A Novel HCI based on EMG and IMU

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Abstract—The technology of human-computer interaction (HCI) is developing rapidly in tandem with the advancement of information and biological technologies. Many new types of input device are introduced into this field, some of them are aimed to benefit special groups of people like old or disabled persons. In the meantime, Electromyography (EMG) and Inertia Measure Unit (IMU) have been readily available and extensively applied in control systems in many fields. In this paper, we propose a novel EMG-IMU based mouse controller that controls cursor movements based on IMU signals. The displacement of the cursor is determined by integrating the acceleration signal from the IMU, which moves with the operator’s arm. The mouse operations such as left click, right click and wheel scroll, are commanded through EMG signals. The pattern recognition algorithm, Linear Discriminant Analysis (LDA), is adopted to classify the EMG data into several clusters, which correspond to the predefined mouse operations. Experimental results have indicated that the proposed mouse controller can achieve an accuracy of 88%.

I. INTRODUCTION

Personal computer is widely used in our daily life. It could provide a great deal of convenience and change the view of our lives for normal people as well as some disabled. And the mouse, which is touted as a most effective and friendly input device, actually is an impediment to the handicapped that have no palms or fingers. Thanks to the evolution of the sensor technology, human-computer interaction (HCI) like EMG is progressing steadily. Now, EMG can be easily acquired on the surface of human skin through conveniently attachable electrodes [1]. Moreover, researchers have made some advancement in EMG pattern recognition. For example, to identify the various classifications (clicking the mouse or moving the cursor) according to the surface EMG signals of different muscles in the forearm [2]. That will push over the obstacle for disabled who have no fingers to click because it can be controlled by muscles rather than the fingers.

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Meanwhile, some researchers have focused on the kinetic sensors of. They explored new kinds of HCI based on dynamical measuring instruments, such as the gyro to gauge the head nodding [3]. When the head nods or sways, the cursor would move according to the gyro data.

Besides, there is a new kind of accelerometer. If the acceleration is smaller than a certain value, the cursor will move along with the accelerometer; otherwise, the data will be identified as an input command such as left clicking, right click and so on [4].

However, it still seems hard to put the above into practice because they could not move the cursor neatly or accomplish a click promptly.

In this paper, a novel mouse controller is proposed by taking advantage of the two kinds of sensors together. On the one hand, the operation commands are originated by the EMG signals of the muscles in the forearm. On the other hand, the movements of the cursor follow the data of the accelerometer of the IMU. To integrate the two sensors’ merits, the new type of mouse can move agilely and be clicked precisely. It offers a more convenient interface to communicate with computers and consequently benefits people who cannot use traditional mouse freely.

Furthermore, we can read the state of the muscles due to the novel mouse. It is certainly favorable to the amputee’s recovery [5].

The rest of the paper is organized as follows. Section II introduces the classification algorithm and the filtering process. The firmware acquiring the EMG and IMU signals is described in Section III. And Section IV presents the procedure of the experiment in detail. Section IV draws a conclusion.

II. ALGORITHM AND FILTER

A. LDA for EMG

A number of EMG pattern-recognition methods have already been proposed. The LDA is a classical method that has been extensively applied in dimension reduction. In this experiment, we define a linear transfer matrix $A$, which projects the input pattern $x \in \mathbb{R}^r$ (raw EMG signals) onto a reduced subspace $y \in \mathbb{R}^r$ (the clusters), $r << d$, namely

$$y = A^T x$$

(1)

The training dataset is $D = \{x_1, x_2, ..., x_c\}$, and the known subspace is $\{y_1, y_2, ..., y_c\}$, where $y_i \in \{1, 2, 3, ..., c\}$. $D_i$ denotes the $i$th cluster of the dataset.

LDA is mainly based on a set of functions of scatter matrices. The within cluster scatter matrix is defined as
\[
S_w = \sum_{i=1}^{c} \sum_{x \in D_i} (x - m_i)(x - m_i)^T \tag{2}
\]

The between clusters scatter matrix is denoted by
\[
S_b = \sum_{i=1}^{c} N_i (m_i - m)(m_i - m)^T \tag{3}
\]
where \( m_i = \frac{1}{N_i} \sum_{x \in D_i} x \) and \( m = \frac{1}{N} \sum_{x \in D} x = \frac{1}{N} \sum_{i=1}^{c} N_i m_i \).

And the total scatter matrix is
\[
S_T = \sum_{x \in D} (x - m)(x - m)^T = S_w + S_b \tag{4}
\]

LDA optimization is expressed by
\[
\max_A : \frac{\det(A^T S_b A)}{\det(A^T S_w A)} \tag{5}
\]

According to it, the matrix \( A \) can be obtained.

The matrix \( A \in \mathbb{R}^{r \times r} \) is composed of \( r \) eigenvectors corresponding to the \( r \) largest eigenvalues of \( S_w^{-1} S_b \). The dimension of the matrix \( A \) is determined by the number of clusters.

As mentioned in (1), the subspace \( y \) can be calculated accordingly.

**B. Filter**

For the acceleration, the IMU used in the experiment processes the output utilizing the EKF filter itself. We therefore take a simple filter: setting the acceleration to 0 when its absolute value is smaller than a certain value.

**C. Signal process**

The procedure of processing sensors’ data can be described into two parts. On the one side, classify the five actions, including the four gestures and the state of rest, by means of the algorithm of LDA. On the other side, calculate the displacement of the mouse cursor in x-y axes according to the acceleration.

Fig. 1 shows the schematic diagram for the data processing.

**III. SYSTEM REALIZATION**

**A. Sensors for acquiring EMG**

In this experiment, we need 3 electrodes which are made of Silver chloride to detect the surface EMG signals. The electrodes are pasted on the surface of the specific muscles. Fig. 2 shows the appearance of the electrodes.

Since the electric potential of EMG is approximate to 1mv, in order to transmit and process the micro-signal effectively and avoid environmental noise, an amplifier is used to deal with the raw signals and the magnification is about 500. Fig. 3 shows the amplifier and its parameters are shown in Table I.

The EMG signals are sent to an A/D converter card in a computer for the further process. The converter card, Advantech PCI-1716, provides simultaneous acquisition of as much as 16 channels of EMG signals. In our system, the signals are sampled at 1 kHz, and quantized at 16 bits.

**B. Sensor for acquiring acceleration**

The acceleration supplies the information of cursor movement in the system according to the displacement of our hand. The IMU we use in the experiment, VectorNav-VN100, is an advanced and precise instrument integrated with the stm32 process unit, 3-dimension-gyro, accelerometer, magnetic sensor and so on. Fig. 4 shows the appearance of the IMU and its characteristics are shown in Table II.
Fig. 4. The IMU sensor for acceleration

### TABLE II
THE PARAMETERS OF THE IMU FOR ACCELERATION

| Orientation range | Acceleration bias stability | Accelerometer nonlinearity | Data rate | Supply voltage |
|-------------------|-----------------------------|---------------------------|-----------|----------------|
| 360 degree about all axes | 0.5 mg for X, Y < 0.5 % | 1.6 mg Z | 1 to 200Hz | 3.3 to 5.5 |

The data of the IMU are sent to a computer through RS232 serial interface directly. It provides x-y axes accelerations. To integrate the accelerations, the x-y axes displacements are obtained to regulate the mouse pointer movements.

#### C. The useful gestures and muscles

In our experiment, we define 4 gestures, i.e., index finger pinch, middle finger pinch, palm stretch and fist clench, which are interpreted to corresponding control commands of the mouse: left click, right click, wheel scrolling up and wheel scrolling down. The gestures are shown in Fig. 5. The movement of rest, as shown in the middle of Fig. 5, is used constantly as the transition from one movement to the other.

Fig. 5. The 5 gestures: pinching the index finger, pinching the middle finger, spread the palm, clench the fist and rest

Considering the size of the electrodes and the biological knowledge of anatomy, three positions on the skin of forearm are selected to paste the electrodes, which are pronator quadratus, extensor indicis and flexor digitorum superficialis. The locations of the electrodes are shown in Fig. 6.

Fig. 6. The positions for pasting the electrodes

### IV. EXPERIMENTS

The steps of the experiment are shown in Fig. 7

#### A. Gesture learning based on LDA

In this study, the EMG pattern recognition is a supervised classification problem in which the training pattern is identified as a member of a pre-defined class. We sampled eight sets of EMG data for the training stage, which are then divided into five pre-defined classes manually. The same pre-defined-class data are selected and combined together by hand to form a training set. For the off-line learning as well as the real-time implementation, a 128ms moving window with a 32ms increment window is set for classification.

The raw EMG signal is shown in Fig. 8(a). A typical set of EMG data of a same action, selected and combined together artificially, which is denoted by the vector \( S_i \), where \( i = 1, 2, 3, \ldots, 5 \), means the number of the pre-defined cluster, is shown in Fig. 8(b). The clusters projected onto a three dimensional space are shown in Fig. 8(c).

We could get an abstract understanding of classification accuracy of LDA for the five actions according to Fig. 8(c). The more distantly the five clusters separate from each other, the higher accuracy of the classification is. And it guarantees the efficiency of the real time experiments.

As far as the matrix \( \text{Center} \) is concerned, it is composed by the centers of every cluster. \( \text{Center} = S \times A \), where

\[
S = [S_1 \ S_2 \ S_3 \ S_4 \ S_5]^T.
\]

#### B. Real-time implementation

We get the project matrix \( A \) and the center of each cluster which composes the matrix \( \text{Center} \) in the learning process.
In real-time implementation, the EMG signals were divided into pieces by the 128ms time window and 32ms increment window. Consequently, the EMG data became a $1 \times 128$ vector, multiplying with the $128 \times 4$ matrix $A$, then the projected space $y$ is obtained. Calculating the euclidian distance between the vector $y$ and each component of the matrix $Center$, the vector $y$ should be clustered into the corresponding class which has the smallest distance.

Furthermore, one classification procedure can be accomplished in 32ms while an action such as pinching the index finger must be finished in 0.2s. Wherefore, we set a simple rule for the classification procedure: if the sequent 3 classification results are the same, the command takes effect, which can enhance the accuracy of the classification effectively.

On the other hand, the displacement of the mouse cursor can be computed by integrating the acceleration. The minimal acceleration, whose absolute value is smaller than 1.0 m/s$^2$, is ignored to avoid the drift of the cursor.

The following are the real-time raw EMG signals in Fig. 9(a), the real-time accelerations of x and y axes in Fig. 9(b).

![The raw EMG signal](image1)

![Three pieces data indicating grasp from the three channels](image2)

![Five clusters in the lower spaces by LDA](image3)

Fig. 8 The result of the learning

![The real-time raw EMG signals](image4)

![The real-time acceleration data](image5)

Fig. 9. The signals of the experiment
The experimental video captures are shown in Fig. 10, the 4 pictures represent respectively moving the cursor towards left, right click, wheel scrolling backward, and wheel scrolling forward.

The classification accuracy of the experiment could be computed by the recorded data, which is 88.13%.

Fig. 10. The video snapshots of the experiment

V. CONCLUSION

In this paper, a novel mouse controller based on the EMG and IMU signals is designed. The EMG signals of certain muscles on the forearm are classified into the predefined five movements. The intention of the user to operate mouse, such as left click, right click, wheel scrolling forward, and wheel scrolling backward, are recognized by employing the algorithm of LDA. Meanwhile, the cursor moves freely according to the integral of the IMU acceleration data. Due to the real-time experiments, we can see the accuracy of the classification of EMG as well as the promptitude and efficiency of the cursor movement. Thus the EMG-IMU mouse certainly could satisfy the human-computer interface demand of the old or amputee. In the future work, we will improve the accuracy of the classification and ameliorate the control of the cursor movement. Moreover, we will attempt to study the EMG-IMU based mouse which has two cursors and could be controlled by our both hands simultaneously.

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