that by adopting ACC only (Average: 84.72%). This indicates that combining sEMG signal and ACC signal can improve the recognition accuracy compared to only adopting sEMG signal or ACC signal.

Reference

[1]   P. Langhorne, J. Bernhardt, G. Kwakkel. "Stroke rehabilitation". The Lancet, Vol.377(9778): 1693-1702 (2011)

[2]   C. Lingling, "Research of Electromyography Pattern Recognition Based on Support Vector Machine". Tianjin: Hebei University of Technology (2006)

[3]   Daniel Zlatni, Beatrice, "Gerhard Schweitze. Finite-state control of a trans-femoral (TF) prosthesis" . IEEE Transactions On control system technology, Vol.10(3):408-420 (2002)

[4]   A. Kyoung, N. Huynh, "Intelligent switching control of a pneumatic muscle robot arm adopting learning vector quantization neural network" . Mechatronics, Vol.17(4-5):902-905 (2007)

[5] M. Karantonis, R. Narayanan, M. Mathie, et al. "Implementation of a real-time human movement classifier adopting a triaxial accelerometer for ambulatory monitoring". IEEE Transactions on Information Technology in Biomedicine, Vol.10(1): 156-167 (2006)

[6] S. Irene, Chennai C-DAC, M. Shwetha, et al. "Improving classification of sit, stand, and lie in a smartphone human activity recognition system". IEEE International Conference on Computer and Information Technology. Liverpool. 1460-1466 (2015)

[7] Chen, X. Zhang, X. Zhao, et al. "Hand gesture recognition research based on surface EMG sensors and 2D-acceleroineters". Eleventh IEEE International Symposium on Wearable Computers, Proceedings: 11-14 (2007)

[8] J. Kim, J. Wagner, M. Rehm, et al. "Bi-channel Sensor Fusion for Automatic Sign Language Recognition". 2008 8th IEEE International Conference on Automatic Face & Gesture Recognition, Vols.1-2: 647-652 (2008)

[9] Y. Li, X. Chen, X. Zhang, et al. "A Sign-Component-Based Framework for Chinese Sign Language Recognition Adopting Accelerometer and sEMG Data". IEEE Transactions on Biomedical Engineering, Vol.59(10): 2695-2704 (2012)

[10] Roy, S.H., Cheng, M.S., Chang, S.S., et al. "A Combined sEMG and Accelerometer System for Monitoring Functional Activity in Stroke." IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol.17(6): 585-594 (2009)

[11] X. Zhang, X. Chen, Y. Li, et al. "A Framework for Hand Gesture Recognition Based on Accelerometer and EMG Sensors." IEEE Transactions on Systems Man and Cybernetics Parta-Systems and Humans, Vol.41(6): 1064-1076 (2011)

[12] Kosmidou, V. E., et al. "Sign language recognition adopting intrinsic-mode sample entropy on sEMG and accelerometer data." IEEE Transactions on Biomedical Engineering, Vol.56(12): 2879-2890 (2009)

[13] K. Englehart, B. Hudgins, "A robust real-time control scheme for multifunction myoelectric control". IEEE Transactions on Biomedical Engineering, Vol.50, no. 7, pp. 848 (2003)

[14] B. Hudgins, P. Parker, R. N. Scott. "A new strategy for multifunction myoelectric control". IEEE transactions on bio-medical engineering, Vol. 40, no. 1, 82-94 (1993)

[15] L. Hong-Tao, C. Yu-Zhen, X. Xiao-Bo, H. Yong. "Estimation of muscle fatigue degree adopting time-varying autoregressive model parameter estimation of surface electromyography." Chinese Journal of Biomedical Engineering, Vol.26(4): 493-497 (2007)

[16] Z. Pei-Lin, L. Sheng. "Fault feature selection method based on wavelet and GA-PLS algorithm". Journal of Vibration, Measurement & Diagnosis, Vol.34(2): 385-391 (2014)

[17] P. Batista, C. Silvestre, P. Oliveira, B. Cardeira, "Accelerometer Calibration and Dynamic Bias and Gravity Estimation: Analysis Design and Experimental Evaluation". IEEE Transactions on Control Systems Technology, Vol. 19, no. 5, 1128-1137 (2011)

[18] Z. Yongjie, L. Bo, S. Xinjun, Z. Xiangyang. "Towards Chinese sign language recognition adopting surface electromyography and accelerometers". 2017 24th International Conference on Mechatronics and Machine Vision in Practice (M2VIP), 1-5 (2017)

[19] S. Zhong, J. Ghosh, "HMMs and coupled HMMs for multi-channel EEG classification." Proceeding of the 2002 International Joint Conference on Neural Networks, Vols.1-3:1154-1159 (2002)

[20] R. Allen, E. Ambikairajah, H. Lovell, G. Celler "An Adapted Gaussian Mixture Model Approach to accelerometry-based movement classification adopting time-domain features". Engineering in Medicine and Biology Society, 28th Annual International Conference of the IEEE. 3600-3603 (2006)