Surface EMG-based human-machine interface that can minimise the influence of muscle fatigue

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Abstract: It is clear that the surface electromyographic-based (sEMG) human-machine interface (HMI) shows a reduction in stability when the muscle fatigue occurs. This paper presents an improved incremental training algorithm that is based on online support vector machine (SVM). The continuous wavelet transform is used to study the changes of sEMG when muscle fatigue occurs, and then the improved online SVM is applied for sEMG classification. The parameters of the SVM model are adjusted for adaptation based on the changes of sEMG signals, and the training data is conditionally selected and forgotten. Experiment results show that the presented method can perform accurate modelling and the training speed is increased. Furthermore, this method effectively overcomes the influence of muscle fatigue during a long-term operation of the sEMG-based HMI.

Keywords: human-machine interface; HMI; EMG; muscle fatigue; online SVM; improved incremental training algorithm.


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1 Introduction

There has been a steady progress in the field of human-machine interfaces (HMIs) over the last two decades (Zhao et al., 2013). Surface electromyography (sEMG) signal has been widely deployed for advanced HMIs. However, it suffers from poor reliability and robustness in long-term operations. Despite many different reasons, this problem is mainly caused by muscle fatigue leading to non-stationarity in sEMG. HMI performance declines gradually with the occurrence of fatigue in muscles.

Recently, studying fatigue manifestation in muscles has proved that sEMG analysis is useful. For examples, in the field of medicine, ergonomics and sports, sEMG is used to distinguish fast or slow, twitch and objective evaluations of athletes’ muscle fatigue. In Nikooyan and Zadpoor (2012), a modelling approach is used to understand the effects of muscle fatigue on the ground reaction force and tissue vibration during running and the results show that the level of soft-tissue vibrations increase with fatigue.

Zhang et al. (2011) investigated a torque estimation method for muscle fatigue tracking, using stimulus evoked electromyography in the context of a functional electrical stimulation (FES) rehabilitation system. However, how to choose the optimal signal evaluation indices according to specific muscle contraction conditions and how to reduce the influence of muscle fatigue are still not very clear, which have been a hot research topic in recent years.

To investigate the long-term performance of the proposed system, this paper studies sEMG signals from different subjects in different periods. Online support vector machine (SVM) is employed to classify sEMG patterns that have the systematic parameters corresponding to the changes of the signals during the running time. Furthermore, an improved incremental training algorithm is presented and applied on the sEMG-based HMI system and the performance of the proposed system is evaluated in different periods.

The rest of the paper is organised as follows. Section 2 describes the research objects and methodology of the proposed research. In Section 3, the manifestation of muscle fatigue in sEMG is studied in detail. Section 4 describes the novel method of updating samples for online incremental SVM. Some experimental results are presented in Section 5 to show the feasibility and performance of the proposed method. Finally, a brief conclusion and future work are given in Section 6.

2 The research methods

In this research, the subjects who voluntarily participated in experiments are healthy, independent consciousness and have no facial disease, deformity or trauma. In addition, there is no muscle fatigue before the experiments are performed. A Cyberlink system is used to acquire the sEMG signals of the subjects. Figure 1 shows the headband device in this HMI system.

Figure 1 Cyberlink headband EMG device in HMI system

Two facial movements are defined in this paper to be control signals, namely single jaw clenching and double jaw clenching. These movements are generated by the subjects contracting masseter muscle and buccinators muscle with a jaw clenching and chewing-like movement. Every subject uses a designed sEMG-based HMI system to control an intelligent wheelchair (Wei et al., 2009), and the control signals are recorded at the same time.

There are five control states designed for the wheelchair control, namely ‘forward’, ‘backward’, ‘left’, ‘right’ and ‘stop’. The first four states are scanned round. Users can use
a single jaw clenching movement to switch the direction to the state they want.

If the wheelchair is in one of four control states, i.e., ‘forward’, ‘backward’, ‘left’, or ‘right’, a double jaw clenching movement will be used to switch the wheelchair to the ‘stop’ state. Figure 2 shows the simple diagram of the system.

**Figure 2**  The diagram of the proposed sEMG-based HMI (see online version for colours)

3 **Manifestation of muscle fatigue in sEMG**

Muscle fatigue is the decline in ability of a muscle to generate force. It can be a result of vigorous exercise but abnormal fatigue may be caused by barriers to or interference with the different stages of muscle contraction. This causes gradual changes of the system model when sEMG signals are used as the inputs of a HMI system.

The sEMG signals shown in Figure 3 are generated by single jaw clenching and double jaw clenching, which are absolute values. Figure 4 shows the significant different amplitudes of the sEMG signals from muscles before and after fatigue is occurring. The sEMG signals without fatigue is lower than 400μV, and their amplitude rises to 600μV after fatigue occurred. During a long-term operation of a sEMG HMI system, these changes cause the classification accuracy to decline significantly.

We deploy continuous wavelet transform (CWT) here to study the manifestation of muscle fatigue during a long-term operation of the HMI system through the analysis of sEMG frequency shifts (Englehart et al., 2001). Instantaneous mean frequencies (IMNF) are proportional to the signal frequencies and used in this work as a time-scale feature to analyse the manifestation of fatigue in dynamic contractions. This feature represents the dominant frequency in each control signal, and their trends stand for frequency shift of sEMG. So, it can be applied to analyse manifestation of muscle fatigue in dynamic contractions (Georgakis et al., 2003).

Wavelet transform essentially projects signal onto a function space consisted of wavelet functions. At low-frequency it has lower time resolution but higher frequency resolution, at high-frequency has higher time resolution but lower frequency resolution. Wavelet coefficients generated from WT reflect the correlation between wavelets at
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The larger the coefficients of the model are, the greater the correlation between signal and wavelet is, the more concentrated Energy distribution of wavelet coefficients is, the better the classification results are.

sEMG is essentially non-stationary signals. Because of the multi-resolution characteristic of wavelet transform, it is suitable for the extraction of sEMG characteristics. Given $s$ as a scale parameter, and $\tau$ as a translation (time shifting) parameter, the basic function $\psi_{s,\tau}$ is obtained by scaling the mother wavelet $\psi$ at time $\tau$ and scale $s$:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t - \tau}{s}\right)$$  \hspace{1cm} (1)

CWT of signal $x(t)$ is defined as

$$\text{cwt}(s, \tau) = \int x(t) \psi_{s,\tau}(t) dt$$  \hspace{1cm} (2)

The scalogram of a signal is defined as the square of CWT and then the mean scale of the signal in CWT is obtained by

$$MS = \frac{\int_{0}^{s} \int_{s}^{\infty} \|\text{cwt}(s, \tau)\|^2 ds d\tau}{\int_{0}^{s} \int_{s}^{\infty} \|\text{cwt}(s, \tau)\|^2 ds d\tau}$$  \hspace{1cm} (3)

Then, the inverse of the mean scale (MS) is known as IMNF. In this paper, we choose Duabechies 5 (db5) as the wavelet basis function.

Here statistical analysis is conducted to find the differences of sEMG from different subjects during various periods. More specifically, least-square linear regression is used to estimate IMNF shifts after a certain time, which is considered as a quantitative index of fatigue. The subjects are required to perform repetitive movements. Figure 5 shows the IMNF of a section sEMG signals and the trend of its shifts. IMNF shifts of four subjects are illustrated in Figure 6.

From the repetitive experiments, it is clear that fatigue occurs in muscle as the time goes, and makes negative impacts on the trend of frequency. During 0 min to 10 min, sEMG signals have a regular IMNF. As the time increases, IMNF declines to $-21\%$. It is experimentally proven that the manifestation of fatigue in myoelectric signals is significant during long-term muscular activities.
4 Incremental online training algorithm

As mentioned above, sEMG patterns gradually change in long-term muscle activities, owing to fatigue in muscles. sEMG signals inherently have a complex stochastic feature, and their characteristics are intensively dependent on physical and physiological conditions of subjects, as well as data collection conditions. These intense dependencies have encouraged us to develop an online classifier for the myoelectric HMI. This system must be capable of adapting itself with signal characteristics using the samples produced before and during the run-time.

4.1 Theory of incremental training algorithm

A SVM classifier constructs an optimal separating hyperplane in a high dimension feature space of training data, which is mapped using a nonlinear kernel function. The key idea of SVM is getting maximise classification marginal from solving dual optimisation problem, and then an optimal separating hyperplane is obtained (Oskoei et al., 2008; Oskoei and Hu, 2008; Zhang et al., 2013). If the data is linearly separable, the decision function is:

\[ g(x) = (w^T \cdot x) + b^* = \sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^* \]  

(4)

When the data is non-linearly separable, the original data is mapped into a high dimensional feature space by kernel function \((K(x_i, x_j))\), in which the mapped data is linearly separable. Then, the decision function is:

\[ g(x) = \sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x) + b^* \]  

(5)

If Karush.Kuhn.Tucker (KKT) condition is met, there is only one solution for the optimisation problem based on the quadratic optimisation theory. \(\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_l]\) is an optimal solution of the dual problem. When it satisfies the KKT condition, the problem is divided into the following three situations:

\[
\begin{align*}
\alpha_i &= 0 \Rightarrow y_i g(x_i) > 1 \\
0 < \alpha_i < c &\Rightarrow y_i g(x_i) = 1 \\
\alpha_i &= c \Rightarrow y_i g(x_i) \leq 1
\end{align*}
\]  

(6)

where \(\alpha\) is Lagrangian dual, \(c\) is an upper bound for samples that lie on the wrong side of the hyperplane. Non-zero constant \(\alpha_i\) is the sample corresponding to support vector. Samples located on the classification interval as \(0 < \alpha_i < c\). When \(\alpha_i = c\), samples lie in the classification interval.

In the proposed incremental training algorithm, the new samples are added to one of the sets, and the redundant samples are deleted from the three sets while all the other sample is still all belong to one of the three sets. The samples that are meeting the requirements are chosen from the new dataset and then the SVM model is trained based on the original optimal solution. During the online training, the support vector samples are kept for the next training, and the non-support vector samples are abandoned. The training time grows with the number of the training samples by a super linear function when the samples are accumulated during the training process. Therefore, it cannot meet the real-time requirement. A novel method for updating samples is proposed to solve this problem in the next section.

4.2 A novel method for updating samples

As sEMG is complex and time-varying, some of newly updated samples could be enormously changed over the initial boundaries between the classes after constantly online training. This causes a declining impact on the classification accuracy where effective selection of samples is required (Ceseracciu et al., 2010; Paisitkriangkrai et al., 2011). In this paper, we propose a novel method of updating samples for incremental online learning as follows. This method rebuilds the boundaries between the classes during the real-time operation.

In the classical SVM, the hyperplane in \(m\) dimensions can be shown as:

\[ w^T \cdot x + b = 0 \]  

(7)

In this method, the samples that are closest to the current boundary are chosen to train the classifier. The closest samples to the boundary between the two classes are defined as (8). Figure 7 illustrates the scheme of this samples updating method. As can be seen in the picture, the maximum distance of all fresh samples to boundary is defined as \(2\delta\). When the training time comes, samples that closest enough to the boundary are chosen as updating samples for online training.

\[ i^* = \arg \| g(x_i) \| \leq \delta \]  

(8)

This method allows a classifier to perform well in the presence of big sudden changes caused by transient signals or muscle fatigue. It keeps sEMG HMI system running reliable and makes training time much shorter.

In this paper the initial classifier is trained by previously collected label data. The proposed improved incremental training algorithm with the novel updating method is followed.

1. Check the training set. If it is empty, training process is over. Otherwise run to next step.
2. Update samples according to the presented novel method mentioned above.
3. Check those rest samples whether they meet KKT conditions. If not, adjust the parameters unless KKT conditions are satisfied.
4. Construct samples in step (3) as new train set.
5. Train samples online to form a new classifier. When the next training time comes, repeat the steps.
5 Experiment results and analysis

5.1 The wheelchair and HMI

Our intelligent wheelchair is composed of a number of components as follows:

1. DSP TMS320LF2407-based controller for motion control of two differentially-driven wheels.
2. An embedded PC is onboard, which is connected to the DSP motion controller via a USB link.
3. A 24-volt battery to provide power for the DSP controller and drive motors.
4. A local joystick controller is connected to an A/D converter of the DSP-based controller. EPW can be controlled by the joystick, but it is not used for hands-free experiment.
5. Six ultrasonic sensors are fixed at a height of 50 cm for obstacle avoidance (four at the front and second at the back).
6. A Logitech 4000 Pro Webcam for recognising the user’s head gesture.

It should be noticed that ultrasonic range sensors and a webcam have been used for head gesture recognition control, not used in this research. The proposed experimental system contains three parts. The first part is the data acquisition device, namely Cyberlink, which is composed of a data processing box and a wearable headband, as shown in Figure 1. The second part of the system is an intelligent wheelchair platform. The third part is the HMI.

The HMI component is responsible for extracting features and classifying selected face movements and mapping the classified movement patterns into wheelchair control commands. The complete structure of the HMI system is depicted in Figure 8. As can be seen, the core of the system is a human computer interface (HCI) that consists of four subsequent procedures, i.e., active segment detection, feature extraction, pattern recognition and logic control.

In the proposed HMI system, the autoregressive (AR) model is used to extract sEMG features. The AR parameter model is deployed to achieve data compression and extract four coefficients of the 4-order AR model. The coefficients are viewed as four eigenvalues of forehead sEMG signals and sent to the improved incremental SVM classifier. The AR coefficient is decided by the frequency domain characteristics of signals. For the sEMG signals, the frequency domain characteristics are more stable than the time-domain characteristics, so the AR model is one of the better methods in the traditional feature extraction methods.

AR model coefficients have a good capability for characterisation of sEMG signals mode. Table 1 shows four groups of all 4-order AR coefficients of the two movements. Many experiments show that the analysis and recognition results of sEMG signals are the best when the order of AR model is 4. Instead of improving the classification result, a higher-order model may lead a worse result and increase the computation. So the 4-order AR coefficient vector $A = [a_1, a_2, a_3, a_4]$ is input to the SVM classifier.

### Table 1: AR coefficients of single jaw clenching and double jaw clenching

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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</thead>
<tbody>
<tr>
<td>Single jaw</td>
<td>-1.645</td>
<td>-1.464</td>
<td>-0.846</td>
<td>-1.643</td>
</tr>
<tr>
<td>clenching</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_1$</td>
<td>0.776</td>
<td>1.065</td>
<td>-0.443</td>
<td>0.730</td>
</tr>
<tr>
<td>$a_2$</td>
<td>-0.156</td>
<td>-1.169</td>
<td>-0.100</td>
<td>-0.117</td>
</tr>
<tr>
<td>$a_3$</td>
<td>0.0393</td>
<td>0.578</td>
<td>0.409</td>
<td>0.048</td>
</tr>
<tr>
<td>$a_4$</td>
<td>0.087</td>
<td>0.089</td>
<td>0.317</td>
<td>0.224</td>
</tr>
<tr>
<td>Double jaw</td>
<td>-0.963</td>
<td>-0.995</td>
<td>-1.253</td>
<td>-0.981</td>
</tr>
<tr>
<td>clenching</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_1$</td>
<td>-0.224</td>
<td>-0.389</td>
<td>0.122</td>
<td>-0.321</td>
</tr>
<tr>
<td>$a_2$</td>
<td>0.087</td>
<td>0.089</td>
<td>0.317</td>
<td>0.224</td>
</tr>
<tr>
<td>$a_3$</td>
<td>0.128</td>
<td>0.318</td>
<td>-0.168</td>
<td>0.097</td>
</tr>
</tbody>
</table>

5.2 Comparison of the algorithm performance

RBF kernel function is employed for the LIBSVM, traditional incremental online SVM and improved
incremental online SVM with the same parameter ($C = 1$ and $\gamma = 0.5$). The data is normalised and limited to the range of $-1$ to $1$. 800 samples are randomly selected from 2,000 pre-collected signals as training set, and then choose 800 samples in the rest samples randomly as testing set. We make a comparison of training time using LIBSVM (Oskoei and Hu, 2007; Platt, 1999; Tsui et al., 2009), traditional incremental SVM and improved incremental SVM with the novel updating method.

For the reliability purpose, we use the average value of the estimations obtained in repetitive experiments. Figure 9 shows the average time consumptions of three methods in 30 experiments. Also we compared classification accuracy of sEMG data of the improved incremental SVM with LIBSVM and traditional incremental SVM in Table 2.

![Figure 9](image)

**Figure 9** Comparison of time costs for LIBSVM, traditional algorithm and improved algorithm training

<table>
<thead>
<tr>
<th></th>
<th>LIBSVM</th>
<th>Improved incremental online SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single jaw clenching</td>
<td>85%</td>
<td>96%</td>
</tr>
<tr>
<td></td>
<td>92ms</td>
<td>58ms</td>
</tr>
<tr>
<td>Double jaw clenching</td>
<td>83%</td>
<td>94%</td>
</tr>
<tr>
<td></td>
<td>103 ms</td>
<td>62 ms</td>
</tr>
</tbody>
</table>

Table 2 The comparison of the algorithm’s classification accuracy

As can be seen in Figure 9, the training time that improved incremental SVM needs is shorter than that traditional increment SVM and LIBSVM need. When the number of training samples is less than 100, the time consumptions of three methods are close. But when the number of training samples is more than 100, the training time of three methods training is quite different. For example, to train 400 samples, LIBSVM, traditional incremental SVM and improved incremental SVM need 200 ms, 144 ms and 110 ms respectively.

Experiments results indicate that the improved incremental SVM reduces training time about 45% and 24% separately relative to LIBSVM and traditional online SVM. The data in Table 2 illustrate that the proposed method improved the classification accuracy of double jaw clenching movements to 90%, and the accuracy of single jaw clenching movement has also been much improved.

### 5.3 Verification of the algorithm effectiveness

In order to verify the effectiveness of the proposed algorithm for reducing the influence of muscle fatigue, subjects are invited to control an intelligent wheelchair by sEMG-based HMI with the improved online SVM and LIBSVM algorithms. Five subjects are invited to drive the wheelchair by following a specified path repeatedly as shown in Figure 10. Six subjects are required to control the intelligent wheelchair for 90 minutes without a rest during this period.

![Figure 10](image)

**Figure 10** The path designed for experiment

Figure 11 gives the moving trajectory of the intelligent wheelchair controlled by the six subjects by using joystick and the improved SVM system. Figure 12 shows the trajectory of a subject controlling the wheelchair by using two systems, which were recorded during different periods of real-time operation. Table 3 shows the average time consumptions of four subjects controlling wheelchair using HMI system with the two online SVM in different periods.

![Figure 11](image)

Experimental results indicate that the performance of the sEMG-based HMI system with LIBSVM gradually declines as time increases with the occurrence of muscle fatigue. This can be seen as the fluctuation of the curve shown in Figure 12(a). As it is shown in the figure, there is almost no wave in the trajectory during the time from 0 to 10 minutes. This shows that the wheelchair can avoid the obstacles and move smoothly. However, during 30 to 40 minutes we can see much fluctuation taking place in the trajectory. 50 minutes later, wheelchair with LIBSVM is almost out of control which performs for large fluctuation in the trajectory curve. In this situation, the HMI system cannot recognise the control commands accurately and direct the wheelchair motion against the subjects’ intention.
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**Figure 11** Experimental trajectories of wheelchair with (a) joystick and (b) improved SVM when six subjects used the two systems during different periods.

(a) ![Joystick Trajectory](image1.png)  
(b) ![Improved SVM Trajectory](image2.png)

**Figure 12** Experimental trajectories of wheelchair when subject 1 used the two systems during different periods, (a) LIBSYM-based (b) improved SVM.

(a) ![LIBSYM Trajectory](image3.png)  
(b) ![Improved SVM Trajectory](image4.png)

**Table 3** Four subjects’ average time consumptions of repetitive experiments during different periods.

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Time consumptions using system with traditional incremental online SVM in seconds</th>
<th>Time consumptions system with improved traditional incremental online SVM in seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0–10) min (30–40) min (50–60) min</td>
<td>(0–10) min (30–40) min (50–60) min</td>
</tr>
<tr>
<td>A</td>
<td>86.5 80.1 73.8</td>
<td>92.6 88.4 86.7</td>
</tr>
<tr>
<td>B</td>
<td>88.7 81.6 73.3</td>
<td>92.8 89.5 87.4</td>
</tr>
<tr>
<td>C</td>
<td>83.1 79.2 70.9</td>
<td>86.7 82.8 79.3</td>
</tr>
<tr>
<td>D</td>
<td>90.4 85.5 79.2</td>
<td>93.6 90.1 88.3</td>
</tr>
<tr>
<td>E</td>
<td>80.8 75.3 70.1</td>
<td>84.9 81.6 78.4</td>
</tr>
<tr>
<td>Average</td>
<td>85.9 80.34 73.46</td>
<td>90.12 86.48 84.02</td>
</tr>
</tbody>
</table>

On the contrary, sEMG-based HMI system with the improved online SVM still has reliable performance after 90 minutes operation as can be seen in Figure 12(b). Also subjects control the intelligent wheelchair by this system using a little time in different periods as shown in Table 3. Moreover, our system can safely avoid obstacles and has a smooth human-machine interaction. In other words, the proposed algorithm can effectively overcome the influence of muscle fatigue in a long-term operation.

6 Conclusions and future work

Muscle fatigue can negatively influence the performance of human-machine interaction based on sEMG signals. In this paper, we analysed the manifestation of muscle fatigue in sEMG and proposed an improved incremental online training algorithm that can be applied to a sEMG-based HMI system. The proposed algorithm works well and can effectively reduce the effects of muscle fatigue.
Our future work will focus on how to improve the system performance in a real-time operation. Also, intensive experiments will be carried out on different kinds of users, both elderly and disabled people.

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