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Biomedical Applications using Hand Gesture with Electromyography Control Signal

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Abstract

Wearables developed for human body signal detection receive increasing attention in the current decade. Compared to implantable sensors, wearables are more focused on body motion detection, which can support human–machine interaction (HMI) and biomedical applications. In wearables, electromyography (EMG), force myography (FMG), and electrical impedance tomography (EIT) based body information monitoring technologies are broadly presented. In the literature, all of them have been adopted for many similar application scenarios, which easily confuses researchers when they start to explore the area. Hence, in this article, we review the three technologies in detail, from basics including working principles, device architectures, interpretation algorithms, application examples, merits and drawbacks, to state-of-the-art works, challenges remaining to be solved and the outlook of the field. We believe the content in this paper could help readers create a whole image of designing and applying the three technologies in relevant scenarios.

Keywords

Biological signal, EIT, EMG, FMG, human–system interactivities.

INTRODUCTION

In recent years, with the development of material science and electronic information technology, wearable devices have made great progress. Nowadays, wearable devices can be mainly used in two fields, HMI and medical. Among various wearable technologies, EMG, FMG, and EIT are commonly used to detect biological signals related to nerve and limb movement. When an action occurs, nerves send electrical signals to drive muscles. Then, muscle contraction causes changes in muscle volume and internal impedance. The posture and acceleration will change during the action. The electrical signals can be detected by EMG [1], while the changes in muscle volume can be detected by FMG [2], and internal impedance by EIT [3]. As a technique for detecting electrical activities caused by the muscles, wearable EMG systems are used widely. For instance, J. Qi et al. used EMG technology to recognize different hand gestures, as a result, a long-term recognition accuracy of 79% was achieved [4]. Because EMG detects electrical signals from superficial muscles, its performance is limited by the skin impedance changes caused by sweating and contact [5,6], which cause a decrease in the accuracy of pattern recognition. FMG is an alternative technology that directly captures changes in skin surface pressure due to changes in muscle volume caused by muscle activity [7,8]. Compared to EMG, FMG is robust to electrical interference and sweating, whilst also being non-invasive and inexpensive [9,10]. In the work of Islam et al. [11], the performance of motion detection with FMG and surface electromyography (sEMG) were compared in a daily scenario. They tested four different limb motions in five healthy male subjects. As a result, in one-day training, the day-to-day classification accuracy reaches 84.9% while the accuracy of sEMG reaches 77.8%. However, it is not EMG–FMG sensing armband which can detect FMG signal and EMG signal simultaneously. Five healthy subjects performed gestures of ten American sign language (ASL) digits 0–9. The accuracy of EMG-only gesture recognition was 81.5%, while FMG-only was 80.6%, and co-located EMG–FMG had the best performance of 91.6%. Another potential human–machine interaction technology is EIT. It is an imaging technology that detects the internal structural impedance distribution of objects by external electrical excitation signals. To obtain the internal resistivity of the object, EIT uses electrodes on the boundary to apply a high-frequency alternating signal and measure the response signal. For instance, Zhang et al. [3] designed a wearable hand ring called tomography based on 4-pole EIT, which achieved high accuracy in gesture.

We also hope that researchers can further develop the three techniques to overcome their existing problems. The generation, processing, and application of FMG, EMG, and EIT signals are showed in Figure1.

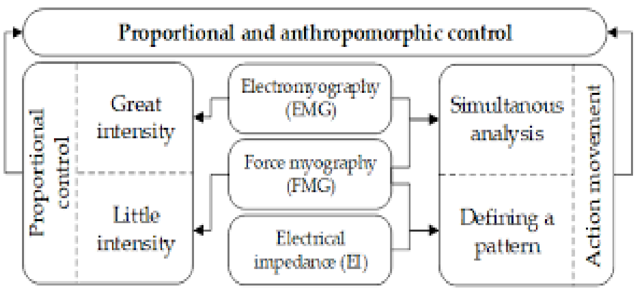

Figure 1. The generation, processing, and application of FMG, EMG, and EIT signals.

PRINCIPLE

EMG, FMG, and EIT are emerging methods to obtain human information in recent years. The advantage of the three techniques is that all of them can be measured non-invasively and harmlessly, which means that they have great potential for human-machine interaction. In this section, we will introduce the principles of FMG, EMG, and EIT.

FMG

FMG is an approach to collecting motion signals by sensing changes in muscle volume. Its basic principle is that different muscle activities cause different movements. When an action occurs, the volume of the underlying musculotendinous complex changes, which results in a change in the distribution of surface mechanical forces. Different movements are encoded into different force images. By decoding these images, original motion information can be obtained, which has been widely used in gesture recognition [2], human–machine collaboration [16], prosthetic control [17], and operational force estimation [12].

Generally, researchers can use force sensors matrix/array to detect the mechanical force in the FMG technique [18]. The force sensor reflects the magnitude of the force applied to the sensor. When a socket with many sensors is wrapped around a part of the limb, the muscle force map can be obtained. With some algorithms, such as machine learning [9], the original motion information (type of movement and magnitude of force) can be obtained by using the FMG signal. An example of FMG signal output is shown in the relax–grasp–relax process.

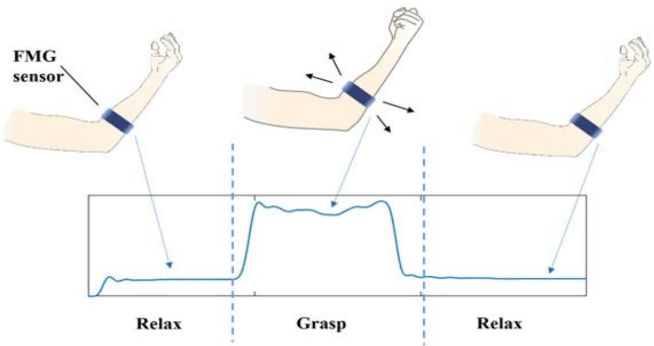

Figure 2. Single FMG sensor output signal during

EMG

EMG refers to a series of electrical signals associated with muscles due to neurological control and generated during muscle contraction. This signal is generally given by the experimental method, which can represent the physiological characteristics of muscles after amplification and processing [19,20].

EMG is derived from the brain to muscle control. It is based on three steps: resting potential, depolarization, and repolarization. Its formation is caused by the concentration difference of Na+ ions, K+ ions, and Cl− ions, but it is dominated by Na+ ions. When the muscle does not contract, the concentration of Na+ ions in muscle cells is greater than that out of muscle cells. With the ion pump, Na+ ions outflow forms a resting potential with positive external potential and negative internal potential on the membrane of muscle fiber. For example, when trying to move upper limbs, our brain sends movement control signals to the muscles, which are transmitted to the muscles through the nervous system. When the signal reaches the muscle fibres, chemicals such as acetylcholine are released at the nerve end, causing a large influx of Na+ ions, which rapidly form an action potential in the muscle fiber, a process known as depolarization. After the signal transmission, with the action ion pump, muscle fibers quickly return to the state of resting potential, which is called repolarization. The combination of all the muscles' action potentials of a motor unit is called a motor unit action potential (MUAP) [21]. The superposition of MUAP in space and time produces EMG. The EMG signal generation process is shown in Figure3.

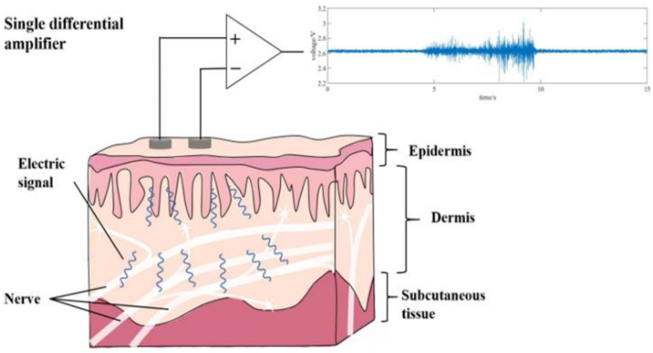

Figure 3. EMG refers to a series of electrical signals associated with muscles due to neurological control and generated during muscle contraction

EIT

EIT is an imaging technology that detects the internal structural impedance distribu- tion of objects by external electrical excitation signals. By placing a set of electrodes on the surface of the conductive object to be measured, EIT applies a high-frequency alternating current to each electrode pair as the excitation signal and measures the electrical response signal on other electrode pairs in turn to obtain the internal resistivity of the object. Due to its advantages of non-radiation, non-damage, low cost, and simple structure, EIT has been widely used in non-destructive testing, geological exploration, and other fields. Nowadays, the application of EIT in biomedical imaging and human–machine interaction has been widely studied.

The human body is a complex structure with different electrical impedance distri- butions. There has been a lot of research on electrophysiology, which is concerned with the electrical properties of biological tissues, and the principle of them is very complex and influenced by frequency, temperature, and direction. This is closely related to the structure and function of the tissues. Generally speaking, the blood and muscle with high extracellular water content and electrolyte concentration have a relatively low electrical impedance. In contrast, fat, bone, and air increase impedance. This difference gives each tissue and state certain characteristics. For organisms, when controlling the amplitude and frequency of excitation signals within a safe range, the output signal and calculate impedance distributions can be harmlessly measured.

The impedance characteristics of organisms often change in certain situations. For example, the electrical impedance of the lungs depends to a large extent on the concen- tration of the internal air. When air is inhaled, the electrical conductivity of lung tissue concomitantly decreases. The flow or clotting of blood also causes impedance changes. When the body tissue is diseased, its electrical impedance may change significantly, which will be detected by EIT, to be applied to medical diagnosis and treatment. Similarly, the limbs in different postures also correspond to different impedance distributions. Therefore, the impedance distribution of the part of the body can be measured by EIT to realize posture detection.

According to the different imaging purposes, EIT can be divided into two types: static imaging and dynamic imaging. Static imaging calculates the absolute value of impedance distribution and has a wider range of applications. However, it is more computationally intensive and vulnerable to noise, resulting in low image resolution. In contrast, dynamic imaging computes the relative impedance distribution and produces a differential image, which suppresses noise very well. Depending on the measurement method, it can be further divided into time difference imaging technique and frequency difference imaging technique. Time difference imaging obtains the difference of impedance at two times, while frequency difference imaging obtains the difference of impedance at different frequencies at the same time. Dynamic imaging is less affected by noise and relatively simple to calculate, but it is essential to ensure that impedance changes exist, so the application is constrained. EIT signal acquisition and reconstruction are shown in Figure4.

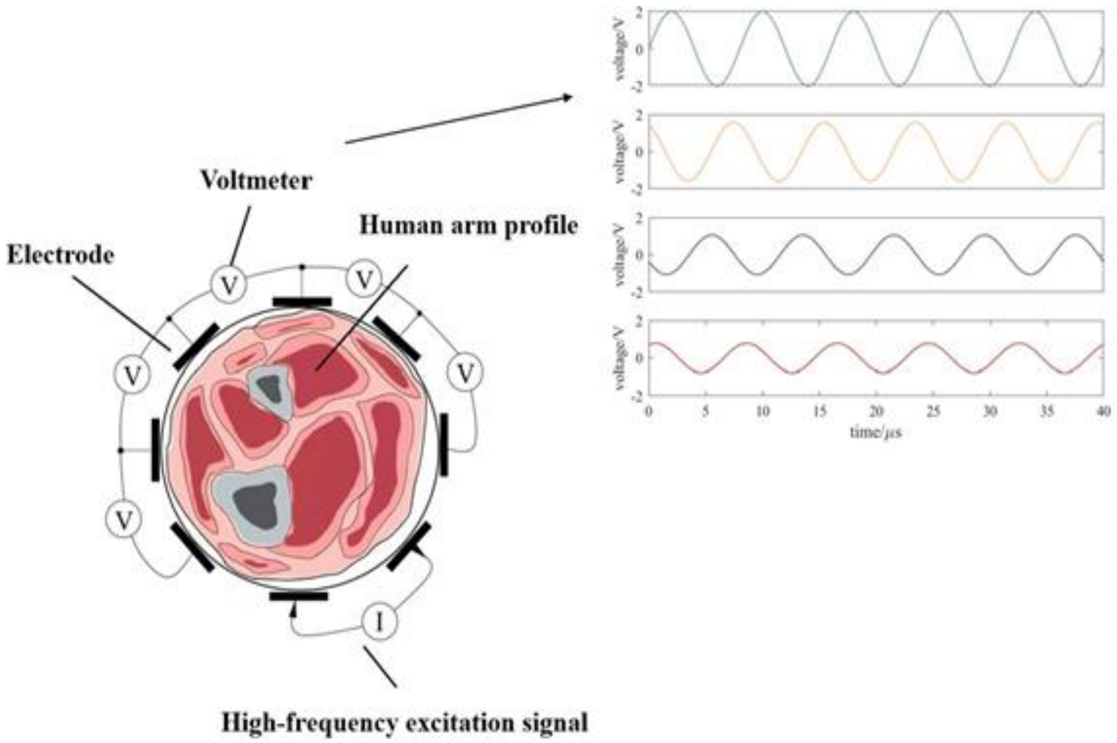

Figure 4. EIT electrode distribution and four−channel voltage signal under high−frequency excitation

DATA ACQUISITION

In this section, we will introduce the signal acquisition methods of FMG, EMG, and EIT. We successively introduced the sensors used for FMG, the sampling frequency and channel number configuration, the EMG sampling method and electrode type, the sampling frequency, and channel number configuration, and finally, we introduced the electrode configuration of EIT and the drive pattern.

FMG Signal Acquisition

FMG technique uses force sensors to obtain information on the underlying mus- culotendinous complex changes during movements [7]. There are many types of force sensors used in FMG, for instance, piezoresistive- [22], capacitive- [23], piezoelectric- [24], optoelectronic- [25] and pneumatic-based [26] sensors.

Piezoresistive Sensors

To acquire effective biosignals, the sensor needs to be in close contact with the skin, and piezoresistive sensors have this characteristic. The most frequently used piezoresistive sensors are force-sensitive resistors (FSR), for instance, FSR 402 [27–29] and FSR 400 [16,30], which are based on resistive polymer thick film sensor (RPTF) technology. Because of their thin profile, flexibility, and low cost, they become a practical solution for prosthetic pressure measurement [31].

The structure of FSR 400 series is often composed of two layers, one is the printed semiconductor layer on the bottom layer and the other is the interdigitating electrode on the semiconductor layer. When pressure applied to the active area increases, the resistance values of the piezoresistive material will decrease. The force sensitivity range of FSR 400 is 0.2 N–20 N, and its hysteresis is 10% [32].

The advantage of the piezoresistive sensor is its simple structure and affordability, but it suffers from heating issues and high hysteresis [33].

Capacitive Sensors

Capacitive sensors are another sensor used to detect FMG signals [23,34]. The capaci- tive sensor reflects the force/pressure loaded on it by detecting the capacitance value of capacitance. To achieve this, an elastic material between two electric layers is necessary. When the pressure applied to the sensor changes, the distance between two electric layers changes, resulting in a change in the capacitance value of the sensor [35].

Polydimethylsiloxane (PDMS) is a frequently used material in dielectric layers. Lei et al. used PDMS as the dielectric layer in a 16:1 mix ratio. The sensor can measure the pressure up to 945 kPa, and obtain a high sensitivity of 6.8%/N [35]. Maddipatla et al. used silver (Ag) ink on a flexible polyethylene terephthalate (PET) as electrodes, and a 16:1 mixing ratio of PDMS as a dielectric layer to fabricate a force sensor. The sensor offered a sensitivity of 0.13%/N from 0 N to 10 N [36].

Capacitive sensors have the advantage of low power consumption and fast response, but they are sensitive to electromagnetic interference (EMI) noise and are not suitable for long-term use.

Piezoelectric Sensors

Piezoelectric sensors have good dynamic force-sensing performance. When pressure is applied to the sensor, a potential difference is generated between the upper and lower plates of the sensor. By measuring its voltage, the magnitude of the pressure can be obtained. Common piezoelectric materials can be divided into ceramics, films, and fibers [33].

The acquisition of human biological information places high demands on the flexibility of sensors. The advantage of piezoelectric sensors is low hysteresis, strong sensitivity, and low power consumption. However, due to their characteristics, piezoelectric sensors cannot be used in static force sensing.

DATA PROCESSING

The original signal obtained by sensors cannot be used directly. In order to apply the collected signals to practice, we need to apply some signal processing steps, such as filtering and feature extraction, and then use algorithms, such as machine learning, to connect the original signals with practical applications. In this section, we will introduce some data processing methods for the three signals. All steps of data processing are shown in Figure5.

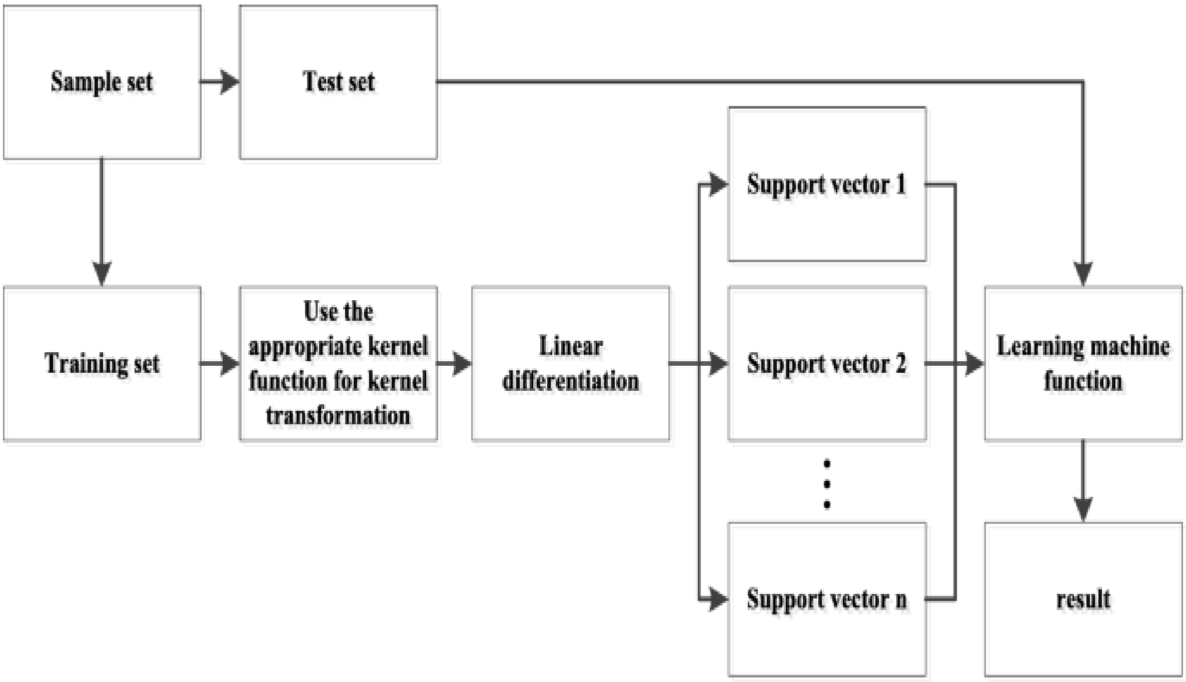

Figure 5. All steps of data processing

Data Pre-processing

In the pre-processing stage, we mainly filter and amplify the signal. At the same time, for different signals, there are their own unique signal pre-processing methods, which will be mentioned in other pre-processing.

Summary and Comparison of the Three Techniques

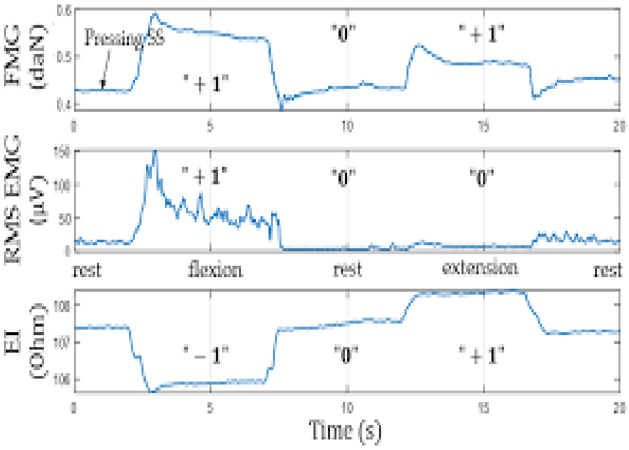

Figure 6. EMG, FMG and EI signals

APPLICATION

FMG, EMG, and EIT are three methods to obtain biological information of the human body, they can reflect different conditions of the human body. Therefore, they are widely used in human–machine interaction (HMI), medical, and healthcare. Some applications are shown in Figure7. In this section, we will introduce some applications of three techniques in HMI, medical, and healthcare.

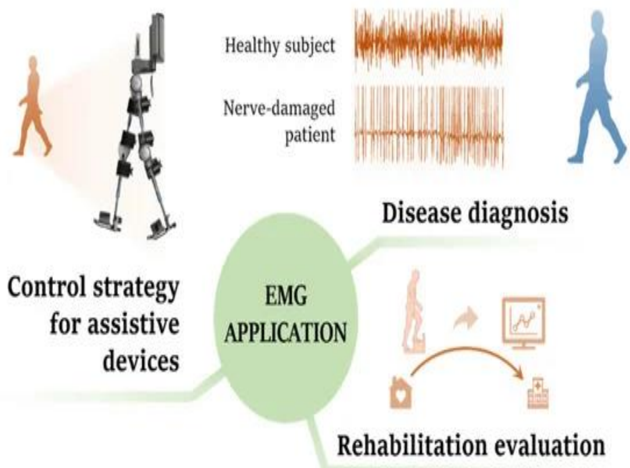

Figure 7. EMG different Applications

CONCLUSION

Despite their various advantages, they still have some problems to solve. In this section, we will analyze the current problems and challenges faced by these three technologies. The comparison of the three technologies is shown in Table1.

Table 1. Comparison of three techniques.

Technique	Robustness	SNR	System	Frequency
FMG	Excellent	High	Simple	0–100 Hz
EMG	Poor	Low	Normal	20–500 Hz
EIT	Poor	Low	Normal	1k–1 MH

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