FMG-Based Body Motion Registration Using Piezoelectret Sensors

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Abstract— **Body motion registration can provide plenty of muscle activity information of human beings, which is applicable in the control of human-computer interfaces or real devices. Forcemyography (FMG) is a method to register real-time body motions by measuring the radially directed force distributions that are generated by muscle contractions. In this work, we recorded FMG maps by using a novel type of sensor, the polymer-based piezoelectrets. With five piezoelectret sensor units attached on the surface of thigh muscles, four basic lower-limb motions, leg-raising, leg-dropping, knee-extension, and knee-flexion, were properly captured on four able-bodied subjects. Motion classification accuracies of 92.9%, 84.8%, and 88.1% were obtained by using different recognition algorithms of KNN, LDA, and ANN, respectively. The pilot experimental results demonstrated the feasibility of FMG recording by using piezoelectret sensors, which may provide an alternative method for body motion registration.**

I. Introduction

Body motion registration can provide useful information about muscle activities and motor commands of human beings, and thus it is commonly used in diagnostics, rehabilitations, and sports [1]. Accelerometers [2] can record body motions based on the multidirectional acceleration data of limbs, but usually provide limited information. Data-gloves [3] incorporating inertial and bending sensors would realize a more precise motion capture; however, they are sometimes inconvenient or restricted, e.g. for amputees. Surface electromyography (sEMG) is a kind of motor neural signal [4] that directly conveys motor commands. The sEMG-based technologies have been applied to monitor rehabilitation progresses [5], or to control human-machine interfaces [6] and myoelectric prostheses [7-8]. However, some issues may limit the applications of sEMG: exact placement of electrodes is essential for signal recording; high-level signal processing for feature extraction may cost lots of work; signals are usually unstable due to muscle fatigue in long-term employments; electromagnetic interference and conductivity variation of skin surface may also influence the signal quality. Forcemyography (FMG) is another method that can directly register the real-time body motions [9-11]. Muscle contractions always generate a change of muscle volume and subsequently cause radially directed force distributions. Thus, FMG maps can be recorded by measuring the force distribution information with force sensors. FMG has been confirmed as an easy-to-perform way for body motion registration with relatively high accuracy [9-11]. Compared with sEMG, there are fewer application limits for FMG, and the force sensors for FMG are much less expensive as well.

Currently, the force-sensitive resistors (FSR) are mostly applied for force distribution measurement in FMG map recording [9-11]. A FSR is a film sensor that changes its resistance upon the stress applied on its active surface. It owns several advantages like simple structure, easy employment, and low power consumption, but on the other hand, it has low measurement precision. Besides, some other force or pressure sensors like myo-pneumatic sensor [12] are also used, but with relatively complicated structure and high fabrication cost. Piezoelectric materials are another alternative candidate for force sensing. They generate voltage in response to stress on their active surface, which is a direct conversion from mechanical to electrical signal. Piezoelectric materials have simple interface and show high measurement precision. In addition, some polymer-based piezoelectric materials like polyvinylidene fluoride (PVDF) and space-charge piezoelectrets [13] are soft and flexible, which is very beneficial to wearable applications during body motions. However, piezoelectric sensors have seldom been used for FMG recording up to now.

As introduced, FMG is a prominent approach for body motion registration in real time and has strong application potentials in many areas. However, it is still relatively less explored and applied compared with the traditional methods such as sEMG. Furthermore, new tools for FMG acquisition would be of great interest both in research and in industry. As a result, in this work, we created FMG maps to register real-time lower-limb motions on able-bodied subjects by applying polymer-based piezoelectret film sensors. The signal features, classification algorithms, and motion recognition performances were studied in detail and possible future work was also proposed.

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II. Experiments

A. Subjects

Four male able-bodied subjects (21 to 24 years old) were recruited in this work. The protocol of this work was approved by the Institutional Review Board of Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. All subjects have given the written informed consent and provided the permission for the publication of photographs with scientific and educational purpose.

B. Sensors

Space-charge piezoelectrets are a novel type of piezoelectric materials that are prepared from polymers such as polypropylene, polyethylene terephthalate, polyethylene naphthalate, and etc. [14-15]. It has small thickness (less than 100 μm), light weight (~330 kg/m^3), low cost, flexibility, stretchability, and strong sensitivity [16]. With the excellent material and sensing properties, piezoelectrets are an appropriate alternative for force sensing, especially in wearable applications.

In this work, piezoelectret films were prepared from commercially available polypropylene films, as introduced elsewhere [16]. They were soft and flexible, with thickness of about 44 μm and effective sensing area of 2×1 cm^2 in each. Each film was folded symmetrically before packaging. The inner electrode was for signal eliciting, and the outer electrode was grounded for electromagnetic shielding. A packaged sensor was 1.2×1.2 cm^2 in area, 0.24 mm in total thickness, and could be bent flexibly when needed. Fig. 1 shows an original piezoelectret film as prepared and a packaged piezoelectret sensor unit ready for use. Five sensor units were utilized to record the force distribution signals in the experiments. For each subject, the sensors were attached at selected positions on the muscle surface of thighs, as shown in Fig. 2, with transparent tapes and further fastened with bandages, as shown in Fig. 3.

C. Motion performance and data acquisition

Four basic lower-limb motions of leg-raising (LR), leg-dropping (LD), knee-extension (KE), and knee-flexion (KF) were tested. All subjects were requested to perform a motion at roughly constant speed within 1 to 1.5 s. A leg-raising started from a balanced standing (not shown) and ended when knee angle was 90 degrees, while a leg-dropping was just the reverse of leg-raising. A knee-extension was achieved when the knee joint was fully opened, and a knee-flexion was completed when knee angle was decreased as much as possible, depending on the subjects' ability. It should be noted that in leg-raising and leg-dropping, the knee angle changed passively as well, however, the muscle activities of leg motions were different from those of knee motions, as will be discussed later.

Each motion class was performed for 30 repeats by every subject for data acquisition. Data were acquired in real time with an acquisition system developed in our lab. The original sensor output was charge signal. It was firstly transferred to voltage signal by a charge amplifier, and then filtered with passing band from 0.7 to 75 Hz. A notch filter was applied to remove the 50 Hz power interference, and a data acquisition card (*USB-0816*) was used to collect signal with sampling rate of 100 Hz. The processed signal was finally transmitted to computer for analysis.

Figure 1. A flexible piezoelectret film as prepared (left and middle) and a packaged sensor unit ready for use (right).

Figure 2. The selected positions for sensor placement.

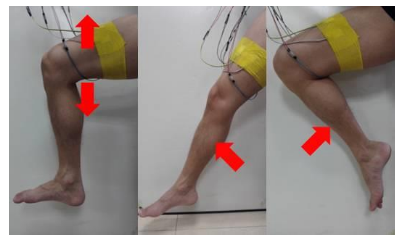

Figure 3. Motions of leg-raising, leg-dropping, knee-extension, and knee-flexion were tested in the experiments.

D. Motion classification

For motion classification, the first half of data was used as training set, and the second half was used as testing set. The data were segmented into a series of 30-ms analysis windows with an increment of 20 ms. For each analysis window both in training and testing set, five time-domain features [17] of mean absolute value, simple square integral, third temporal moments, log detector, and kurtosis coefficient were extracted to represent the signals. Three pattern recognition algorithms [18], K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA), and Artificial Neural Network (ANN), were employed for motion classification. The K value for KNN algorithm was set as 3. In the ANN algorithm, two hidden layers comprising 10 and 4 neurons were designated with the logistic regression transfer function, respectively.

III. Results

Fig. 4 shows a typical five-channel sensor output of four lower-limb motions for a subject. As can be seen, obvious force distribution signals caused by muscle contractions were recorded with the piezoelectret sensors. For each channel output, a sudden peak occurred when a motion was performed, and it dropped down quickly to the baseline when the motion performance was completed. The FMG maps of each subject were different from each other, as not shown here, which was mainly the result of different muscle shape, size, synergy, and also sensor placement among the subjects.

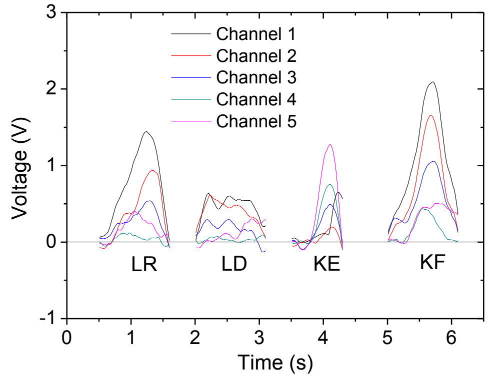

Figure 4. Typical force distribution signals for leg-raising (LR), leg-dropping (LD), knee-extension (KE), and knee-flexion (KF).

TABLE I. CONFUSION MATRIX (%) BY KNN ALGORITHM.

	LR	LD	KE	KF
LR	96.4	0	0	3.6
LD	2.3	97.7	0	0
KE	7.0	1.5	91.5	0
KF	12.2	1.9	0	85.9

TABLE II. CONFUSION MATRIX (%) BY LDA ALGORITHM.

	LR	LD	KE	KF
LR	71.0	29.0	0	0
LD	6.2	87.5	0	6.3
KE	2.0	1.7	96.3	0
KF	5.6	10.1	0	84.3

TABLE III. CONFUSION MATRIX (%) BY ANN ALGORITHM.

	LR	LD	KE	KF
LR	81.6	14.2	0	4.2
LD	0	87.3	0	12.7
KE	5.5	0	94.5	0
KF	2.5	8.6	0	88.9

TALBE I, II, and III show the confusion matrices of motion classification accuracies obtained with different recognition algorithms of KNN, LDA, and ANN, respectively. The classification accuracy for LR, LD, KE, and KF are 96.4%, 97.7%, 91.5%, and 85.9% by KNN, 71.0%, 87.5%, 96.3%, and 84.3% by LDA, and 81.6%, 87.3%, 94.5%, and 88.9% by ANN, respectively. The average performance for all the four motion classes by the three algorithms are compared in Fig. 5, where classification accuracies of 92.9%, 84.8%, and 88.1% are achieved with KNN, LDA, and ANN, respectively. In addition, the classification performance for each motion class by different algorithms are summarized in Fig. 6 to get a clearer visual inspection.

IV. DISCUSSION

As shown by the results, clear force distribution signals corresponding to different lower-limb motions are successfully recorded by the piezoelectret sensors prepared in our lab, with which FMG maps of leg-raising, leg-dropping, knee-extension, and knee-flexion can be created. By properly extracting the FMG signal features, the motions can be recognized by some commonly used algorithms like KNN, LDA, and ANN with desirable classification accuracies. This work has demonstrated that the piezoelectret sensors are a feasible tool for FMG recording, which would provide an alternative approach for body motion registration.

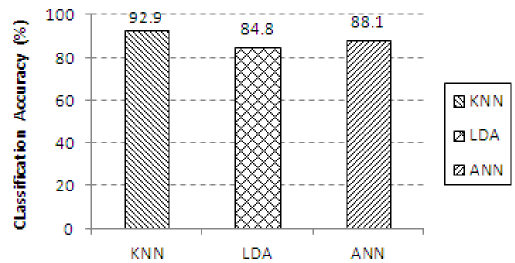

Figure 5. The average classification accuracy for all motion classes by KNN, LDA, and ANN algorithms, respectively.

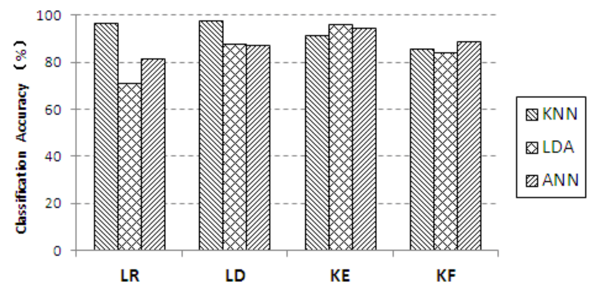

Figure 6. The classification accuracy for each motion class by KNN, LDA, and ANN algorithms, respectively.

Piezoelectrets have been actually utilized as advanced sensors or actuators in several areas with prominent performances, especially in force or pressure sensing. In addition, the excellent polymer-based material properties like flexibility make piezoelectrets very suitable for wearable applications. With all the strong points mentioned in [13-16], some novel applications of piezoelectrets would be exploited in new disciplines, including the work presented in this paper. It should be noted that the piezoelectret sensors only generate signals upon force variations, and there is no response to static forces [13]. This is quite different from most of other force/pressure sensors like FSR, where sensor output always exists if a load is applied. This particular property may make the piezoelectret sensors more suitable for force measurement during motions, where the dynamic part of motion information is more important and needed than the static part. It can be observed in Fig. 4 that the signals increase apparently at the start point of a motion, since the forces generated by muscle contractions increase rapidly. Then the signals drop down because the exerted forces become more and more constant near the end of motion performance. In addition, the corresponding muscle contraction strength can be mainly estimated according to the amplitude of force signals. For the same subject, the leg-dropping usually produces the lowest muscle tension and the knee-flexion produces the highest muscle tension, which is in accordance with our daily experience.

The KNN, LDA, and ANN algorithms have proven useful for FMG pattern recognition, however, different performances are achieved among the algorithms. Fig. 5 shows the highest average classification accuracy is obtained by KNN. It may suggest that for the FMG-based motion classification in this work, a simple algorithm with low computation cost, like KNN, would be more practical in clinic use than a sophisticated algorithm with just theoretically promising performance like ANN. The performance of LDA is less satisfied compared with other two algorithms. The possible reason might be that the FMG signal features extracted in this work are unsuitable for LDA, and a study on signal feature selection for different algorithms is in progress. On the other hand, however, for each single motion class, LDA shows the best performance on knee-extension and ANN shows the best on knee-flexion. Therefore, a combination of two or more algorithms might be a solution to improve the overall performance in motion classification, which is part of the suggested future work.

In this work, only five piezoelectret sensors were used for signal acquisition, which may not provide enough force distribution information related to muscle activities and subsequently limit the motion classification accuracy. Besides, the data recording position should be optimized with an associated physiological study of human muscle structures. A sensor array with high density of sensing unit is suggested for a more precise recording of FMG maps. Some special material properties of piezoelectrets would be taken into account to design an advanced FMG acquisition device in next step. Combined with the small thickness, flexibility, and stretchability, piezoelectret sensors can be integrated into fabrics. Instead of using wrist straps, belts, or even sockets and gloves that are cumbersome to wear, the fabric-based FMG acquisition device will be completely flexible, which enhances the wearing comfort and frees the body motions. In addition, more subjects including limb amputees should be recruited to implement an in-depth investigation of the proposed approach for body motion registration, especially when the FMG-based prostheses are desired for limb amputees.

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