Preliminary Testing of a Hand Gesture Recognition Wristband Based on EMG and Inertial Sensor Fusion

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Abstract. Electromyography (EMG) is well suited for capturing static hand features involving relatively long and stable muscle activations. At the same time, inertial sensing can inherently capture dynamic features related to hand rotation and translation. This paper introduces a hand gesture recognition wristband based on combined EMG and IMU signals. Preliminary testing was performed on four healthy subjects to evaluate a classification algorithm for identifying four surface pressing gestures at two force levels and eight air gestures. Average classification accuracy across all subjects was 88% for surface gestures and 96% for air gestures. Classification accuracy was significantly improved when both EMG and inertial sensing was used in combination as compared to results based on either single sensing modality.

Keywords: Surface EMG · Inertial motion sensing · Human-machine interface · Hand gesture recognition

1 Introduction

Mobile devices such as smart phones, tablets and laptops are increasingly integral in our daily lives. Traditional interaction paradigms like on-screen keyboards can be an inconvenient and cumbersome way to interact with these devices. This has led to the advancement of bio-signal interfaces such as speech based and hand gesture based interfaces. Compared to speech input interfaces, hand gesture devices can be more intuitive in resembling physical manipulations related to spatial tasks such as navigation on a map or manipulating a picture [1].

Different technologies have been proposed for hand gesture recognition, including devices based on optical depth sensing [2,3], magnetic sensing [4], force sensitive resistors (FSR) [5], inertial motion sensing (IMU) [6–11] and electromyography (EMG) [12–14]. Depth sensing and magnetic sensing are susceptible to ambient light and magnetic disturbances and FSR may require unnatural

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hand gestures. IMUs have advantages in discriminating dynamic gestures involving direction change but are not as strong in discriminating gestures involving minimal movement like making a fist. The advantage of EMG sensing is detecting static gestures involving distinct muscle activations but can be sensitive to electrode placement and susceptible to sweat and skin impedance changes over time [15–18]. Thus combining inertial and EMG sensing could increase hand gesture classification accuracy by combining the strengths of each.

Previous research has combined inertial and EMG sensing by primarily placing sensors on the forearm [1,19–22]. Georgi et al. [1] used a system consisting of an IMU worn on the wrist and 16 EMG sensors worn on the forearm to classify 12 gestures, which achieved a recognition rate of 97.8% in session-independent and 74.3% in person-independent testing. Zhang et al. [21] used a three-axis accelerometer and 5 EMG sensors to classify 72 Chinese Sign Language (CSL) words at a 95.8% recognition rate. Chen et al. [22] improved recognition rates by 5-10% for 24 hand gestures with 2D-accelerometers and EMG sensors together as compared to using EMG sensors alone. Additionally, Wolf et al. [19] used a sleeve with an IMU and 8 EMG sensors and get 99% accuracy for 9 dynamic gestures. Though these studies provide promising results, for practical applications it may be inconvenient to place EMG sensors on the forearm.

This paper presents a hybrid recognition wristband based on surface EMG and inertial sensor fusion for hand gesture recognition. We aimed to combine EMG and inertial sensing in a practical wristband form with relatively high accuracy.

2 Materials and Methods

2.1 Hand Gestures

We choosed two kinds of gestures: four surface pressing gestures with the hand pressing against a flat, hard surface and eight air gestures which are performed in the air without any contact forces. For the surface gestures, we distinguished between two levels of pressing force. Gestures were selected to be familiar and intuitive to users, accustomed to interacting with mobile devices. The four surface gestures were: index finger press (T1), index finger, middle finger and ring finger pressing together (T3), all five fingers pressing together (T5), and making a fist (F), as shown in (Fig. 1). The eight air gestures were: okay sign (OK), peace sign (PS), hang loose (HL), finger snap (FS), thumbs up (TU), thumbs down (TD), turn palm over (TP), and walking fingers (WF), as shown in Fig. 2. The two force levels for the surface gestures were set to 10% of maximum voluntary contraction (MVC) and 50% of MVC.

2.2 Hybrid EMG and Inertial Sensing Wristband System Configuration

The aim of the hybrid system was to detect EMG and motion signals simultaneously. Dry gold-plated copper electrodes were deployed to capture EMG signals

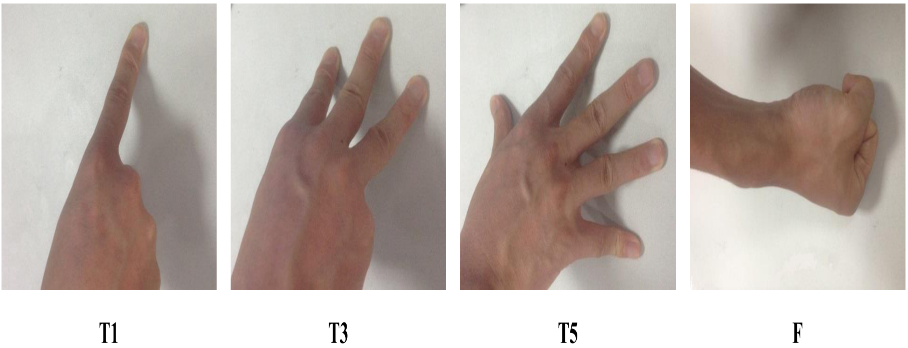


Fig. 1. Four surface gestures: index finger press (T1), three finger press (T3), five finger press (T5), and making a fist (F).

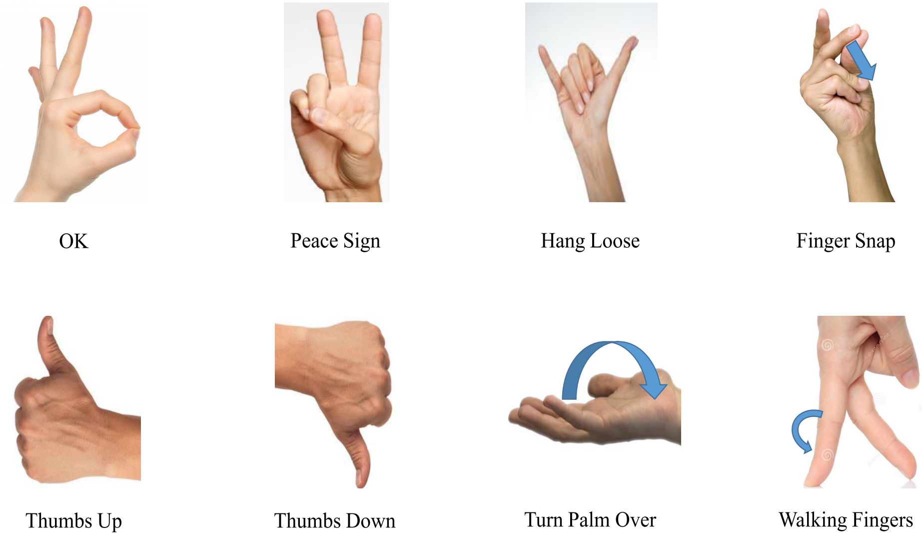


Fig. 2. Eight air gestures: okay sign (OK), peace sign (PS), hang loose (HL), finger snap (FS), thumbs up (TU), thumbs down (TD), turn palm over (TP), walking fingers (WF).

for their stable and reliable contact with skin. To attenuate common-mode noise and crosstalk, differential amplification was adopted to capture EMG signals. An instrumentation amplifier (INA326, Texas Instruments) was used for differential amplification because of its high common mode rejection ratio (CMRR) and input impedance. The differential EMG signals were bandpass filtered at 20–450 Hz to remove unwanted noise. EMG signals were further amplified with a gain of 500 to improve the signal to noise ratio. Inertial motion sensors consisted of a 3-axis analog accelerometer (ADXL335, Analog Devices) and a dual-axis pitch and roll analog gyroscope (LPR4150AL, STMicroelectronics). EMG and motion signals were digitalized via analog to digital conversion AD7607

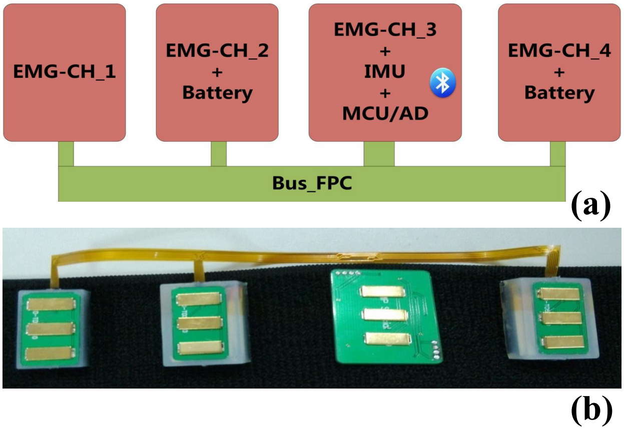


Fig. 3. Overall structure of the hybrid EMG and IMU acquisition system: (a) system block diagram; (b) hardware implementation.

(Analog Devices) with a sampling rate of 1 kHz. Digitized signals were wirelessly (Bluetooth) transmitted to a PC for storage and further processing. A microcontroller C8051F310 (Silicon Labs) was employed to manage signal digitization and transmission. The overall structure of the hybrid EMG and IMU system is shown in Fig. 3.

2.3 Experimental Protocol and Testing

Four able-bodied male subjects (20 to 30 years old) participated in this study. Informed consent was obtained from subjects before the experiment, which was performed in accordance with the Declaration of Helsinki. For preliminary testing of the classifier algorithm, four wireless electrodes (Trigno TM Wireless system, Delsys Inc.) were used to collect data, and each electrode contained one EMG channel and one 3-axis accelerometer. All four EMG sensors and the 3-axis

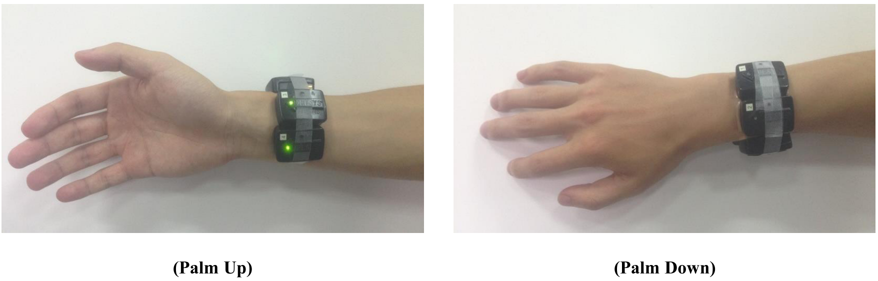


Fig. 4. Experimental setup: two electrodes were placed on the anterior muscles, and two were plced on the posterior muscles, 5 cm away from the edge of the palm

accelerometer on the top lateral wrist were used for classification. Electrodes were placed 5 cm away from the edge of the palm, of which two were on the anterior muscles, and two were on the posterior muscles (Fig. 4). For surface gestures recognition, each subject performed twenty trials, half of which were conducted at 10% MVC and another half were conducted at 50% MVC. For air gestures recognition, each subject performed ten trials with the moderate force. Each trial consisted of one repetition of the defined gestures, where each gesture sustained 5 seconds with 5 seconds rest between them. Half of the trials were used for training and the left half were used for testing.

2.4 Feature Extraction and Pattern Recognition

Motion classification was performed in two stages: feature extraction and pattern recognition. First, EMG and motion signals were segmented into a series of 200 ms windows with an overlap of 50 ms, which were used to extract the feature vectors. Each feature vector consisted of the EMG features (mean absolute value, waveform length, zero crossing and sign slope change) and acceleration features (mean value and standard deviation). The linear discriminant analysis (LDA) classifier was used for the pattern recognition.

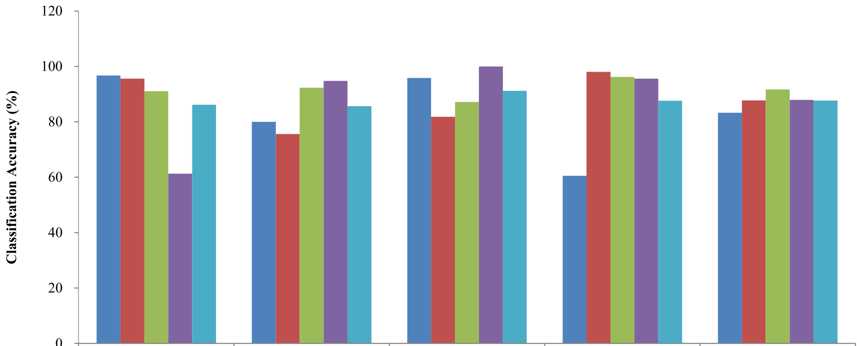
3 Experimental Results and Discussion

Classification accuracy (CA) was computed as:

$$CA = \frac{Number\ of\ correct\ testing\ samples}{Total\ number\ of\ testing\ samples} \times 100\% \tag{1}$$

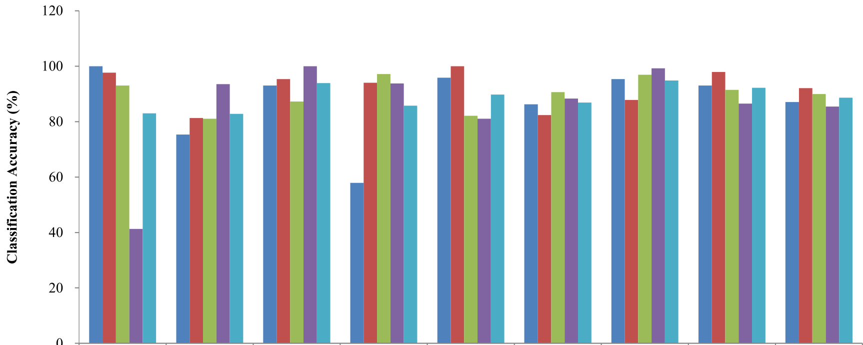
Only EMG features were used in surface gesture recognition because of the minimal hand movements. Mean classification accuracies for T1, T3, T5 and F surface gestures were 86.17%, 85.68%, 91.20% and 87.60% respectively, as seen in (Fig. 5). For surface gestures at two force levels, the average CA for T1-10%, T3-10%, T5-10%, F-10%, T1-50%, T3-50%, T5-50% and F-50% were 82.99%, 82.79%, 93.90%, 85.71%, 89.74%, 86.88%, 94.81% and 92.21% respectively, as seen in (Fig. 6). Average CA across all subjects was 88.63% for all surface gestures in this study which is better than another studies [12] which reported a recognition rate of 79% and similar to the recognition accuracy of 94% reported by Kim et al [13]. Provided that the system was worn on the wrist where muscular activation signals are relatively lower, the classification accuracy in this study is promising.

Furthermore, classification performance based on EMG and inertial sensing fusion for eight air gestures is shown in Fig. 7. Average CA using EMG alone improved from 86.81% to 95.97% when combining EMG with inertial sensing. We expected EMG and inertial sensing to be complementary because they capture different aspects of movement. For static gestures such as OK, PS and HL which involve minimal movement, classification using EMG alone can be quite accurate, because movement features are negligible. Hand gesture recognition



	T1	T3	T5	F	AVR
Subject1	96.75	80.00	95.84	60.52	83.28
Subject2	95.58	75.58	81.82	98.05	87.76
Subject3	91.04	92.34	87.14	96.23	91.69
Subject4	61.30	94.81	100.00	95.58	87.92
Mean	86.17	85.68	91.20	87.60	87.66

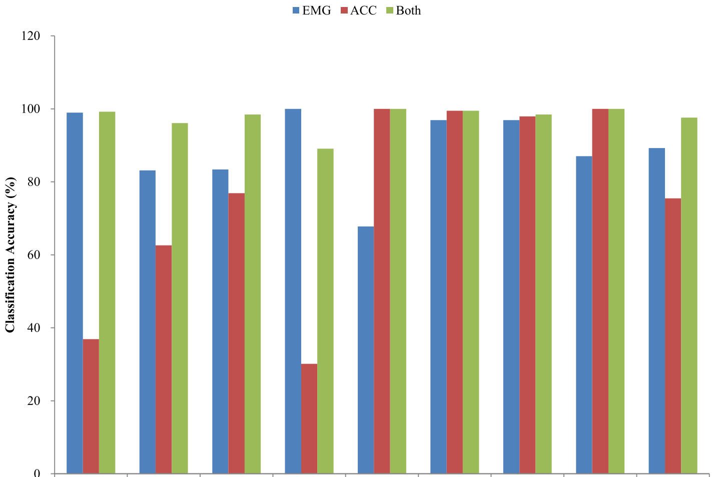
Fig. 5. Classification accuracy for four surface gestures (T1, T3, T5 and F) without force discrimination.



	T1-10%	T3-10%	T5-10%	F-10%	T1-50%	T3-50%	T5-50%	F-50%	AVR
Subject1	100.00	75.32	92.99	57.92	95.84	86.23	95.32	92.99	87.08
Subject2	97.66	81.30	95.32	94.03	100.00	82.34	87.79	97.92	92.05
Subject3	92.99	81.04	87.27	97.14	82.08	90.65	96.88	91.43	89.94
Subject4	41.30	93.51	100.00	93.77	81.04	88.31	99.22	86.49	85.45
Mean	82.99	82.79	93.90	85.71	89.74	86.88	94.81	92.21	88.63

Fig. 6. Classification accuracy for four surface gestures at two force levels (T1-10%, T3-10%, T5-10%, F-10%, T1-50%, T3-50%, T5-50% and F-50%) for each subject.

based on motion signals for minimal movement gestures may result in a classification overfitting problem. For dynamic gestures such as TU, TD, TP and WF which involve large direction changes during rotation or translation, classifiers based on motion signals alone can discriminate gestures accurately. In this case, hand gesture recognition based on EMG alone might have difficulty identifying dynamic gestures that differ primarily in direction. Overall accuracy is higher



	OK	PS	HL	FS	TU	TD	TP	WF	AVR
EMG	98.96	83.12	83.38	100.00	67.79	96.88	96.88	87.01	89.25
ACC	36.88	62.60	76.88	30.13	100.00	99.48	97.92	100.00	75.49
Both	99.22	96.10	98.44	89.09	100.00	99.48	98.44	100.00	97.60

Fig. 7. Classification accuracy of eight air gestures (OK, PS, HL, FS, TU, TD, TP and WF) for one representative subject. For each gesture, classification accuracy is shown when using EMG or inertial sensing (ACC) individually, and in combination (Both).

when using EMG and inertial sensing together compared to performance using either modality alone.

4 Conclusion

This paper presents a wrist-based hand gesture recognition system that combines EMG and inertial motion sensing. A classification algorithm was validated via preliminary testing of four surface gestures at two force levels and eight air gestures. EMG sensing is particularly accurate for static hand gestures because of its ability to track muscle contractions. Inertial sensing is well suited for dynamic hand gestures due to its inherent ability to sense motion direction and amplitude changes. Used in combination these sensor signals can provide complementary information for higher classification accuracy. Classification accuracy using combined EMG-motion features was significantly improved as compared to EMG or motion sensing classification used in isolation.

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