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Exploration of Force Myography and surface Electromyography in hand gesture classification

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ABSTRACT

Whereas pressure sensors increasingly have received attention as a non-invasive interface for hand gesture recognition, their performance has not been comprehensively evaluated. This work examined the performance of hand gesture classification using Force Myography (FMG) and surface Electromyography (sEMG) technologies by performing 3 sets of 48 hand gestures using a prototyped FMG band and an array of commercial sEMG sensors worn both on the wrist and forearm simultaneously.

The results show that the FMG band achieved classification accuracies as good as the high quality, commercially available, sEMG system on both wrist and forearm positions; specifically, by only using 8 Force Sensitive Resisters (FSRs), the FMG band achieved accuracies of 91.2% and 83.5% in classifying the 48 hand gestures in cross-validation and cross-trial evaluations, which were higher than those of sEMG (84.6% and 79.1%). By using all 16 FSRs on the band, our device achieved high accuracies of 96.7% and 89.4% in cross-validation and cross-trial evaluations.

1. Introduction

Hand gestures are an important means of interaction between humans and their environment. For example, people grasp various objects for different purposes and functions using corresponding hand and finger configurations [1,2], communicate using sign language [3], and move individual fingers and hand joints for various purposes such as for rehabilitation exercises [4]. Sensing technologies are needed to detect various hand gestures in various situations and applications, including human computer interactions (HCI) [5,6], tele-manipulation of robots for upper extremity rehabilitation [7,8], prosthesis control [9–12], and virtual reality (VR) interactions [13]. The technologies employed for hand gesture recognition mainly can be categorized into vision [5,8], inertial senor [14,15], data glove [16,17], and muscular activity sensor [3,6,9,18] based technologies. As a non-invasive technique for registering electrical activities generated by the motor units of the skeletal muscles, surface Electromyography (sEMG) of the upper limbs has been well established and extensively investigated to decipher hand gestures [18–20]. A benchmark database has also been set up for evaluating algorithms recognizing hand gestures using sEMG [21].

Force Myography (FMG) is an alternative technology that has been recently developed for hand gesture recognition [6,22,23], which utilizes force resisting sensors surrounding a limb to register the volumetric changes of the underlying musculotendinous complex during muscle activities. By employing sophisticated machine learning technologies, FMG has been widely applied to gesture recognitions for prosthesis operation and rehabilitation [23–25]. For example, Li et al. [23] combined the use of a support vector machine (SVM) with an array of 32 FSRs in a prosthetic socket to distinguish 17 types of finger motions. The authors found that the FMG patterns generated by these 17 different finger motions were distinctive, and reported a high accuracy of about 99% for the in-session test and accuracies ranging from 79% to 98% for the intra-wearing cross-session (without taking off and resetting the sensors) test. Compared to sEMG, FMG has advantages including it is robust to external electrical interference and sweating, inexpensive, and easy-to-use [26,27]. Most of the FMG-based hand gestures recognition studies have evaluated the performance based on FMG sensors without comparison to other sensing technologies. Regarding this, we are interested in whether FMG is comparable to sEMG in distinguishing hand gestures, both performed in exactly the same situation. Confirmation of the comparable performance of FMG to sEMG would imply wide application of this new sensing technology.

In the work of Ravindra and Castellini [28], a comparison of prediction accuracy, stability over time, wearability, and cost was performed using the sensing technologies FMG, ultra-sound

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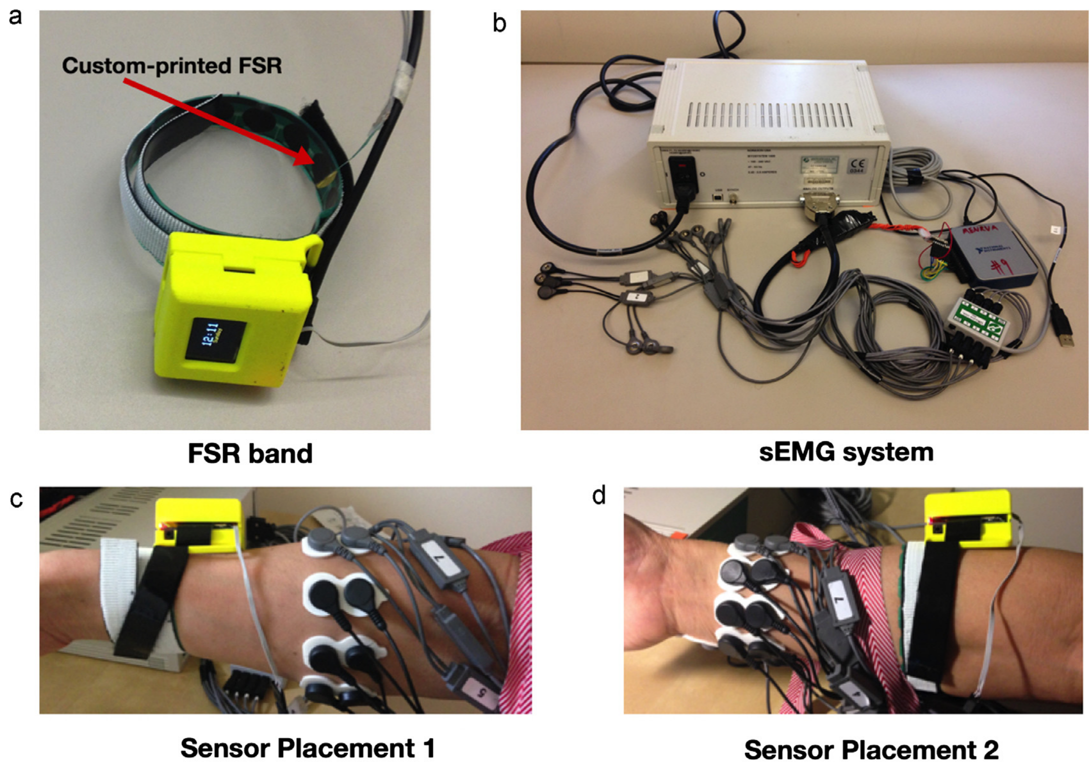

Fig. 1. Hardware for signal acquisition and the sensor placement in the study. A lace fabric was used to fasten the wire of the sEMG sensors on the forearm.

imaging, and sEMG to predict finger forces while healthy participants flexed their fingers. The sEMG and FSR bracelets were both worn on the forearm for the data collection. The raw sEMG and FSR signals were used to train and predict a force regression model. The authors found that the FMG technology yielded comparable prediction accuracies and wearability, had better stability than sEMG, and was much more affordable. However, only individual finger movements were tested in this study. Studies need to be performed to see how FMG compares to sEMG in distinguishing more complex hand gestures such as grasps and sign language gestures. Furthermore, recent research and technologies show that muscle activities on the wrist also provide ample information for hand gesture recognition [3,6,29–31]. It will be interesting to explore the performance of FMG and sEMG sensing technologies in terms of the wearing positions on the wrist and forearm.

The purpose of the research presented in this paper was to comprehensively evaluate the performance of a novel FMG device in recognizing multiple sets of hand gestures by comparing to a conventional sEMG system. Twelve able-bodied participants performed 3 different sets of 48 hand gestures, wearing both FMG and sEMG sensors on the wrist and forearm simultaneously in one session. The sensor positions for FMG and sEMG were then reversed, respectively, and the same set of hand gestures was repeated. A custom-made FMG band with a row of 16 FSR sensors was employed in this study, and was long enough for covering one loop of the forearm or the wrist. A sEMG system with 8 equally spaced sensors was worn on the wrist or the forearm. The accuracy of classifying the 48 hand gestures using 8 FSRs selected from the first loop sensors was compared to that of using the 8 sEMG sensors.

2. Materials and experimental setup

2.1. Signal acquisition systems

Fig. 1 shows the FMG and sEMG signal acquisition hardware for this study. The Force Sensing Resisters (FSRs) device is a polymer thick film (PTF), which exhibits decreasing resistance as increasing force is applied to the active area. The FSR band used in this study consists of 16 FSR sensors and an FMG signal acquisition unit (the yellow cube), as shown in Fig. 1A. The FSR sensors are custom-printed on the band, each 1.3 cm in diameter and .3 cm apart from each other. The characteristics of the printed FSR sensor are the same the FSR402 from Interlink [32]. The total length of the FSR band is 32 cm, and the width is 2.1 cm. The backside of the band is adhered to a 38 cm length, 1.5 cm wide strap (6 cm of the strap remains at the end of the band). One end of the band inserts into a ZIF connector on the electronic circuit unit and the other end is fixed using the strap when wearing. The band is longer than the average forearm size of the participants (24.8 ± 1.5 cm)[1] in this study and can be worn by looping the band more than once in parallel on the forearm or wrist to maximize the sensor utilization during data collection. A built-in Universal Serial Bus (USB) interface connects the band to a working laptop.

A commercial medical-grade sEMG acquisition system from Noraxon (Myosystem 1400 L) was used, and has 8 bipolar sEMG active electrodes, as shown in Fig. 1B. The gain of the preamplifier was set to 500, which can differentiate between a small signal of interest and much larger interference signals that are present on the skin. It also has a very high input impedance to cope with mismatches in skin contact resistance. After the pre-amplification, the signals of the 8 pairs of electrodes were fed into the main amplifier unit for further signal amplification and filtering. Finally, the filtered signals were digitized using a data acquisition device (DAQ), which is connected to the working laptop.

Both signals from the FSRs and sEMG sensors were synchronized and recorded using a customized Labview (National Instruments Inc.) visual interface (VI) on the working laptop, using sample rates of 10 Hz for the FSRs and 1000 Hz for the sEMG sensors, respectively. Since only the stationary part of gestures are of interest and the frequency of human hand motion is typically

[1] The ± denotes 1 standard dev. throughout the paper.

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