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Real-time continuous recognition of knee motion using multi-channel mechanomyography signals detected on clothes

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ABSTRACT

Mechanomyography (MMG) signal has been recently investigated for pattern recognition of human motion. In theory, it is no need of direct skin contact to be detected and unaffected by changes in skin impedance. So, it is hopeful for developing wearable sensing device with clothes. However, there have been no studies so far to detect MMG signal on clothes and verify the feasibility of pattern recognition. For this study, 4-channel MMG signals were detected on clothes from the thigh muscles of 8 able-bodied participants. The support vector machines (SVM) classifier with 4 common features was used to recognize 6 knee motions and the average accuracy of nearly 88% was achieved. The accuracy can be further improved up to 91% by introducing a new proposed feature of the difference of mean absolute value (DMAV), but not by root mean square (RMS) or mean absolute value (MAV). Furthermore, the first-order Markov chain model was combined with the SVM classifier and it can avoid the misclassifications in some cases. For application to wearable power-assisted devices, this study would promote the developments of more flexible, more comfortable, and minimally obtrusive wearable sensing devices with clothes and recognition techniques of human motion intention.

1. Introduction

With the development of human-machine interaction technology, power-assisted devices would gradually turn from accepting instructions passively to understanding the human motion intention actively, especially for wearable power-assisted robot or powered prosthesis. Human motion intention, which is required for improving the naturality and flexibility of human-machine coordinated motion, can be detected and recognized by means of wearable sensing device and real-time continuous pattern recognition approach. Many previous works have been carried out on this topic using surface electromyography (sEMG) signal. sEMG signal is generated by the electrical activity of muscle motor units during muscle contraction, and it is presently considered more practical to reflect the human motion intention than other signals (AbdelMaseeh et al., 2016; Lee et al., 2014; Pomboza-Junez and Terriza, 2016; Rahman et al., 2015; Triloka et al., 2016). However, due to the properties of wet or dry electrodes of bioelectric signal which are in need of skin contact (Searle and Kirkup, 2000), sEMG signal is easily influenced by the individual's physiological conditions such as the thickness of adipose tissue, body temperature, perspiration and fatigue, and is also affected by the placement, size, and orientation of electrode (Kiguchi et al., 2005; Rahman et al., 2015; Young et al., 2011).

Afterwards, noncontact electrodes were developed to overcome the drawbacks of wet or dry electrodes. Noncontact electrodes used capacitive-coupled technology which is no need of direct contact between electrode and skin. They have been applied in electrocardiography (ECG) and electroencephalography (EEG) for both medical and research use (Chi et al., 2010; Rachim and Chung, 2016). Also, a capacitance-based sensing approach was developed for sEMG sensor in steady locomotion mode recognition on passive prostheses (Zheng et al., 2014; Zheng and Wang, 2017). This improved the convenience and wearable ability of sEMG sensing devices. Due to the original signal belonging to electrical signal, however, noncontact capacitive-coupled electrode is still limited by the materials between electrode and skin which act as the dielectric of coupling capacitors (Zheng and Wang, 2017).

While sEMG signal is generated by the electrical activity of muscle motor units, there is also a counterpart known as mechanomyography (MMG) signal, which is generated by the mechanical vibration of muscle fibers during muscle contraction (Barry and Cole, 1990; Beck et al., 2004; Orizio, 1993; Orizio et al., 1990). The studies showed that MMG signal can provide information about the number and firing rates of recruited motor units that reflect the features of muscle activity

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(Akataki et al., 2004; Beck et al., 2007; Orizio et al., 1996), and can be detected on the surface of skin by microphone, accelerometer, etc. (Barry et al., 1986; Islam et al., 2013; Watakabe et al., 2003). Several advantages of MMG signal over the sEMG signal have been demonstrated as follows: (1) the original MMG signal can produce a 50 mV intensity from a standard microphone that is generally higher than original sEMG signal, so it is relatively easier to overcome the interference of environmental noise with less amplification and electrical shielding (Barry et al., 1986; Tarata, 2003); (2) there is no need of direct skin contact and it is unaffected by changes in skin impedance due to its propagation properties (Barry et al., 1986); (3) it is qualitatively less sensitive to placement on the muscle than sEMG signal (Barry et al., 1986); and (4) the sensor cost per channel of MMG signal is reduced than sEMG (Silva et al., 2005). Accordingly, it has been studied on muscle fatigue (Hendrix et al., 2010; Xie et al., 2010), estimation of muscle force (Fara et al., 2014; Sarlabous et al., 2013), recognition of muscle activity (Alves and Chau, 2010a, 2010b), prosthesis control, etc. (Ibitoye et al., 2014; Silva et al., 2004; Xie et al., 2009).

In previous studies, several different methods have been investigated to achieve a robust and efficient pattern recognition strategy using multi-Channel MMG signals with skin contact. Xie et al. recorded 2-channel MMG signals and extracted robust features by the integration of the wavelet packet transform, singular value decomposition, and a feature selection technique based on distance evaluation criteria. They adopted a linear discriminant analysis classifier to recognize 4 hand motions and showed the highest average classification accuracy up to 89.70% (Xie et al., 2009). Alves and Chau recorded 6-channel MMG signals and selected 14 features by a genetic algorithm. They adopted a linear discriminant analysis classifier to identify on average 7 ± 1 hand motions and showed an accuracy of 90.20 ± 4.00% (Alves and Chau, 2010b). Song et al. recorded 4-channel MMG signals and extracted 50 time-domain and frequency-domain features utilizing diffusion maps to reduce the feature dimensionality. They adopted fuzzy K-nearest neighbor classifier to identify 6 finger-motion patterns and showed a high accuracy of 95.48 ± 2.47% (Song et al., 2012). However, there have been no studies so far to detect MMG signal on clothes and verify the feasibility of pattern recognition.

Consequently, further investigations are needed for developing minimally obtrusive wearable sensing devices with clothes so as to be more flexible and more comfortable. The purpose of the present paper is to determine if the pattern recognition can be achieved using multi-channel MMG signals detected on clothes, and implement a real-time continuous recognition approach of human motion. The block diagram of this study is shown in Fig. 1. In this study, a knee was taken as a case for it is one of the most important joints in the lower limb motions, which can be helpful to recognize human motion intention for wearable lower limb power-assisted robot or powered lower limb prosthesis. We detected 4-channel MMG signals on clothes from the thigh muscles, and extracted features from time domain and frequency domain after signal processing. We recognized 6 knee motions states using the support vector machines (SVM) classifier combined with the first-order Markov chain model.

2. Methods

2.1. Experiment and data acquisition

In this experiment, we attempted to real-timely and continuously recognize 6 states during the isokinetic motion of right leg around knee as shown in Fig. 2: static standing, knee flexion, knee extension, knee external rotation, knee internal rotation, and a pause at the end of knee flexion, external rotation, or internal rotation. The sequences of knee motion were defined as follows (the time is approximate): static standing (2 s)—knee flexion (external rotation, or internal rotation by turns) up to knee angle of about 90 degrees (angular velocity of about 1 rad/s)—a pause (2 s)—knee extension (angular velocity of about 1 rad/s)—static standing (2 s). This experiment was approved by the Medical Ethics Committee of Hefei Institutes of Physical Sciences, Chinese Academy of Sciences, Hefei, China. All of 8 able-bodied participants (aged 24–36 years, 3 of them are females) knew the contents of the study and agreed to participate in the experiment. Participants were asked to continuously perform at least 10 repetitions of each sequence for 4 times with a full rest every time (training and test half and half).

As shown in Fig. 2, 4-channel MMG signals were detected using custom sensors made by triaxial accelerometers (ADXL335, Analog Devices, Inc., Z-axis was used only with a 50 Hz bandwidth), and the overall mass of an MMG sensor is about 2.89 g. For marking the classification labels conveniently, the signal of knee angle sensor (WDD35D4-5k, SENTOP) was used to segment the onset and offset of knee motion according to the signal waveform. All sensors were wire connected to a portable data collector (NI USB-6215, National Instruments), and signals were sampled at a rate of 500 Hz. A graphical user interface of data acquisition was programmed by LabVIEW and all the algorithm codes were programmed by MATLAB on a personal computer or notebook computer (Intel Core, 3.40 GHz). The participants wore a pair of trousers (blended fabrics with above 60% cotton and thickness of about 0.70 mm) and a pair of long johns (pure cotton fabrics with thickness of about 0.30 mm). The MMG sensors were placed on the clothes against the rectus femoris, biceps femoris, semitendinosus, and gracilis which are the muscles concerned with knee motion as shown in Fig. 3, and were bound to the clothes by a fixing band which is like a kneepad and made of neoprene (OK cloth) with vent holes (thickness of about 2.20 mm) as shown in Fig. 2. Sensor location could be roughly selected by participants but the center of muscle surface is suggested. We detected the MMG signals all from the thigh muscles in order to apply this study for the lower limb amputees in future.

2.2. Signal processing

The response time of a myoelectric control system should not introduce a delay over 300 ms that is perceivable by the user (Englehart and Hudgins, 2003). For the real-time continuous pattern recognition, the continuous signal streams acquired by the collector were all read from the data buffer to the computer every 200 ms (100 samples), and all processes including data acquisition, algorithms execution, and classification output should be completed before the next reading. MMG signal is also partly non-stationary like the sEMG (Alves and

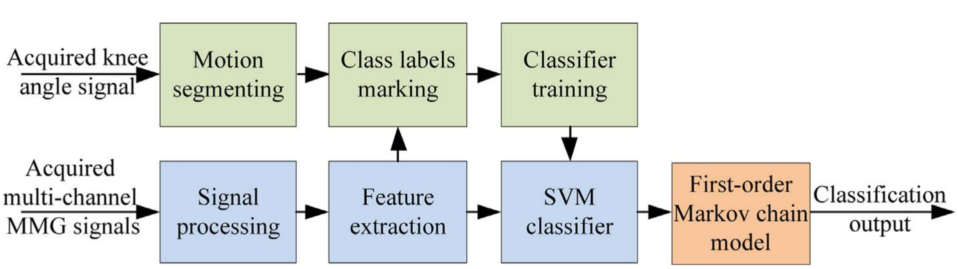

Fig. 1. The block diagram of pattern recognition using MMG signals detected on clothes.