The Fourth IEEE RAS/EMBS International Conference
on Biomedical Robotics and Biomechatronics
Roma, Italy. June 24-27, 2012

A Wearable Capacitive Sensing System with Phase-Dependent Classifier for Locomotion Mode Recognition

Enhao Zheng, Baojun Chen, Qining Wang, Kunlin Wei and Long Wang

***Abstract*— Locomotion mode recognition is one of the most important aspects for the control of motion rehabilitation systems, e.g. lower-limb prostheses and exoskeletons. In this paper, we propose a capacitance based sensing system for recognizing human locomotion modes. The proposed system includes two rings as sensing front-ends of body capacitance, two sensing circuits for processing the signals and the gait event detection system. The deformation of muscles can be reflected by the changes of capacitance signals. To validate the developed prototype, nine locomotion modes are monitored and ten channels of capacitance signals are collected for locomotion mode recognition. With the combination of capacitive sensing approach and phase-dependent classification method, satisfactory recognition results are obtained.**

I. Introduction

Though people's usual gaits tend to be natural and simple, the movement of human body differs for different locomotion modes. Thus, the selection of strategies for the control of rehabilitation devices, e.g. lower-limb prostheses and exoskeletons depends on specific motion patterns. Optimal control approach can be determined only with current motion state known. When current state changes, the control strategy will be adjusted in response. For most of the existing exoskeletons and prostheses, the control mode is changed by the user himself during motion, which is complicated and sometimes even unsafe. Therefore, the development of an interface for automatic locomotion mode detection and control mode selection draws increasing attentions of researchers. Previous studies on motion mode recognition of lower limb are realized in different ways: using electromyography (EMG) sensors [1], [2] and inertial sensors [3]–[6]. [1] measured EMG signals from 16 muscles of lower limb while the subjects were walking on different terrains or paths. The recognition of a total of 7 motion modes were tested on eight able-bodied subjects and two subjects with long transfemoral amputations and promising recognition results were shown. Inertial sensors (accelerometers and gyroscopes) are wearable and convenient to be fixed on human body and it is more preferable to be applied in daily life. It is one of the main advantages of this kind of sensors used for human motion mode recognition. [4] used AM-FM model for gait pattern classification based on accelerometry data. The experiments recognized five modes of motion and received some promising results. [5] designed an intelligent shoe, equipped with inertial measurement unit (IMU), which was more convenient for applications. Flat walking, descending stairs and ascending stairs can be recognized by using this device. In [6], a commercial IMU (Xsens MTx-28A53G25) was used for recognition of human motion mode. With Bayesian Networks, seven motion modes including falling, jumping and lying were recognized.

However, challenges for recognizing locomotion modes using the apparatus mentioned above still exist. EMG signals are weak signals with a microvolt-level voltage and easy to be disturbed by external noise signals. As a consequence, in order to obtain available EMG signals, filtering, amplifying and other complex processing approaches are needed, which put forward high expense for circuit design. For the inertial sensors, the signals can be full of noise (as the shifting of the sensors). In order to acquire higher accuracy, more sensors that provide complimentary information have to be integrated on different positions of human body , which are independent sources of noise [9].

In this paper, we develop a capacitance based system for locomotion mode recognition, which is cheaper and needs simpler signal processing approaches comparing with the methods using EMG sensors and inertial sensors. The cost of this sensing system is about 150 U.S. dollars, which is lower than the average price of a commercial EMG measurement system [7] or an inertial sensor module [8]. Whats more, the body capacitance is a representation of humans motion intention by reflexing the contraction of muscles. Capacitance sensing of human body was previously studied by [9], [10]. The technology is also applied on touch sensing in cell phones. In [9], the designed prototype was validated to detect human-neck activities. In [10], the authors designed a prototype based on oscillator for detecting heartbeat and respiration. The sensing principle used in [9] and [10] was based on colpitts oscillator detecting the change of frequency. According to [9], the body capacitance makes part of the characteristic capacitance of Colpitts oscillator, which determines the oscillation frequency. The oscillation frequency was 17 MHz and it was easily disturbed by external noise. Thus, the circuit requirement of the prototype was high (with 24-bit ADC). In touch sensing, many sophisticated microchip solutions for capacitance sensing are developed. However, the capacitance range are limited (several decades of picofarads) for our use. To overcome these problems, we designed a wearable capacitive sensing system based on the

This work was supported by the National Natural Science Foundation of China (No. 61005082, 61020106005), Doctoral Fund of Ministry of Education of China (No. 20100001120005) and the 985 Project of Peking University (No. 3J0865600).

E. Zheng, B. Chen, Q. Wang and L. Wang are with the Intelligent Control Laboratory, College of Engineering, Peking University, Beijing 100871, China. K. Wei is with the Department of Psychology, Peking University, Beijing 100871, China.

Email: Q. Wang (qiningwang@pku.edu.cn)

principle of sensing impedance, which reduced the noise and enhanced the reliability. By generating a sinusoid signal with the frequency constant, the equivalent impedance of body capacitance changes with the muscle deformation.

This paper is organized as follows. In Section II, we describe the design of capacitive sensing device. Experiment protocol and classification methods are illustrated in Section III. Performance of our approach for motion mode recognition is verified by experimental results in Section IV. Summary and discussion of this work are shown in Section V and we conclude in Section VI.

II. Measurement system

A capacitor is a passive two-terminal electrical component used to store energy in an electric field. The forms of capacitors vary widely depending on the practical use, but all contains at least two electrical conductors separated by a dielectric. The most common example is the parallel plate capacitor, having two parallel conductive plates separated by an insulated gap. The capacitance is determined by three parameters, the electrodes' area, the distance between them and the dielectric constant of the filled material. When the area and distance are constant or change very little, the capacitance mainly depends on the material between the electrodes, i.e. the shape, the structure and the molecular properties. Thus, we can detect the condition of an object by placing electrodes on it and measuring the capacitance.

The electrodes of the capacitor can be separated as two parts, the transmitter electrode and receiver electrode [11]. Exciting the transmitter electrode with a signal at a frequency of several hundred kilohertz, the receiver electrode will receive the wave. The magnitude of the signal is proportional to the frequency and voltage of the transmitted signal. According to the equation, $Z=\frac{1}{j\omega C}$, the impedance of the capacitor Z is only determined by the capacitance C with the frequency ω constant. We can detect the human motion by fixing the electrodes on the human body. The muscle deformation and contact conditions can be reflected by the change of capacitance. With proper regulation, the magnitude of the signals on receiving electrodes will vary with the human movement. By measuring the voltage, we can get the motion information accordingly.

Hence, we designed a prototype which can detect the human motion mode. The design concept of the prototype is shown in Fig. 1. The capacitor C_{body} is constructed with two electrodes and the body part as its dielectric. By applying a sinusoid signal on the transmitter electrode with amplitude and frequency invariable, the equivalent impedance of C_{body} and the resistor R_c in series makes a current loop. Thus, the voltage across the resistor will vary with C_{body}. The original signal contains noise and incompetent for direct sampling. For this reason, the signal is preprocessed and converted to root mean square (RMS) value before the analog to digital converter (ADC). Based on this, our prototype is made up of five parts, the sensing front-ends, signal processing circuits, gait event detection subsystem and a computer to receive data stream. Fig. 2 shows the sensing front-end of the prototype.

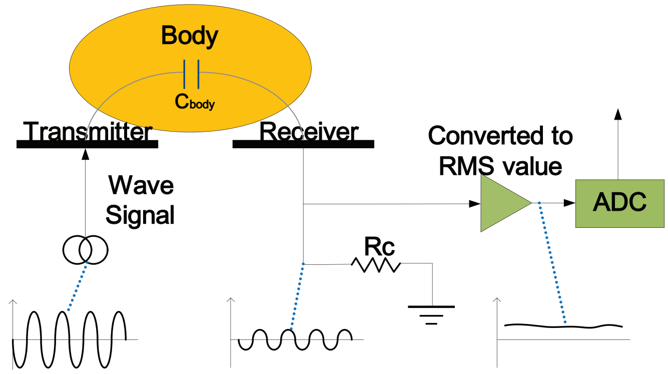
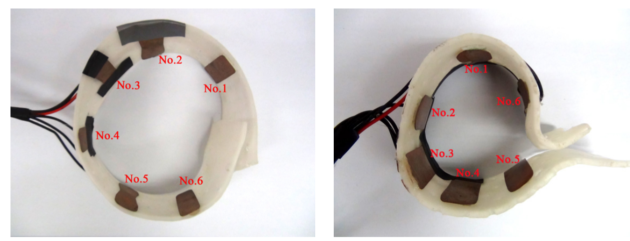


Fig. 1. Design concept of the prototype. The magnitude of the signal on the receiver electrode is influenced by the body movement. The signal was converted to RMS value before the ADC.



(a) Above-knee sensing front-end (b) Above-ankle sensing front-end

Fig. 2. The electrodes are made from copper pieces of 0.3mm and fixed to the thermomaterial ring by double-faced adhesive tapes. The area of each copper film is about 5cm$\times$2.5cm. The black parts on the electrodes are insulating tapes.

The device consists of two rings. One is utilized for the thigh and the other for the shank. Each ring is fabricated with six copper electrodes on inner surface. For each group of the electrodes, five of them are utilized as receivers, sampling five channels of capacitance signals. For each ring, there is only one transmitter electrode as the signal source. The sensing principle of the system is detecting the change of the muscle shape, as shown in Fig. 3. The muscular cross section of the thigh changes visibly according with lower-limb movement. The shape change of lower limb can slightly change the relative positions between the electrodes and skin. This tiny change will have a strong effect on the capacitance signals.

However, like most of the other biomechatronic sensors, there exist some problems in sensing. First of all, although the muscle deformation has a strong effect on the signal, it contains useless information which is the major source of noise. Second, the sensing front-end rings, although fixed to the lower limb with ties, may glide down because of sweats. Due to this, the signals can be variable and unstable during the experiment or practical use. To remedy these problems, we implemented our sensing front-end with thermoplastic material. The material can be easily reshaped when heated up to about 70 °C and hardens when cooled to normal temperature. We designed the sensing front-end in accordance with the shape of lower limb to prevent the undesired shifting, and we pasted insulating tapes at the intervals of electrodes

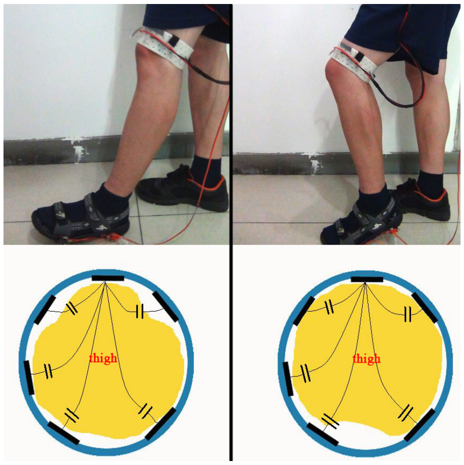


Fig. 3. The sensing principle of lower limb movement detection based on our prototype. The top half shows the flexion and extension of lower limb, and the bottom half shows the cross section of thigh accordingly. The shape change of thigh was reflected by the five channels of the capacitance signals. Note that the capacitive sensing system including two parts: above-knee module and above-ankle module. Here we only show the above-knee module for example.

to keep the electrodes from sweats.

The architecture of the hardware is shown in Fig. 4. Two circuits were designed to process the capacitance signals from the sensing front-ends, including oscillation circuits, RMS-converting circuit,control module and wireless module. The oscillation circuit was built using MAX038 as its signal source and a high-slew-rate amplifier (TL3474) as the driver module. MAX038 is a waveform generator that can generate sinusoid signal at specific frequency with the peripheral circuit properly designed. The oscillation frequency is 100 kHz. To prevent from waveform distortion, the signal was amplified by the driver module before applying on the front-end. The driver module also provided enough output current to transmitter electrodes for being signal source although the current was several dozen milliamperes (mA) at most. We extracted the signals from the receiver electrodes and converted them to RMS voltage by RMS-converting circuit. The regulated signals were then converted to digital data and processed by the control module. STM32 was used as the processor of the control module, which was an ARM-based 32-bit Microprogrammed Control Unit (MCU) imbedded with a 10-channel 12-bit ADC. What's more, the MCU was low-power consumption and high-speed (72 MHz CPU frequency), which is well suited for applications requiring multichannel signal processing, as that utilized in this study. The input voltage range of ADC is 0 to 3.3 V. The power supply of the circuits was ± 5 V which was converted from a 9.6-V Ni-MH battery. For the gait event detection system, two mechanical switches were fixed on the positions of toe and heel of a shoe to detect gait events.

As mentioned above, we measured the voltage across the body capacitors. The resistor divides the voltage with the body capacitor. To make the voltage vary in the range of 0 to 3.3 V, the value of the resistors should be carefully adjusted. With the excited frequency (100 kHz), the estimated capacitance between electrode pairs is 1 to 30 nF and the average dielectric constant is about 60 to 80. According to the sensing principle we utilized, it is not necessary to specify the body capacitance. We just need to maintain the baseline invariable during the experiment. Then the value of resistor was set at about 1.5 kΩ.

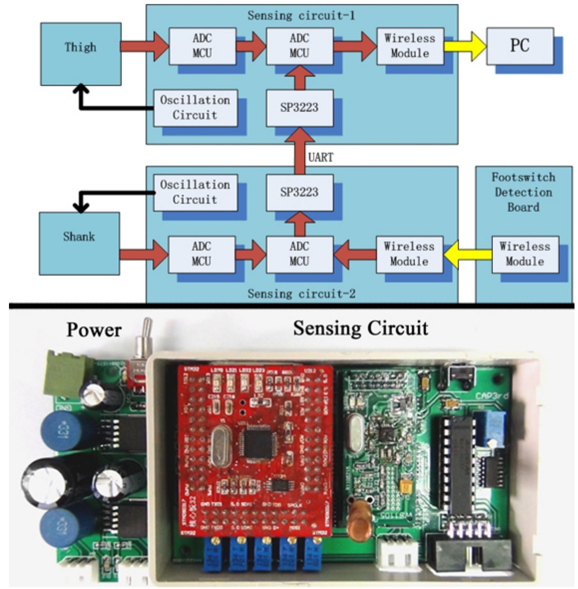


Fig. 4. The top half shows the structure of measurement system. The data flow is as follows, sensing circuit-2 detects the capacitance signals of shank and receives the data from footswitch detection board as well. It then transmits the data to sensing circuit-1. Sensing circuit-1 detects the signals of thigh and transmits all the data to the computer (PC). The bottom half shows the sensing circuit and power circuit.

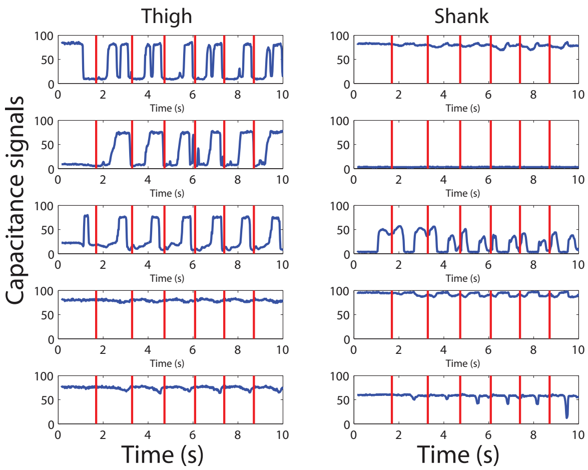
To guarantee the validity of the data, the flow of sample data is conducted as follows, as shown in top half of Fig. 4, two circuits communicate with each other via Universal Asynchronous Receiver Transmitter (UART). For the gait event detection board, the data was sent out only if there were changes on the switches. While the main circuit transmitted data to computer through the wireless module and the actual sampling rate was 50 Hz.

III. Method

A. Experiment Protocol

One able-bodied subject was recruited in this experiment. The subject was 24 years old, 181 cm height and 70 kg weight. The positions of sensors should be carefully chosen to obtain more useful information of human motion. Two capacitive sensing rings were worn on the thigh and the shank, respectively. For the thigh, we fixed the ring around the up edge of the knee, because the fat distributed here is little so the shape change is more obvious relatively. What's more, it can prevent the front-end from gliding down which may bring much noise. For the same reasons, we placed another ring on the ankle. To ensure the consistency of the sampled data, the rings should be carefully dressed with No.1

(a) Normal walking



(b) Capacitance signals

Fig. 5. Sequences of photos captured during normal walking of the subject with capacitive sensing devices worn is shown in subfigure (a). Here we only show one motion mode for example. The raw data of capacitance signals is shown in subfigure (b). The red vertical lines denote foot contact(FC), which are boundaries of gait cycles in our experiments.

electrode heading forward. Specifically, the No.1 electrode of above-ankle ring should be adhered to tibia and the above-knee ring to the knee. In this experiment, nine locomotion patterns were investigated: standing, sitting, stair ascending, stair descending, ipsilateral turning, contralateral turning, obstacle climbing, normal walking and giant-step walking on level ground. For the task of standing, the subject was asked to stand still for every trials. As for the sitting experiment, the subject was required to sit on a 42 cm high chair for every set of experiment. Stair ascending and stair descending were tested on a 14-step staircase. The stairs were 110 cm in width, 30 cm in deep and 15 cm in height. In turning tasks, the subject was asked to turn around a circle about 100 cm in diameter. When the subject turned toward the tested leg, the task was called ipsilateral turning, otherwise the task was termed contralateral turning. Obstacles were 17 cm high cones, with 14 cm diameter. The distance between two adjacent obstacles was 120 cm and only the tested leg was required to pass over obstacles. The subject was encouraged to walk at his favorite speed for normal walking. With respect to giant-step walking, the subject was asked to walk with a larger step length compared with normal walking. Rests were allowed for the subject between trials to avoid fatigue. The circumstance of the subject walking with capacitive sensing devices worn are shown in Fig. 5 (a).

B. Classification

Capacitance signals, although time-varying, are quasi-cyclic, which can be seen from Fig. 5 (b). In other words, although capacitance signals change a lot for different gait phases of the same motion mode, the signals are similar at the same phase of a certain locomotion pattern. As a consequence, we used a phase-dependent pattern recognition method mentioned in [1]. Gait events of foot contact (FC) and foot off (FO) can be detected using footswitches fixed on the shoe. FC is determined when the state of at least one footswitch changes from ”off” to ”on”, while FO is determined when the states of both footswitches become ”off”. Four phases are defined according to these two gait events: 200 ms prior to FC, 200 ms after FC, 200 ms prior to FO and 200 ms after FO. Be different from [1], only one analysis window with 200 ms was used in each phase. Linear discriminant analysis (LDA) classifier was used for locomotion mode recognition. 15 feature values were calculated for feature extraction according to the following expressions:

$f_1 = avg(X)$,
$f_2 = std(X)$,
$f_3 = \min(X)$,
$f_4 = \max(X) - \min(X)$,
$f_5 = rms(X)$,
$f_6 = iqr(X)$,
$f_7 = mad(X)$,
$f_8 = std(diff(X))$,
$f_9 = \max(diff(X))$,
$f_{10} = \min(diff(X))$,
$f_{11} = avg(|diff(X)|)$,
$f_{12} = \max(|diff(X)|)$,
$f_{13} = rms(diff(X))$,
$f_{14} = iqr(|diff(X)|)$,
$f_{15} = mad(|diff(X)|)$,

where X is the data matrix of the analysis window, $avg(X)$ is the mean value of X, $rms(X)$ is the root mean square of X, $diff(X)$ is the differences between adjacent elements of X, $iqr(X)$ is the interquartile range of X and $mad(X)$ is the mean absolute deviation of X. As a result, a 150-dimension feature value set was used for classifier training and testing.

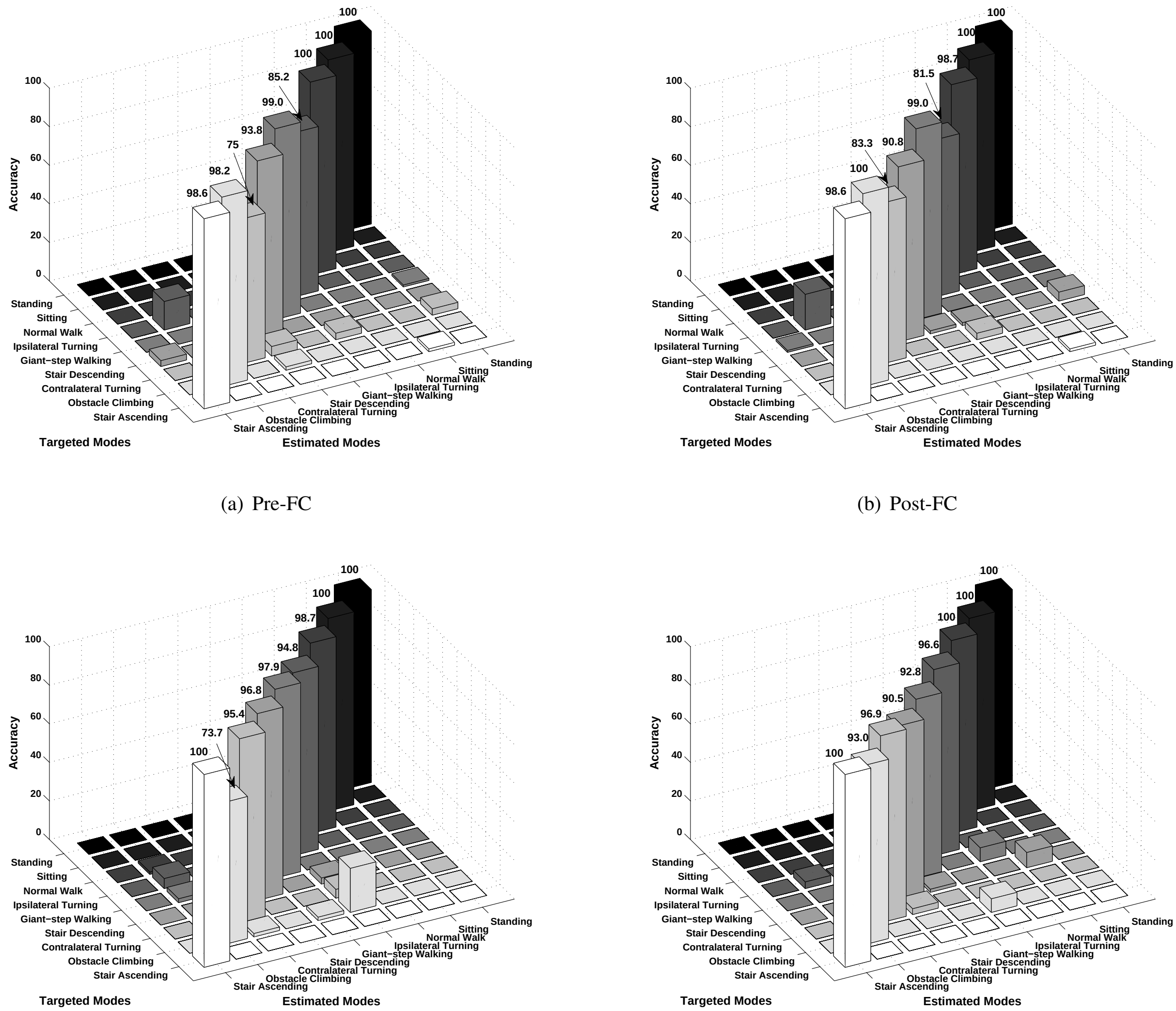
The overall recognition error (RE) is calculated by

$$RE = \frac{N_{mis}}{N_{total}} \times 100\% \tag{1}$$

where N_{mis} is the number of misrecognized testing data and N_{total} is total number of testing data.

To better illustrate the recognition performance of certain locomotion patterns, confusion matrix was defined as

$$C = \begin{pmatrix} c_{11} & c_{12} & \dots & c_{19} \\ c_{21} & c_{22} & \dots & c_{29} \\ \dots & \dots & \dots & \dots \\ c_{91} & c_{92} & \dots & c_{99} \end{pmatrix} \tag{2}$$



(a) Pre-FC

(b) Post-FC

(c) Pre-FO

(d) Post-FO

Fig. 6. Recognition results of nine motions using capacitance signals from four phases Pre-FC, Post-FC, Pre-FO and Post-FO are shown in Subfigure (a), (b), (c) and (d), respectively. Diagonal values of the bar chart of confusion matrix represent the recognition accuracies of corresponding motion modes. And off-diagonal values indicate the confusability of two relevant motions.

where each element is defined as

$$c_{ij} = \frac{n_{ij}}{\bar{n}_{i\bullet}} \times 100\%. \quad (3)$$

n_{ij} is the number of testing data in mode i recognized as mode j and $\bar{n}_{i\bullet}$ is the total number of testing data in mode i. A higher value of c_{ij} ($i \neq j$) denotes that it is easier for mode i to be misclassified as mode j.

IV. Experimental Results

To acquire enough data for classifier training and testing, measurement time and the number of trials for different tasks are shown in Table I. For the tasks of stair ascending, stair descending, ipsilateral turning, contralateral turning, obstacle climbing, normal walking and giant-step walking on level ground, the selection of analysis windows and the calculation of feature values were carried out using phase-dependent analysis window approach. For the tasks of sitting and standing, whose footswitch signals remained unchanged during experiments, analysis windows were uniformly distributed along the time for each trial and feature values were calculated just like tasks mentioned before.

Experiment data were divided into two sections: 60% for classifier training and 40% for recognition performance testing. Overall recognition accuracies for phase Pre-FC, Post-FC, Pre-FO, Post-FO were 95.05%, 95.21%, 95.77%, 96.58%, respectively. Detailed recognition results expressed by confusion matrixes are shown in Fig. 6. As shown in the charts, sitting and standing are the most robust modes to identify, whose classification accuracies keep at 100%. Normal walking and stair ascending also show almost perfect performances. Recognition accuracies of giant-step walking

TABLE I

PARAMETERS OF EXPERIMENTS

Tasks	Trial number	Trial time (s)
Stair ascending	30	12
Stair descending	30	12
Obstacle climbing	35	12
Normal walking	20	15
Giant-step walking	20	15
Ipsilateral turning	20	15
Contralateral turning	20	15
Standing	20	10
Sitting	20	10

and stair descending ranged from 90.5% to 99.0%. As was expected, the recognition for obstacle climbing and two kinds of turnings didn't perform well. And we can see from the charts that these three motions are easy to be confused with each other.

V. DISCUSSION

Distinct differences between different motion modes and similarities between different experiment trials of the same motion patterns are two of the most important influencing factors for motion recognition. As for the former, the performance could be improved by reconsidering device wearing and sensor distribution. Since the essential for capacitance based recognition is the variances of the distances between the skin and sensors, which are caused by the deformations of muscles during contractions and relaxations. However, only some parts of human bodies show significant variances while the changes of other positions are negligible. Thus, more reasonable consideration of sensor positions will result in better recognition performance. The latter will also benefit from reconsideration of sensor positions. In addition to this, the influence of external interference should be reduced. During experiments, more external noise signals were observed when muscles were fatigued and sweaty. Thus, how to improve the comfortability of sensor wearing and the robustness of sensor design are what we will investigate in the following research.

Capacitive sensing approach showed encouraging results in the experiment, which was comparable with the results obtained using EMG sensors. In [1], the classification errors in the Post-HC, Pre-TO, Post-TO and Pre-HC were $12.4\% \pm 5.0\%$, $6.0\% \pm 4.7\%$, $7.5\% \pm 5.1\%$ and $5.2\% \pm 3.7\%$ by measuring ten channels of EMG signals from muscles in pelvis segment and thigh segment. Adding six channels of EMG signals from calf segment and foot reduced the errors by 1.8%-3.0%. In our work, the errors were 4.79%, 4.23%, 3.42% and 4.95% for these four phases by motoring ten channels of capacitance signals from thigh and shank. Besides, two more locomotion modes giant-step walking and sitting were considered in our work. Thus, capacitive sensing seems promising for locomotion mode recognition. However, this work is a preliminary study for evaluating whether capacitive sensing devices will be applied for rehabilitation device control. Although satisfactory recognition accuracy was obtained, only one able-bodied subject was measured in the experiment. The practical applicability of capacitive sensing devices need a further verification with more able-bodied subjects and amputees to be measured.

VI. CONCLUSION AND FUTURE WORK

In this paper, we have proposed an approach for recognizing locomotion modes with wearable capacitive sensing system, which is cheaper and needs simpler signal processing approaches comparing with the methods using EMG sensors, cameras and inertial sensors. The proposed capacitive sensing system shows an encouraging performance for off-line locomotion recognition. With further studies, this sensing approach may become a potential tool for the real-time control of powered lower-limb prostheses and exoskeletons.

In the future, the convenience of device wearing need to be improved. In addition, the most sensitive positions in lower limbs for capacitance signal measurement will be investigated. To provide new practical signal source for the control of lower-limb rehabilitation devices, real-time recognition of locomotion modes will be studied.

REFERENCES

[1] H. Huang, T. A. Kuiken, R. D. Lipschutz, A strategy for identifying locomotion modes using surface electromyography, *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 1, pp. 65-72, 2009.

[2] E. Ceseracciu, M. Reggiani, Z. Sawacha, M. Sartori, F. Spolaor, C. Cobelli, E. Pagello, Svm classification of locomotion modes using surface electromyography for applications in rehabilitation robotics, *IEEE Workshop on Robots and Human Interactive Communications*, 2010, pp. 165-170.

[3] T. Ito, Walking motion analysis using 3D acceleration sensors, *Proc. of the Second UKSIM European Symposium on Computer Modeling and Simulation*, 2008, pp. 123-128.

[4] N. Wang, E. Ambikairajah, B. G. Celler, N. H. Lovell, Feature extraction using an AM-FM model for gait pattern classification, *Proc. of the IEEE Biomedical Circuits and Systems Conference*, 2008, pp. 25-28.

[5] M. Chen, J. Yan, Y. Xu, Gait pattern classification with integrated shoes, *Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009, pp. 833-839.

[6] F. Korbinian, V. Nadales, M. Josefa, R. Patrick and A. Michael, Reliable real-Time recognition of motion related human activities using MEMS inertial sensors, *ION GNSS*, 2010.

[7] http://bio-medical.com/products/myotrac-infiniti-2-channel-semg-no-stim-60hz.html

[8] http://www.analog.com/en/mems-sensors/imu/adis16385/products/product.html

[9] J. Cheng, O. Amft, P. Lukowicz, Active capacitive sensing: exploring a new wearable sensing modality for activity recognition, *Pervasive Computing*, 2010, LNCS 6030, pp. 319-336.

[10] J. H. Oum, S. E. Lee, D. W. Kim, S. Hong, Non-contact heartbeat and respiration detector using capacitive sensor with Colpitts oscillator, *Electronics Letters*, 2008, pp.87-88.

[11] J. Rekimoto, Gesturewrist and gesturepad: unobtrusive wearable interaction devices, *Proc. of the Fifth International Symposium on Wearable Computers*, 2001, pp. 21-27.