Non-Contact Capacitance Sensing for Continuous Locomotion Mode Recognition: Design Specifications and Experiments with An Amputee

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***Abstract*—Locomotion mode recognition plays an important role in the control of powered lower-limb prostheses. In this paper, we present a non-contact capacitance sensing system (C-Sens) to measure the interfacial signals between the residual limb and the prosthetic socket. The system includes sensing front-ends, a sensing circuit, a control circuit and foot pressure insoles. In the proposed system, the electrodes are fixed on the inner surface of the socket, which couple with the human body forming capacitors. The foot pressure insoles are built for detecting gait phases. The data sequence is controlled by the control circuit. To evaluate the capacitance sensing system, experiments with a transtibial amputee are carried out and seven kinds of locomotion modes are recorded. With the continuous phase dependent classification method and the quadratic discriminant analysis (QDA) classifier, the average recognition accuracies are 93.8% and 95.0% for the stance phase and the swing phase respectively. The results show the potential of the proposed system for the control of powered lower-limb prostheses.**

I. Introduction

Prostheses have a profound impact on the daily life of amputees. The development of powered lower-limb prostheses can extend the functions that a prosthesis can perform [1]–[8]. The control strategies of powered prostheses are determined only with current motion mode known. Thus, automatic recognition of locomotion modes is necessary for controlling the powered prosthesis.

Previous studies presented various strategies for recognizing locomotion modes. Several neural-machine interfaces based on electromyographic (EMG) signals have been developed [9]–[12]. Huang *et al.* used EMG signals of 16 muscles to recognize different locomotion modes [9]. In the experiment, eight able-bodied subjects and two transfemoral amputees were asked to perform seven locomotion modes. With linear discriminant classifier, they obtained promising recognition results. Then the authors extented their previous work by implementing the interface with the sensor fusion method [12]. EMG signals and ground reaction forces/moments measured from the prosthetic pylon were used as the input to the classifier. In the experiment, five amputees were recruited and six static locomotion modes were monitored. In addition to EMG sensors, researchers used mechanical signals as the interface for locomotion mode recognition, such as inertial signals [13]–[15] and foot pressures [16]. Yang *et al.* utilized motion sensors to classify continuous human actions [13]. Each sensor node was embedded with a triaxial accelerometer and a biaxial gyroscope. The authors classified thirteen kinds of motions and obtained promising results. Recently, Wang *et al.* developed pressure insoles to measure the foot pressure [16]. The average recognition errors of five locomotion modes were 19.6%, 12.6%, 5.2% and 6.3%, respectively.

Challenges of recognizing locomotion modes using current approaches still exist. EMG signals precede the movement and are useful to predict motion intent [12]. However, surface EMG signals are weak and prone to external noise [17]. To obtain signals with higher quality, the sensors have to be fixed on the skin and the positions of the sensor nodes have to be selected carefully each time. Moreover, EMG signals of the residual limb may not be available due to the muscle loss. Inertial signals can accurately record the kinematic information of human motion and the sensors can be highly integrated due to the development of MEMS. However, the noise and the drifting of the signals limit the performance of the inertial sensors. To regulate the signals, more sensors for compensation have to be added which are independent sources of noise. The foot pressure is an important parameter during locomotion with physical significance. However, the signals of foot pressures lag behind the motions.

In our previous work [18], we have developed a capacitance sensing system for locomotion mode recognition. The system records the shape changes of the leg muscles which includes two capacitance rings on the thigh and the shank respectively. To validate the capacitive system, an able-bodied subject was recruited and nine locomotion modes were measured. Satisfactory recognition results are obtained. However, there are some limitations in this system. Firstly, similar to EMG based systems, the sensing bands have to contact with the skin directly, which is inconvenient in daily use. Secondly, the position of the capacitance ring on the thigh has to be selected each time to prevent from gliding down. Thirdly, the system was only validated on able-bodied subjects. The situations of the system on amputees can be different. In this paper, we designed a non-contact capacitance sensing system

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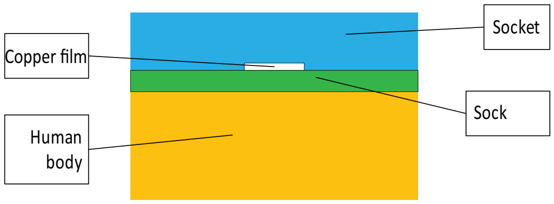


Fig. 1. The sensing method of the capacitance system. The human body is a conductor and can be seen as the ground. The copper film and human body forms a capacitor. The stump sock makes the dielectric of the capacitor. The stump sock usually contains two layers of sock made of nylon and a layer of cushion. In fact, the dielectric material is not the key factor, as long as it is nonconductive.

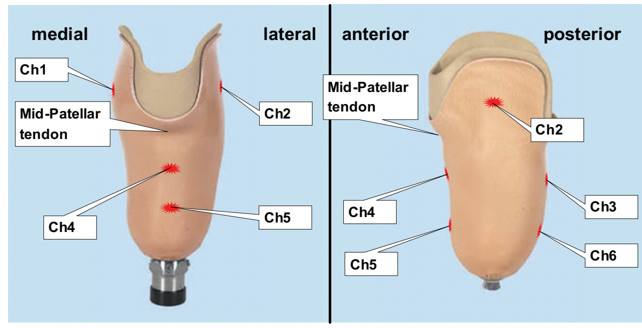


Fig. 2. The positions of the capacitance electrodes inside the socket. Here we just take the socket of left leg as an example. The electrodes of channel 1 and channel 2 were fixed on the medial side and lateral side respectively, which was the same as the right leg.

for transtibial amputees which record the capacitance changes between the residual limb and the socket. The electrodes were placed on the inner surface of the socket. The sensing circuit measured the capacitance changes by recording the charging time. To preliminarily validate the designed system, a transtibial amputee was recruited and seven locomotion modes were monitored. In this paper, continuous classification method was used, and we segmented a gait cycle into two phases-stance phase and swing phase. To detect the gait phases, a single-foot pressure insole was used. With the quadratic discriminant analysis (QDA) classifier, the recognition accuracies were 95.0% for swing phase and 93.8% for stance phase.

This paper is organized as follows. In Section II, we describe the design of the capacitance sensing system, including the setups of the electrodes and the processing circuits. Experiment protocol and classification methods are illustrated in Section III. The performance of locomotion mode recognition is verified by experimental results in Section IV. Discussion is shown in Section V and we conclude in Section VI.

II. Measurement system

A. Sensing Front-Ends

The interaction information between the residual limb and the prosthetic socket can be useful for locomotion mode recognition. The main design concept of the proposed system is to detect the interaction information of different locomotion modes with a set of capacitors. The copper film that was fixed on the inner surface and human body made up the capacitance electrodes (see Fig. 1). The stump sock in the middle made up the dielectric of the coupling capacitor. During the motion, the contact forces between the residual limb and the socket change periodically. Meanwhile, the forces result in periodic deformations on the stump sock. Therefore, the capacitance can reflect the motions of the lower limbs.

The distribution of the stump/socket interactions varies with the motion of the lower limb. Most of the human motions take place in the sagittal plane. What's more, for the transtibial amputees, the side parts of the socket can clamp the knee during the swing periods to prevent from gliding down. Therefore, the positions of the electrodes were placed on three parts, the anterior part the posterior part and the coronal parts, which is shown in Fig. 2. For the anterior part, two electrodes were fixed along the front of the tibia. For the posterior part, two electrodes were placed close to the residual gastrocnemius. The other two electrodes were fixed on the lateral side and medial side of the patella.

B. Sensing Circuit

The deformation of the stump sock produces tiny but clear changes of capacitance during the human motion. In our previous work [18], we used AC signals to couple the electrodes and the impedance of the capacitors were recorded. The dielectric of the capacitors was the human muscle, and the range of the capacitance was 1 to 30 nF. In this study, the capacitance changes can be much weaker than [18], since the deformation of the stump sock is not so prominent as human muscles and the dielectric constant of nylon is much smaller than human body. In this paper, we measured the charging time to record the capacitance changes. An integrated microchip PCap01AD (Acam Inc.) was used to convert the capacitance charging time to digital data. This conversion principle offers high resolution at conversion times as short as 2 us. The programmable microchip can sample seven channels of capacitance at most. The output data format of each channel is 21-bit data which stands for the ratio of capacitance and the reference capacitor. The PCap01AD worked in the maximum speed mode in which the programs would run in the static random access memory (SRAM). Thus, PCap01AD should be programmed first after power on. The program of PCap01AD controls the sampling parameters and sends out the results to the micro control unit (MCU) via serial peripheral interface (SPI).

C. Foot Pressure Insoles

The foot pressure insoles were used for detecting gait phases. To collect as much information as possible from foot pressures, the positions of the sensor have to be selected. As shown in the left bottom of Fig. 3, the sensors were placed at the hallux toe, the first metatarsal bone, the spot between the fourth and fifth metatarsal bone and the calcaneus tuberosity. The positions were similar to previous studies [16], [19], [20].

FlexiForce A401 (Tekscan, Inc.) was used as the force sensor in this study. The FlexiForce is a kind of tiny thin force-sensitive resistors (FSRs) whose resistors vary with the pressure. The resistance of the sensor is inversely proportion to the applied force on it. Thus, we designed an inverting amplifier circuit based on LMV324 (STMicroelectronics Inc.) to convert the force to the voltage. The voltage was then sampled with the 12-bit analog-to-digital converter (ADC).

D. Data Acquisition

The sensors and all the processing circuits worn on human body are shown in Fig. 3. The control circuit on the waist controls the sequence of all the sensor data. The sampling data set was then sent out to the computer by the wireless module. STM32F103 (STMicroelectronics Inc.) was used as the MCU of the processing circuits. STM32 is an ARM-based 32-bit micro control chip with 72 MHz frequency. It is also integrated with a 12-bit ADC controller which was used for sampling the voltage of foot pressure insoles. The wireless module was built based on nRF24L01P (Nordic semiconductor Inc.) which is a single-chip 2.4GHz transceiver.

The sampling rate of the sensors was 100 Hz. The control circuit collected all the sensor data and sent out wirelessly. Recommended standard 485 (RS485) bus was used for communication between the sensor nodes. The data sequence was controlled with the polling method. In this method, each sensor node was assigned a device number (ID). The sampling interval (10ms) was separated into several time slices. In each slice, the control circuit broadcast an ID and waited for the response. Then the circuit with the same ID would send out the result. The polling method guaranteed the unobstructed communication on the bus. The wireless module would send out the data of one sample to the receiver circuit during the sampling interval. In the designed system, Cyclic Redundancy Checking (CRC) and automatic retransmission methods were used to prevent data error.

III. Method

A. Subject and Experiment Protocol

One transtibial amputee was recruited in this experiment and provided written and informed consent. The subject is a 55 years male with 178 cm in height and 76 kg in weight. In this experiment, seven locomotion modes were investigated, including standing, normal walking, stair ascending/descending, ramp ascending/descending and obstacle climbing. There were seven groups of monitoring in this experiment. In each group, there were four trials for each locomotion mode. At the intervals of the groups, the subject was asked to rest for five minutes. For normal walking, the subject was asked to walk at his self-selected pace for six strides. There was a four-step staircase for stair ascending/descending. For the task of ramp ascending/descending, the inclination of the ramp was 30 degrees. For standing, the subject was asked to stand still for 8 seconds during each trial. The table below shows the number of gait cycles of one group.

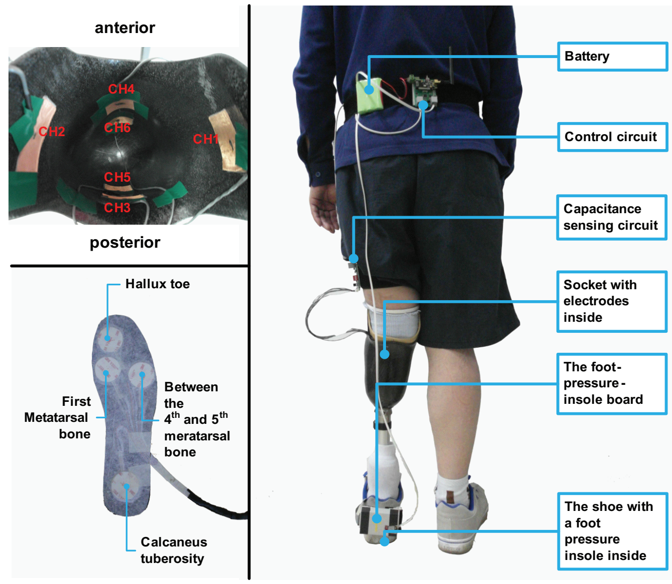


Fig. 3. Left top: The positions of the capacitance electrode on the socket. The electrodes were pasted on the inner surface with double-side adhesive tapes. The wires of the electrodes were shielded lines to prevent from distributed capacitance. Left bottom: The foot pressure insole and the positions of the sensors. Right: The placement of the sensors and boards on human body. The control circuit and the lithium battery were on the waist. All the processing boards were fixed on human body with velcro strips. HYV4x1/0.4 line was used to communicate on human body.

TABLE I
Gait cycles and trial time of different locomotion modes

Task	Gait cycles	Trial time (s)
Stair ascending	2	12
Stair descending	2	12
Obstacle climbing	3	12
Normal walking	6	12
Ramp ascending	2	10
Ramp descending	2	10
Standing	-	8

B. Classification Method

The capacitance signals reflect the interaction forces between the residual limb and the socket. Although not linearly dependent with the forces, the signals are cyclic during the motions and similar in different gait cycles of the same locomotion mode. Different from our previous study [18] and some other related studies (e.g. [9]) which used data of four discrete phases to classify the locomotion modes, in this study, two phases (stance and swing) were segmented by detecting the foot contact (FC) and foot off (FO) from a stride. The foot pressure insoles was used to automatically detect the gait events of the amputated limb. The summation of the four-channel foot pressure signals was filtered with one order lag filter to remove the noise, and a threshold was defined to detect FC and FO. To continuously classify the locomotion modes, data of sliding windows was used for feature calculation. In this study, the window length was 250 ms and the window increment was 10ms. The data was labeled the new phase if the analysis window slid into it more than half of a window

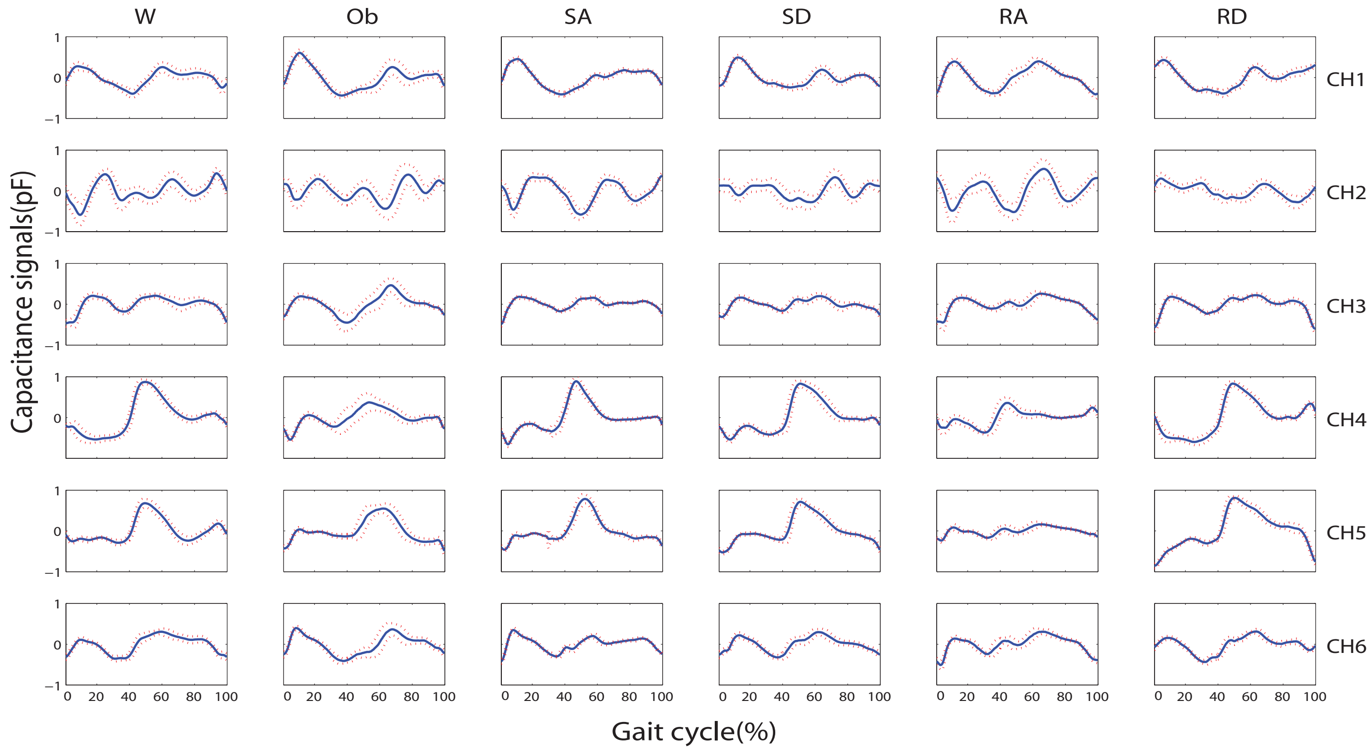


Fig. 4. The average capacitance signals (blue lines) and the variation (red dotted lines) over different gait cycles. The signals were time normalized to a gait cycle (from a foot contact to the next foot contact). Each row of the figures stands for one of the six channels of the signals (from CH1 to CH6).Each column stands for a specific locomotion mode. W stands for normal walking, Ob stands for obstacle climbing, SA/SD stand for stair ascending/descending and RA/RD stand for ramp ascending/descending respectively. The base line of the signals keeps at zero after the DC notch filter.

length.

Quadratic discriminant analysis (QDA) classifier was used in this study. QDA is a nonlinear classifier and is capable of classifying the data when the boundaries are difficult to define. What's more, QDA is time efficient for both training and classifying. Nine time domain features were extracted from the analysis windows as the following expressions:

$$
\begin{aligned}
&f_1 = avg(X),\\
&f_2 = std(X),\\
&f_3 = sum(abs(diff(X))),\\
&f_4 = avg(diff(X)),\\
&f_5 = \max(X),\\
&f_6 = \min(X),\\
&f_7 = sum(abs(X)),\\
&f_8 = std(abs(diff(X))),\\
&f_9 = corr(X),
\end{aligned}
$$

where X is the data matrix of one analysis window. $avg(X)$ and $std(X)$ are the average value of X and the standard deviation of X respectively. $diff(X)$ is the difference of X. $mad(X)$ is the mean absolute deviation of X. $abs(X)$ is the absolute value of X. $corr(X)$ is the correlation coefficient of two data channels of X. As a result, a 63-dimension feature vector set was obtained for training and classification.

In this study, 7-fold Leave-one-out cross-validation (LOOCV) was used for the training and testing of the classifier. In this procedure, data of one group of experiment was used as the testing data set, and the rest of the data was used as the training set. The process was repeated for seven times until all the group data was used for testing set.

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

$$C = \begin{pmatrix} c_{11} & c_{12} & \dots & c_{17} \\ c_{21} & c_{22} & \dots & c_{27} \\ \dots & \dots & \dots & \dots \\ c_{71} & c_{72} & \dots & c_{77} \end{pmatrix} \tag{2}$$

where each element is defined as

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

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.

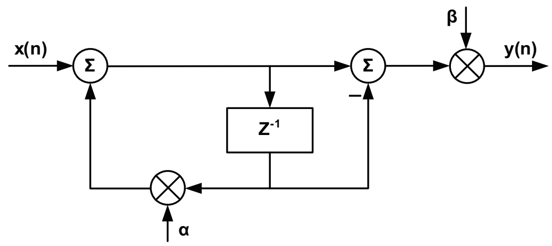


Fig. 5. The structure of the filter of a single channel. x(n) stands for the input signal and y(n) stands for the output. The parameters α and β were all the same for each channel.

IV. Experimental Results

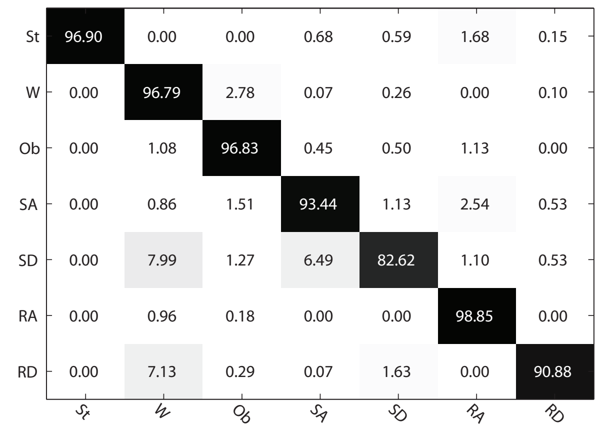
A. Signal Preprocessing

The raw signals of C-Sens reflected the interaction forces between the residual limb and the socket. The average peak to peak capacitance signals ranged from 0.5 to 2 picofarads. Some tiny shifting of the signals can reduce the repeatability and recognition performance. The drifting of the baseline was influenced by the distributed capacitance and temperature changes. Although the shielded lines were used to keep from distributed capacitance, the influence still exists. In addition, the frequency of the drifting was very low (lower than 0.1 Hz), so the high pass filter can not be used. To solve this problem, a DC notch filter [21] was designed to remove the low-frequency drifting, as is shown in Fig. 5. In the DC notch filter, α determined the phase response, while the amplitude response was determined by both α and β. The signal distortion caused by the filter can be ignored for the task of motion mode recognition. Furthermore, the filter can be implemented real-timely. The filtered signals of different locomotion modes are shown in Fig. 4. The task of standing was not shown, since the signals were almost straight lines for all the channels.

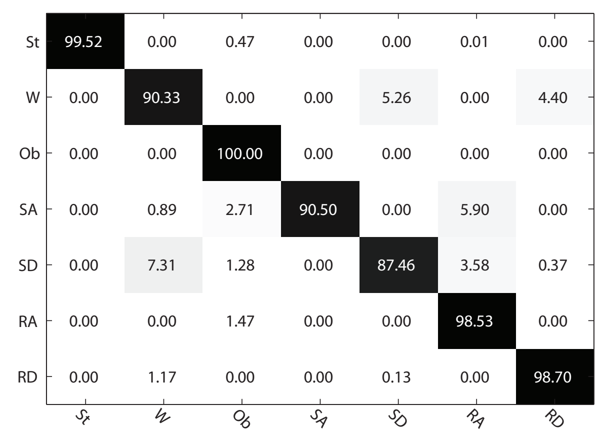
B. Recognition Performance

After the experiment, 28 trials of data was collected. For the task of normal walking, stair ascending/descending, ramp ascending/descending, and obstacle climbing, the continuous phase dependent method was used. For the task of standing, the foot pressure remained nearly unchanged. Analysis windows were randomly selected from the experiment trials and feature extraction method was the same as all the other tasks. To automatically detect the phases, thresholds of foot contact and foot off were set to the 1/10 of the maximum value. With the thresholds set and one order lag filter, all the gait phases were correctly detected.

The overall recognition accuracies during stance phase and the swing phase were 93.8% and 95.0% respectively. The detailed results of the recognition performance were shown in Fig. 6. The modes of standing, normal walking, obstacle climbing and ramp ascending performed better than the other locomotion modes. Stair descending performed the worst for both phases. Among the misclassification data, most part of it was misclassified as normal walking. One of the reasons is that during stair descending, the subject walked in small steps (one foot stepped on the staircase then the other foot followed to the same staircase) which was very similar to normal walking.



(a) stance phase



(b) swing phase

Fig. 6. Recognition performance of seven locomotion modes of stance phase (a) and swing phase (b). Diagonal values of the chart of confusion matrix represent the recognition accuracies of corresponding motion modes. And off-diagonal values indicate the confusability of two relevant motions. St is short for standing.

V. Discussion

The main design concept of the proposed C-Sens is to detect the interaction information of different locomotion modes with a set of capacitors. Different from EMG based systems, the C-Sens solves the problems of daily wearing. The sensing bands have no direct contact with human skin. It is more convenient in daily uses.

The interaction between the socket and the residual limb can provide useful information of human motion. The designed system in this study (C-Sens) record the interaction by capacitance signals. Although not linearly dependent with the contact forces, the signals could well record the the difference between different locomotion modes and showed good repeatability in the same ones. The C-Sens improved our previous work [18] in the following aspects. Firstly, C-Sens can be built inside the socket and non-contact with the skin, making it more applicable in daily life. Secondly, C-Sens showed higher stability in fixing on human body than the previous system. Our first capacitance system was placed on human body with two sensing bands and might glide down during the experiment. Thirdly, the sensing circuit had higher resolution than the previous system. The capacitance changes were several picofarads which were much smaller than the previous ones. Therefore, the signals of swing phase is obvious as the stance phase. Compared with our previous work [18], the tasks of ipsilateral turning, contralateral turning, giant-step walking and sitting were removed from the experiment and ramp ascending/descending were added, since some locomotion modes like turning and sitting were not so important for the control of powered lower-limb protheses.

In the study of [12], four phases detected from both feet were used to segment a gait cycle and sensor fusion method was used to recognize motion modes. In our study, only two phases of a single foot were used which reduced the redundancy of the sensors on human body. Moreover, only one type of sensor was used in our study. Although the recognition accuracy of the stance phase was lower than the static state of [12] (99%), the performance of the swing phase was comparable (95%), during which the performance was more important for prosthetic control.

VI. Conclusion

In this paper, we have proposed a non-contact capacitance sensing system (C-Sens) for recognizing locomotion modes of transtibial amputees. The system has higher resolution than the previous one and more stability in wearing on human body. The performance of the locomotion modes recognition was encouraging. Capacitance sensing for locomotion mode recognition showed comparable results than EMG based systems. With further studies, the sensing approach can become a potential tool for the control of powered lower-limb prostheses.

In the future, more potentials of C-Sens need to be exploited. The positions of the electrodes and the phase detection method will be optimized. In addition, to control the prosthesis real-time, sensor fusion with other types of sensors and motion transitions will be studied.

Acknowledgment

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