The Classification for "Equilibrium Triad" Sensory Loss Based on sEMG Signals of Calf Muscles

Hairong Yu[1], Kairui Guo[1], Jie Luo[2], Kai Cao[1], Hung T. Nguyen[1], Steven W. Su[1]

***Abstract*— Surface Electromyography (sEMG) has been commonly applied for analysing the electrical activities of skeletal muscles. The sensory system of maintaining posture balance includes vision, proprioception and vestibular senses. In this work, an attempt is made to classify whether the body is missing one of the sense during balance control by using sEMG signals. A trial of combination with different features and muscles is also developed. The results demonstrate that the classification accuracy between vision loss and the normal condition is higher than the one between vestibular sense loss and normal condition. When using different features and muscles, the impact on classification results is also different. The outcomes of this study could aid the development of sEMG based classification for the function of sensory systems during human balance movement.**

I. INTRODUCTION

Electromyography (EMG) is the superposition of the motor unit action potential (MUAP) of many muscle fibers in time and space. Surface Electromyography (sEMG) is a comprehensive effect of EMG of superficial muscle and electrical activity on the skin surface, which can reflect the neuromuscular activity to a certain extent. Therefore, sEMG, which has an important practical value, is widely used in clinical medicine, ergonomics, rehabilitation medicine and sports science fields. There is a consensus that the patterns of EMG signals contain information about the movements of the human body. In the human movement, body balance is a vital part to ensure normal human life. The sensory system of maintaining the posture balance generally includes vision, proprioception and vestibular sense, which is clinically referred as "Equilibrium Triad". There are lots of studies of EMG classification and body balance analysis individually but only few relate them together.

EMG signals have been used by numerous researchers for classification of body gesture, movement status, myopathy or other fields. Lucas's research [1] applied Discrete Wavelet Transform (DWT) as the representation space and Support Vectors Machine (SVM) as classifier to classify six hand movements. Alkan et al [2] used discriminant analysis and SVM classifier to classify four different arm movements using the mean absolute value (MAV) as the feature input to the classifier.

Some groups also applied EMG classification in body movements [3] [4]. Bajaj and Kumar [5] intended to classify the normal and abnormal EMG signals. They used empirical-mode-decomposition (EMD) method to decompose sEMG signals into Intrinsic Mode Function (IMFs) which is the function of the two features-number of extrema (NE) and zero crossings (ZC). Furthermore, some recent studies [6] [7] [8] applied the EMG classification in myopathy analysis. One of them [8] used Ensemble-EMD, which is an improvement of EMD for classification. Five time-domain features were used in this research: waveform length (WL), zero crossings (ZC), slope sign changes (SSC), Willison amplitude (WA), root mean square (RMS).

For the posture balance, Horlings et al [9] engaged in distinguishing between normal and deficient balance control due to vestibular sense loss (VL) or proprioception loss (PL) using pelvis and shoulder sway measures. Hansson et al [10] did a research on the effect of vision, proprioception and the position of the vestibular organ on postural sway. Patel's study [11] illustrated how the foam surface affected the proprioceptive sense on postural stability assessment while standing.

The previous studies have made deep analyses in posture balance, and achieved high classification accuracy. However, there is little research applied EMG classification in body balance related to "Equilibrium Triad". In this study, we collected the sEMG on calf muscle of the single-legged standing subjects, when they are interfered by different means, including vision loss, proprioception loss, vestibular sense loss or the combination of them. We intend to extract the features of sEMG and try to classify whether the subjects are losing one of the sense by SVM. The combination of different features and muscles has been utilized to achieve desired classification results.

The remainder of this article is organized as follows. The methods including data acquisition, data collation and preprocessing, feature exaction and classification are presented in Section II. The result and discussion are presented in Section III. Finally, conclusions are drawn in Section IV.

II. METHODOLOGY

The whole data collection and classification procedure of this study is shown in Fig. 1.

A. Subject Information and Experiment Overview

8 healthy young people of similar age, including 4 males and 4 females, participated in this experiment. Between the male and female subjects, the body height and body weight are positively correlated with each other. After the initial balance assessment, subjects are ensured to have a similar

[1] Faculty of Engineering and Information Technology, University of Technology, Sydney, NSW 2007, Australia; [2] Biomedical Engineering, School of Engineering, Sun Yat-sen University. Email: Hairong.Yu@student.uts.edu.au; Kairui.Guo@student.uts.edu.au; luoj26@mail.sysu.edu.cn; Kai.Cao-1@student.uts.edu.au; Hung.Nguyen@uts.edu.au; Steven.Su@uts.edu.au

978-1-5090-2809-2/17/$31.00 ©2017 IEEE

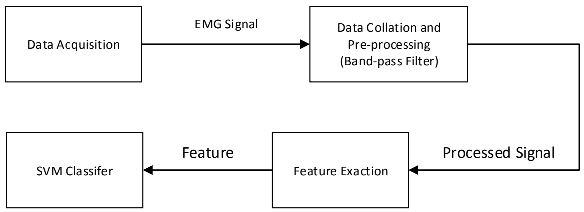

Fig. 1. The procedure of this research.

balance ability. The subjects are without abnormalities disease; nervous system, motor system and the sense organ are all in a normal status; no history of vertigo; occasional but not regular exercise. Before the test, they did not take drugs that may affect the balance function; no drinking; no carrying out a special balance training. An information sheet is given and all the participants signed a consent form before the experiment. The experimental site is shown in Fig. 2.

Fig. 2. The three scenarios of one-leg standing subjects during experiment. From left to right: T1 (proprioceptive senses lost); T5 (vision lost); T2 (proprioceptive senses and vision lost).

Subjects should be assessed by subjective observation of balance and Tinetti equilibrium gait scale assessment [12] to ensure the basic balance ability:

- Subjects should score up to 24 points in the Tinetti assessment which the full score is 28.
- Subjective observation of the balance ability assessment means that the subjects should meet the following requirements in Table I when they are standing by single-leg.

The details of the subjects are shown in Table II.

In the experiment, eye closing can completely remove visual information. Head-back can partially interfere with a correct input of vestibular information. While foam base can significantly interfere with information of the proprioception.

TABLE I
SUBJECTIVE OBSERVATION OF THE BALANCE ABILITY ASSESSMENT

Assessment	Time
Eyes-closing Noramal base Normal head position	10s
Eyes-closing Noramal base Head-back	4s
Eyes-closing Foam base Normal head position	5s

TABLE II
DETAILS OF THE SUBJECTS

NO.	Gender	Age	Height(cm)	Weight(kg)	Score
01	Male	20	166	46	28
02	Male	20	172	60	28
03	Male	19	183	75	28
04	Male	18	187	70	28
05	Female	21	153	36	28
06	Female	21	156	60	28
07	Female	21	163	53	28
08	Female	20	168	53	28

During the experiment, the subjects are allowed to stand by one leg under different interference conditions. The duration of each test is 20 seconds, three times for each test, and the rest time is not less than 2 minutes after each test. The assignment of the experiment is shown in Table III.

TABLE III
INTERFERENCE METHOD IN EACH TEST

Test	Vision	Proprioception	Vestibular sense
T1	Eyes-opening	Normal	Foam base
T2	Eyes-closing	Normal	Foam base
T3	Eyes-closing	head-back 50°-55°	Foam base
T4	Eyes-opening	Normal	Common base
T5	Eyes-closing	Normal	Common base
T6	Eyes-closing	head-back 50°-55°	Common base

B. Data Acquisition

During the experiment, the sEMG signal of Gastrocnemius, Soleus Muscle, Tibialis Anterior Muscle, Extensor Digitorum Longus, Peroneal Muscle are recorded. Before surface electrode placement, the leg is cleaned with ethyl alcohol. The function of the calf muscles are as followings [13].

- Gastrocnemius: Make foot bent down and assist knee bending.
- Soleus Muscle: Drive standing, rotating and foot lifting.
- Tibialis Anterior muscle: Assist Dorsiflexion.
- Extensor Digitorum longus: Stretch toes.
- Peroneal Muscle: Make foot adapted to uneven ground.

6-channel sEMG data are acquired by DAQ acquisition card of NI, which is connected to a PC. We use the Labview program to achieve the synchronous monitoring and storage of sEMG signal.

C. Data Collation and Preprocessing

Due to the instability of laboratory equipment, the noise from other equipment in the lab and the acquisition difficulty of some muscle signal, the features of Extensor Digitorum Longus and Peroneal Muscle are not obvious. In the final classification procedure, there are 14 groups of data valid for the Gastrocnemius, Soleus Muscle and Tibialis Anterior Muscle. There are 17 groups of data valid for the Soleus Muscle and the Tibialis Anterior Muscle.

The first 20,000 data points are selected and filtered. Sampling is performed at 1000 Hz and bandpass filtered between the frequency of 20-450hz.

D. Feature Extraction

The following features are extracted for classification [2] [8]. The time index of the recorded sEMG signal is n. $x(n)$ is the sEMG signal at time n. And the total number of samples to be analyzed is N.

1) Root Mean Square (RMS)
   RMS is often used to describe the static characteristics of the data. It mainly expresses the change of sEMG amplitude and reflects the effective value of the potential activity. It is the average level of muscle discharge over a period of time.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x(n)^2}. \tag{1}$$

2) Mean Absolute Value (MAV)
   The absolute value of the individual patterns is used to elaborate the features of the signals [14].

$$MAV = \frac{1}{N}\sum_{n=1}^{N} \left|x(n)\right|. \tag{2}$$

3) Zero Crossings (ZC)
   ZC is a total number of the signal switching from positive amplitude to a negative one. It can indicate the frequency with which the signal undergoes obvious changes. The sgn is a signum function and a is a user defined threshold.

$$ZC = \sum_{n=2}^{N} f(n), \tag{3}$$

   where

$$f(n) = \begin{cases} 1, & \text{if} \quad sgn(-x(n) \times x(n-1)) = 1 \\ & \text{and} \left|x(n) - x(n-1)\right| \geq a \\ 0, & \text{otherwise.} \end{cases}$$

4) Waveform Length (WL)
   The information, such as amplitude, frequency and duration of the waveform, in recorded sEMG signal can be captured by WL.

$$WL = \sum_{n=2}^{N} \left|x(n) - x(n-1)\right|. \tag{4}$$

E. Classification

SVM (Support Vector Machine) [15] is a useful technique for data classification. If there is a data set of training $(\mathrm{x}_i, y_i), i = 1, ..., l$ where $\mathrm{x}_i \in R^n$ and $\mathrm{y} \in \{1, -1\}^l$, the solution of the optimization problem Eq.(5) can be used to construct the SVM classifier:

$$\min_{\mathrm{w}, b, \xi} \quad \frac{1}{2}\mathrm{w}^T\mathrm{w} + C\sum_{i=1}^{l}\xi_i$$

subject to

$$y_i(\mathrm{w}^T\phi(\mathrm{x}_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0. \tag{5}$$

Furthermore, $\mathrm{K}(\mathrm{x}_i, \mathrm{x}_j) \equiv \phi(\mathrm{x}_i)^T\phi(\mathrm{x}_j)$ is called the kernel function. One of the basic kernels is radial basis function(RBF):$\mathrm{K}(\mathrm{x}_i, \mathrm{x}_j) = exp(-\gamma \parallel \mathrm{x}_i - \mathrm{x}_j \parallel^2), \gamma > 0$.

We use Libsvm toolbox (https://www.csie.ntu.edu.tw / cjlin/libsvm/oldfiles/index-1.0.html) and select RBF kernel function in this study. The Matlab program automatically finds the appropriate value of C and γ in a certain range.

III. Results and Discussion

Various combination of features (MAV, RMS, ZC, WL) and muscles (Gastrocnemius (G), Soleus Muscle(S) and Tibialis Anterior Muscle (T)) are taken in SVM classifier. Since the vestibular sense cannot be totally removed, the classification of T4 (preserving all senses) and T5 (vision loss), as well as the classification of T4 (preserving all senses) and T1 (proprioception senses loss) are firstly performed at first. The performance of the classifier is measured by the classification accuracy rate(AR) [16], which is defined as Eq. (6).

$$AR = \frac{Number\ of\ Correctly\ Samples}{Total\ Number\ of\ Testing\ Samples} \times 100(\%). \tag{6}$$

The accuracy of the classification is summarized in Table IV and Fig. 3.

TABLE IV
Accuracy rate of classification(T4 with T1 and T4 with T5).

Muscle	Feature	T4 vs T5	T4 vs T1	Train:Test
G+S+T	RMS+MAV+ZC	64.29%	42.86%	7:7
G+S+T	RMS+MAV	78.57%	50.00%	7:7
G+S+T	RMS	78.57%	50.00%	7:7
G+S+T	MAV	64.29%	35.71%	7:7
S+T	RMS+MAV+ZC+WL	56.25%	37.50%	9:8
S+T	RMS+MAV+ZC	56.25%	37.50%	9:8
S+T	RMS+MAV	75.00%	68.75%	9:8
S+T	RMS	75.00%	68.75%	9:8
S+T	MAV	56.25%	62.50%	9:8
S	RMS+MAV	75.00%	75.00%	9:8
T	RMS+MAV	68.75%	50.00%	9:8

We selected 7 training groups with 7 testing groups for using all three muscles (G+S+T) and 9 training groups with 8 testing groups for the rest of the cases according to the valid data of different combinations for some cases. The accuracy rate for some cases is not high enough due to the complexity of muscle activity and synergistic effect. However, in terms of the test categories, the accuracy rate for T4 and T5 is generally higher than T4 and T1. This indicates that in regards to muscle activity status, the comparison between removal of visual and normal circumstance is more significant than the contrast of removing proprioception and normal circumstances. In the aspect of feature exaction, WL

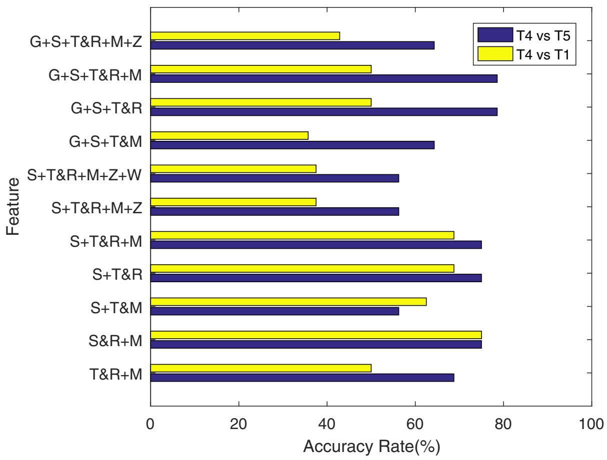

Fig. 3. Accuracy rate comparison of classification(T4 with T1 and T4 with T5).

has no obvious effect on the classification result, and after removal of ZC, the classification accuracy is improved. When we compare the accuracy of using RMS and MAV and both of them, it indicates that RMS plays a more positive role on the classification results. Regarding the muscles, when adding Gastrocnemius signal, the classification result is slightly better than using only Soleus Muscle and Tibialis Anterior Muscle.

Due to time and equipment limitation, the current experimental samples are not sufficient, the conclusion requires more experiments to validate. In the view of the complicated movement of different muscles during balance movement, the selection and measurement of muscles can also be further studied. Besides, the combination of the kinematic signal can also be considered. In the future study, We will record the force data by a force platform and calculate the position of the center of gravity. In this way, we can relate the shaking status of subjects to this study. Furthermore, the classification for the other test (T2, T3 and T6) can be carried out to explore a deeper relation in “Equilibrium Triad”. In addition, more subjects are needed to eliminate the individual differences, including height, weight and their balance ability or the way they adjust their posture when they lose their balance.

IV. Conclusion

In this study, sEMG signal is used to classify whether the subjects lack proprioception or vision during balance movement. This work is a significant but still preliminary step towards the accuracy classification. Due to the small number of experimental samples, the complexity of muscle activity in the balance movement for various of the subjects, the classification results need to be further improved. Based on the experimental results, it is concluded that the classification between vision loss and normal conditions is more obvious than the classification between proprioception loss and normal condition. As for the feature selection, the RMS feature and the sEMG signal of Gastrocnemius play a positive role in classification. However, further research with more subjects and trial of muscles and features is necessary to carry on.

Acknowledgment

The authors would like to thank Biomedical Engineering laboratory in Sun Yat-sen University for providing the experimental equipment and the subjects who participated in the experiment. Special thanks to Professor Rong Song for giving the guidance in the experiment.

References

[1] M.-F. Lucas, A. Gaufriau, S. Pascual, C. Doncarli, and D. Farina, “Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization,” *Biomedical Signal Processing and Control*, vol. 3, no. 2, pp. 169–174, 2008.

[2] A. Alkan and M. Günay, “Identification of EMG signals using discriminant analysis and SVM classifier,” *Expert Systems with Applications*, vol. 39, no. 1, pp. 44–47, 2012.

[3] Z. O. Khokhar, Z. G. Xiao, and C. Menon, “Surface EMG pattern recognition for real-time control of a wrist exoskeleton,” *Biomedical engineering online*, vol. 9, no. 1, p. 1, 2010.

[4] Z.-g. Yan, Z.-z. Wang, and X.-m. Ren, “Joint application of feature extraction based on EMD-AR strategy and multi-class classifier based on LS-SVM in EMG motion classification,” *Journal of Zhejiang University SCIENCE A*, vol. 8, no. 8, pp. 1246–1255, 2007.

[5] V. Bajaj and A. Kumar, “Features based on intrinsic mode functions for classification of EMG signals,” *International Journal of Biomedical Engineering and Technology*, vol. 18, no. 2, pp. 156–167, 2015.

[6] A. Subasi, “Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders,” *Computers in biology and medicine*, vol. 43, no. 5, pp. 576–586, 2013.

[7] L. Silva, J. R. Vaz, M. A. Castro, P. Serranho, J. Cabri, and P. Pezarat-Correia, “Recurrence quantification analysis and support vector machines for golf handicap and low back pain EMG classification,” *Journal of Electromyography and Kinesiology*, vol. 25, no. 4, pp. 637–647, 2015.

[8] G. Naik, S. Selvan, and H. Nguyen, “Single-channel EMG classification with ensemble-empirical-mode-decomposition-based ICA for diagnosing neuromuscular disorders,” 2015.

[9] C. Horlings, U. Küng, B. Bloem, F. Honegger, N. Van Alfen, B. Van Engelen, and J. Allum, “Identifying deficits in balance control following vestibular or proprioceptive loss using posturographic analysis of stance tasks,” *Clinical Neurophysiology*, vol. 119, no. 10, pp. 2338–2346, 2008.

[10] E. E. Hansson, A. Beckman, and A. Håkansson, “Effect of vision, proprioception, and the position of the vestibular organ on postural sway,” *Acta oto-laryngologica*, vol. 130, no. 12, pp. 1358–1363, 2010.

[11] M. Patel, P.-A. Fransson, D. Lush, and S. Gomez, “The effect of foam surface properties on postural stability assessment while standing,” *Gait & posture*, vol. 28, no. 4, pp. 649–656, 2008.

[12] M.-R. Lin, H.-F. Hwang, M.-H. Hu, H.-D. I. Wu, Y.-W. Wang, and F.-C. Huang, “Psychometric comparisons of the timed up and go, one-leg stand, functional reach, and Tinetti balance measures in community-dwelling older people,” *Journal of the American Geriatrics Society*, vol. 52, no. 8, pp. 1343–1348, 2004.

[13] T. Häggmark, H. Liedberg, E. Eriksson, and T. Wredmark, “Calf muscle atrophy and muscle function after non-operative vs operative treatment of Achilles tendon ruptures,” *Orthopedics*, vol. 9, no. 2, pp. 160–164, 1986.

[14] K. Englehart and B. Hudgins, “A robust, real-time control scheme for multifunction myoelectric control,” *IEEE transactions on biomedical engineering*, vol. 50, no. 7, pp. 848–854, 2003.

[15] C.-W. Hsu, C.-C. Chang, C.-J. Lin, *et al.*, “A practical guide to support vector classification,” 2003.

[16] G. Li, A. E. Schultz, and T. A. Kuiken, “Quantifying pattern recognition - Based myoelectric control of multifunctional transradial prostheses,” *IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 18, no. 2, p. 185, 2010.