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Use of Forehead Bio-signals for Controlling an Intelligent Wheelchair

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Abstract: This paper presents a novel method to classify human facial movement based on multi-channel forehead bio-signals. Five face movements form three face regions: forehead, eye and jaw are selected and classified in back propagation artificial neural networks (BPANN) by using a combination of transient and steady features from EMG and EOG waveforms. The identified face movements are subsequently employed to generate five control commands for controlling a simulated Intelligent Wheelchair. A human-machine interface (HMI) is designed to map movement patterns into corresponding control commands via a logic control table. The simulation result shows the feasibility and performance of the proposed system, which can be extended into real-world applications as a control interface for disabled and elderly users.

Keywords: Intelligent Wheelchair, Neural Networks, Face Movement Classification, EMG, EOG

I. INTRODUCTION

Facial movement plays an important role in human computer interaction for rehabilitation of disabled people. Wheelchair users who have limitation in controlling an electric-powered wheelchair with their limbs, for example, people who suffer from spinal cord injury, quadriplegia, hemiplegia or amputation, and on the other hand have potential ability in generating facial movement, can adopt face movements as an alternative control method for HMI purpose. Compared with limb or hand, face region contains complicated muscle groups that can generate delicate movements especially in forms of facial expressions and specific face motions from which plenty of information can be retrieved by attaching sensors to designated face area.

Various face movement based input interfaces such as sip and puff controller, infrared head controller [1], head gesture controller [2], voice controller [3] and eye-gaze controller [4] are developed for manipulability, safety, and comfortableness of the user. Besides, signals such as Electromyography (EMG), Electrooculography (EOG) and Electroencephalography (EEG) can also be received from specific muscle groups and organs on the face. By using these bio-signals, multiple HMIs are developed in [5][6][7] for controlling the electric-powered wheelchairs.

Based on the Intelligent Wheelchair platform jointly developed by Chinese Academy of Sciences and University of Essex [8], Tsui et al. built an HMI interface using finite state machines for controlling the intelligent wheelchair via forehead EMG and EOG signals. In [9], Firoozabadi distinguished five facial movements through forehead EMG signals and converted them into five wheelchair control commands. Based on their work, this paper introduces a new control strategy based on further classified human facial movements using a combination of both transient and steady features from EMG and EOG signals. Extracting transient and steady features by fusing multiple bio-signals such as EMG and EOG for facial movement classification allows for a more reliable and flexible wheelchair control. The key issue in this experiment is to effectively avoid noisy face movements made by the user during talking and looking around.

The rest of the paper is organized as follows. Section II describes the system architecture which consists of three parts: a wearable sensory device Cyberlink^{TM}; an Intelligent Wheelchair system and the HMI. Control movement and feature subset selection is presented in Section III. Section IV discusses the methodology for extracting useful features from EMG and EOG waveforms and combining them into recognizable movement patterns. Experimental results are given in Section V, which show the feasibility and performance of the proposed system in simulated setting. Finally, a brief summary and potential future extension of the system are given in Section VI.

II. SYSTEM ARCHITECTURE

The proposed experimental system contains three parts. The first part is the data acquisition device Cyberlink^{TM} [8], which is composed of 1) a data processing box and 2) a wearable headband. The second part of the system is an Intelligent Wheelchair platform which is used for evaluating real-world performance of the control system in the future. The third part is the human machine interface which is responsible for extracting features and classifying selected movement patterns and mapping the classified patterns into wheelchair control commands; Details of this part will be discussed further in Section III and IV.

A. *Data Acquisition*

The raw bio-signals from forehead surface skin are adopted from the user by wearing a custom-built sensory headband (as shown in Fig. 1 left). Three electrophysiology sensors embedded in a headband are consequently attached to user forehead skin by fastening the wearable band to the vertical centre of the user forehead (as shown Fig. 1 left).

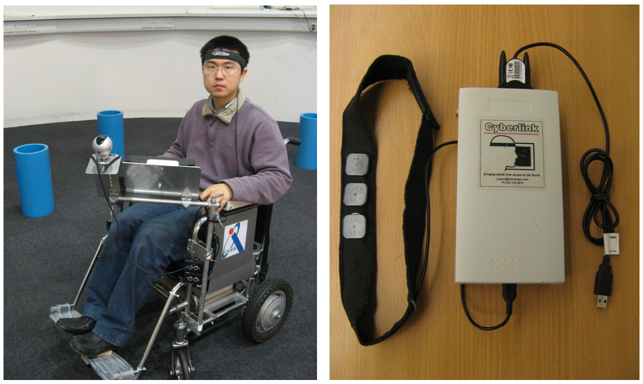

Fig. 1 A subject wearing the headband in Intelligent Wheelchair (left); The Cyberlink^{TM} data acquisition box and the headband (right).

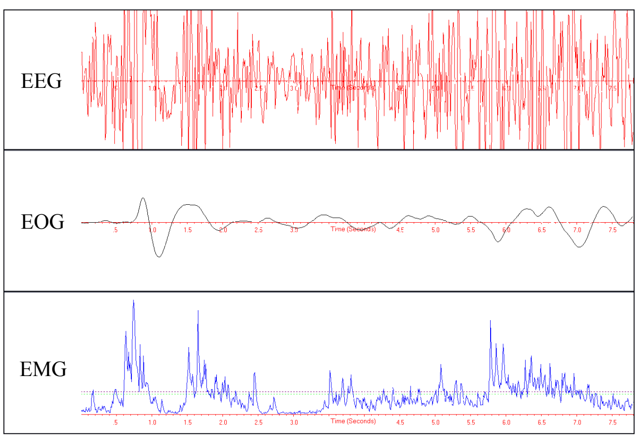

Fig. 2 Sample EEG, EOG and EMG data from Cyberlink^{TM}.

The faint surface bioelectricity signals obtained from three sensors (in milli-volt scale) are then transmitted to amplitude amplifiers and magnified into magnitude distinguishable signals and hence encoded into digital EEG, EOG and EMG data by a frequency decomposition process of passing through band pass filters and A/D converters. The frequency ranges for the three-channel waveforms shown in Fig. 2 are: for EEG signal, the range is 0.5 ~ 45Hz, while for EOG signal, the range is 0.2 ~ 3.0Hz, and for EMG signal, the range is 70~1000Hz. Note that in this experiment, the EEG signal adopted from Cyberlink^{TM} device is abandoned.

B. *The Intelligent Wheelchair*

As shown in Fig. 1 left, the wheelchair test bed is an electric-powered mobile vehicle equipped with an industrial PC and a built-in motor controller board embedded with a digital signal processing (DSP) unit; Multiple sensors such as encoders, ultrasonic sensor arrays and laser range finder are equipped on board the vehicle. These sensors transmit distance information of surrounding obstacles to on-board computer via standard RS232 ports by which a basic obstacle avoidance function is performed. Detailed description of the Intelligent Wheelchair system concerning its hardware structure can also be found in [2].

C. *Human-machine Interface (HMI)*

The complete structure of the HMI system is depicted in the Fig. 3. As shown, the core of the system is a human computer interface (HCI) consists of four subsequent procedures i.e. data segmentation, feature extraction, classification and logic control.

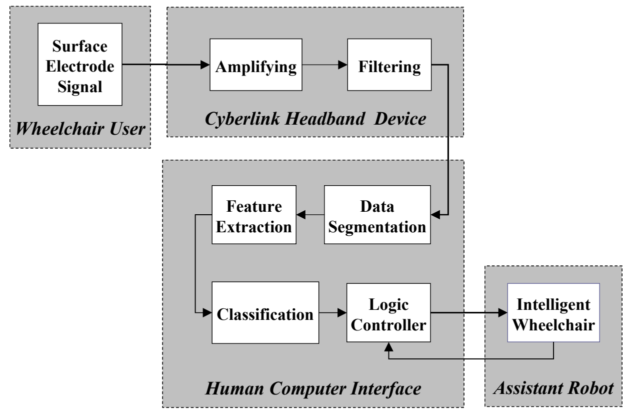

Fig. 3 The HMI System Architecture.

III. Control Movement and Feature Subset Selection

A. *Control Movement Selection*

Five face movements namely forehead single click (FSC), forehead double click (FDC), left eye closing (LEC), right eye closing (REC) and rhythmic jaw movement (RJM) are selected as control movements due to a joint consideration of uniqueness and distinguishability of movement patterns reside in their EMG and EOG waveforms and the easiness for the user to exert and learn.

FSC is a short time eyebrow lifting movement and FDC is produced by two consecutive FSC. The process of LEC and REC start from closing movement of left or right eye and last by keeping the eye closed. The finishing of the movement is marked by the opening of the closed eye. RJM is a repetitive jaw movement that can be produced by the user imitating a jaw clenching chewing-like motion. These five control movements are easy for the user to perform and learn as they are derived from the natural facial movement in daily life.

B. *Transient Feature Selection*

Transient features are waveform features picked up during the transition of the selected movement patterns. Multiple waveform features such as number of continuous outshoots (NCO), local maximum value (LMAV), local minimum value (LMIV) an local mean value (LMV) are extracted and combined into transient patterns. In this experiment, four transient patterns namely FSC pattern, FDC pattern, LEC pattern and REC pattern are retrieved from selected face movements. These patterns are directly treated as event triggers when identified by the system. This means, if any one of these four transient patterns is detected in the respective waveform, the trigger assigned to the pattern will be activated to drive a later process, which can be either a feature abstraction and classification process (depicted in section V) on steady patterns or an immediate execution of a control command. In this experiment, four triggers named after their movement patterns are denominated as:

- forehead single click trigger (FSCT)
- forehead double click trigger (FDCT)
- left eye closing trigger (LECT)
- right eye closing trigger (RECT).

C. Steady Feature Selection

Steady features are extracted from EMG waveform segments after a data segmentation process (depicted in section V). For each of the divided waveform sections, a series of steady features from both time and frequency domains are calculated. The set of steady features calculated by statistical means in time domain are:

- Mean Absolute Value (MAV)
- Root Mean square (RMS)
- Waveform Length (WL)
- Zero Crossing (ZC)
- Slope Sign Changes (SSC)

The set of frequency domain steady features calculated after discrete Frontier transform are:

- Frequency mean (FMN)
- Frequency median (FMD)
- Frequency ratio (FR)

These features from both time and frequency domains are combined together and classified by BPANN into three steady movement patterns stated in section IV and V.

IV. Feature Extraction and Pattern Construction

In order to construct recognizable movement patterns, a number of transient and steady features are extracted from EMG and EOG waveforms during the user performing the corresponding movements. The extracted features are subsequently assembled into feature groups to label a number of seven movement patterns selected from five control movements. The constructed seven movement patterns (four transient patterns and three steady patterns) are: two transient patterns from EMG waveform are FSC pattern and FDC pattern; and the rest two from both EMG and EOG waveforms are LEC pattern and REC pattern; while the other three steady patterns from EMG waveform are denominated as normal (NR) pattern, eye closing (EC) pattern and rhythmic jaw movement (RJM) pattern.

A. Transient Pattern Recognition

<u>a). Forehead single click and forehead double click (FSC&FDC) pattern recognition</u>: We calculate one step gradient function $\nabla f(n)$ of the discrete EMG waveform function $f(n)$ displayed in Fig. 4 as:

$$\nabla f(n) = \begin{cases} f(n) - f(n-1) & n = 2\ldots, N., \\ 0 & n = 1. \end{cases} \quad (1)$$

where $f(n)$ is the quantified absolute deviation value (QADV) of raw EMG amplitude at the n^{th} discrete sampling with a fixed sampling rate of 100 Hz, N is the total number of EMG samplings. The value of $f(n)$ reflects the extent of tension in the target muscle, the tenser the muscle contracts the bigger the value will be. $f(n)$ is set between 0 and 2048 by Cyberlink^{TM} device since the device is originally designed for effortless manipulation, any bigger EMG QADV result from heavy face movements is truncated to 2048. By defining $f(n)$ and $\nabla f(n)$, we define a FSC state function $S(n)$ as:

$$S(n) = \begin{cases} 1 & if \left|\{n : f(n) \ge h, n \in \Delta T\}\right| \ge \lambda \ \& \\ & \sum\limits_{n \in \Delta T_1} \dfrac{f(n)}{n_1} \le h_1 \ \& \sum\limits_{n \in \Delta T_2} \dfrac{f(n)}{n_2} \le h_2, \\ 0 & otherwise. \end{cases} \quad (2)$$

where T_1, T_2, T_3 and T_4 are time points which divide EMG waveform in time domain and determine the length of the time intervals (as marked in Fig. 4). ΔT_1, ΔT_2 and ΔT are time intervals in which the features of EMG waveform are calculated. T_2 and T_3 are settled on points where LMAV and LMIV of gradient function $\nabla f(n)$ are reached (as shown in Fig. 4), while T_1 and T_4 are settled upon an experiential length of time away from T_2 and T_3 in which the range of FSC movement is covered. The length of the time intervals ΔT_1, ΔT_2 and ΔT can be calculated by: $\Delta T = T_3 - T_2$, $\Delta T_1 = T_2 - T_1$, $\Delta T_2 = T_4 - T_3$; λ is the threshold set for EMG NCO value calculated in time interval $\Delta T_s = T_4 - T_2$, EMG NCO is the number of continuous $f(n)$ samplings whose value exceed an designated threshold h; n_1, n_2 are the total number of samplings during ΔT_1 and ΔT_2 respectively; h_1, h_2 are the thresholds set for LMV of $f(n)$ over time intervals ΔT_1 and ΔT_2. The above parameters can be customized to each user and in this experiment ΔT_1, ΔT_2 and ΔT are set to 150 ms, h_1, h_2 and h are set to 400, 600 and 2000 respectively.

The waveform in Fig. 4 shows an example of FSC pattern recognition process in which the pulse in the middle of $f(n)$ is recognized as effective click and activates FSCT by setting $S(n)$ value to 1, the other two in front and behind are filtered out as noise due to their weak eyebrow lifting power and overtime lifting respectively.

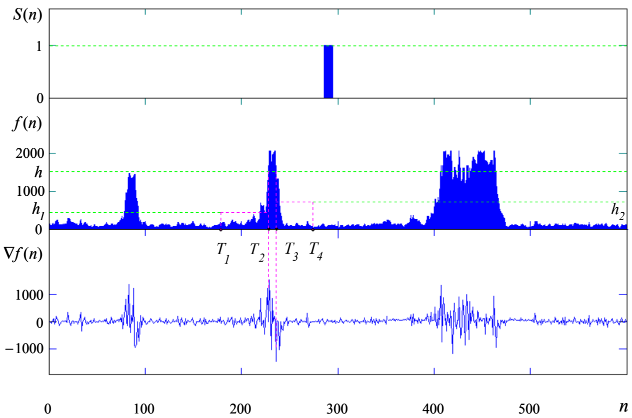

Fig. 4 Forehead single click (FSC) pattern recognition.

Since FSC can be identified from EMG waveform, we define a new trigger composed of two consecutive FSC patterns within a designated time interval ΔT_d as FDCT. This trigger is used for activating a control command named 'Stop' which is a emergency stop command used for reducing the speed of the wheelchair at a maximum deceleration, ΔT_d is set to 150 ms in this experiment.

<u>b). Left and right eye closing (LEC&REC) patterns recognition</u>: The State function of eye closing trigger $K(n)$ is described as:

$$K(n)=\begin{cases} 1 & if\left|\{n:g(n)\geq h, n\in\Delta T_1\}\right|\geq\lambda_1\ \& \\ & \left|\{n:g(n)\leq -h, n\in\Delta T_2\}\right|\geq\lambda_2 \\ -1 & if\left|\{n:g(n)\leq -h, n\in\Delta T_1\}\right|\geq\lambda_1 \\ & \&\left|\{n:g(n)\geq h, n\in\Delta T_2\}\right|\geq\lambda_2 \\ 0 & otherwise. \end{cases} \quad (3)$$

where $K(n)$ is the state function (as shown in the first column of Fig. 5) which indicates the states of the eye movement triggers, for $K(n)=1$ represents LECT is setup while $K(n)=-1$ means RECT is enabled. $g(n)$ is the discrete waveform function of EOG samplings (as shown in Fig. 5), the absolute value and phase of SINE-like waveform $g(n)$ reflects the speed and direction of lateral eye movements. ΔT_1 and ΔT_2 are time intervals divided by T_1, T_2, T_3 and T_4, in which NCO of $g(n)$ values that either above h or below $-h$ are counted, λ_1 and λ_2 are thresholds set for the NCO counted in time interval $\Delta T_1 = T_2 - T_1$ and $\Delta T_2 = T_4 - T_3$. λ_1 and λ_2 are user dependent parameters and can be preset by user on their own condition, in this experiment, they are both set to 5.

The diagram in Fig. 5 shows a complete process of LEC movement recorded by synchronous EOG and EMG waveforms. As shown in Fig. 5, the SINE-like EOG signal fluctuates enormously at the beginning and finishing of the LEC as LEC movement can cause concomitant lateral eye movements. At the same time, a simultaneous change in EMG waveform function $f(n)$ is aroused by the contracted muscles as a result of LEC movement. Thus, after $g(n)$ is filtered by rules denoted in equation (3), LECT and RECT are set up separately at the beginning and finishing of LEC. The triggers are then used to drive a later process of EMG pattern classification to uniquely feature entire LEC pattern. REC movement pattern can be recognized in a similar way as the variation of $g(n)$ during LEC and REC are symmetry by time series axis n.

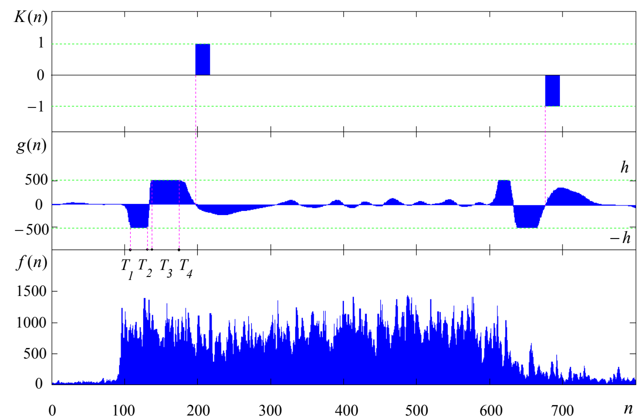

Fig. 5 Left eye closing (LEC) pattern recognition.

For the selected face movement such as LEC or REC shown above, the movement pattern can be featured by a transient EOG pattern accompanying with a simultaneous steady EMG pattern (as shown in Fig 6); As a result, LEC or REC patterns can be recognized by employing both transient EOG and steady EMG patterns. Compared with recognizing movement patterns by steady EMG patterns along, this strategy can avoid noisy patterns in eye blink and facial expression movements during the user talking and looking around.

B. Steady Pattern Construction

Steady patterns are classified in BPANN by windowing EMG waveform into segments and extracting designated time and frequency domain features described in section III. Three EMG waveform patterns namely normal (NR) pattern, eye closing (EC) pattern and rhythmic jaw movement (RJM) pattern in Fig. 6 are selected as the EMG steady patterns.

NR is an inclusive pattern which has a group of subset movement patterns. As shown in the first row of Fig. 6, NR is composed of five subset movement patterns namely relax, generated by the user relaxing face muscles; random expression, generated by the user performing talking and looking around; single click and double click, generated by FSC and FDC movements respectively; and frown, generated by eyebrow lift holding movement. In this experiment, the training samples of BPANN for NR pattern are collected by the subject deliberately performing the above five designated movements and especially, talking and looking around movements are sampled intensively to ensure the ergoclicity of the NR sample set.

As shown in the second row of Fig. 6, EC pattern contains two subset patterns namely left eye close and right eye close which are the simultaneous EMG patterns generated in LEC and REC movements respectively. Considering that there may be variation in steady EMG features (MAV in particular) between LEC and REC movements with the same user due to the user's personal movement custom in making left and right eye movements, LEC and REC patterns are sampled under same sampling condition with the same total sampling time.

In the third row of Fig. 6, a single movement pattern is classified as RJM. As we can see in the waveform chart, this pattern can be basically distinguished from frequency domain features. Due to its distinctive steady frequency features steady pattern can be reliably classified (shown in Fig. 8), the classification result for this pattern is used to drive control command 'Speed up' directly after recognition.

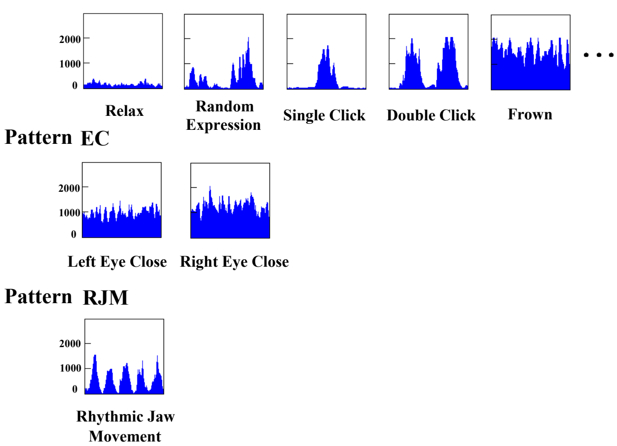

Fig. 6 Steady pattern division of EMG signals

Note the ordinate width of each chart in Fig. 6 represents 50 unit samplings while the abscissa represents $f(n)$.

V. Experimental Results and Analysis

A. Experiment Setup

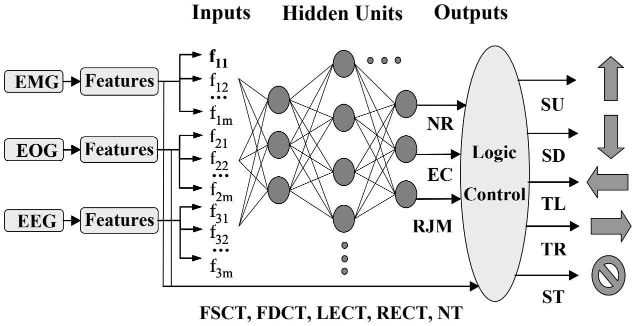

Fig. 7 Schematic diagram of BPANN classification

Fig. 7 is the schematic diagram of the proposed BPANN classification architecture, in which f_{1m} f_{2m} and f_{3m} represent the m^{th} steady feature form EMG, EOG and EEG waveforms respectively. The EEG signal included here is for the purpose of system integration showing potential applicability of Cyberlink^{TM} in the future, in this experiment, only EMG and EOG is applied. As shown in Fig. 7, the BPANN classified steady patterns: NR, EC and RJM together with the triggers from recognized transient patterns: FSCT, FDCT, LECT and RECT are inputted into a logic control table (Table I) and formed into five control commands, namely Speed up (SU), Slow down (SD), Turn left (TL), Turn right (TR) and Stop (ST).

The following table shows the control strategy of the logic table during logic control process in Fig. 7. The first row of Table I lists three classified steady patterns, i.e. NR, EC and RJM, the first column lists five triggers derived from four identified transient patterns.

TABLE I
LOGIC CONTROL TABLE

PATTERN / TRIGGER	NR	EC	RJM
FSCT	SD	N/A	N/A
FDCT	ST	N/A	N/A
LECT	N/A	TL	N/A
RECT	N/A	TR	N/A
NT	N/A	N/A	SU

As shown in Table I, the triggers in the first column are listed in a descending order of FSCT, FDCT, LECT, RECT and NT. The principle of the control logic, taking the second row of the table for example, can be explained as: If trigger FSCT is set and NR is detected, then SD, else N/A. N/A means the corresponding combination is not available and will be filtered out as noise, and the wheelchair will keep the current speed. NT is a trigger set by a designated time period of 400ms in which no other trigger is detected.

B. EMG Segmentation and Classification

In order to testify the applicability of the proposed system, EMG data are collected by the subject performing eight designated face movements (as shown in Fig. 6) in turn, each movement lasts for 8 seconds to avoid muscle fatigue.

The sampled data are then divided into 400ms segments and the steady features presented in section III are extracted from each segment. So far, a number of 390 segments of feature clusters are randomly mixed and divided into two sets: training set (contains 60% of the sample data) and testing set (contains the rest 40% of the sample data). The training set is used for supervised learning process of training different BPANN structures with Levenberg-Marquardt algorithm. All the structures in BPANN structure set that made up of as much as three hidden layers and with a number of 12 neurons each layer at most are trained. After training, all the 390 samples are regressed back into each trained BPANN structure to calculate the performance value R, which evaluates the separability of a neural network structure on the sample data set. Fig. 8 shows the regression results of the selected best performance BPANN structure with a performance value R of 0.98726. As shown, The regression outputs of the selected BPANN structure A with respect to the pattern indices T of the total 390 samples are plotted, and a statistical classification error of 1.79% (7 errors out of 390 pattern samples) is achieved by calculating the best linear fit among outputs of the BPANN and the corresponding sample indices T, by which the three patterns are divided by two decision boundaries with the minimized empirical classification error. The classification result demonstrates the applicability of this experiment system into a real-world electric-powered wheelchair controller.

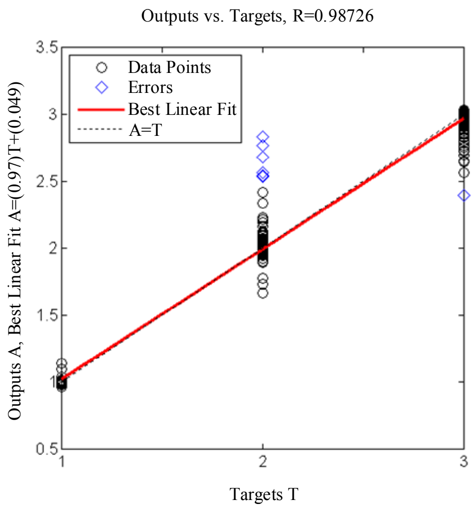

Fig. 8 Best performance BPANN structure with a classification error of 1.79%.

As shown in Fig. 8, target T = 1,2,3 denote indices of three patterns corresponding to RJM, EC and NR respectively, In real-world operation, the error rate of 1.79% can lead to serious failure considering the fact that a user may make hundred of commands each day, however, as the result in Fig.8 shows that the errors are all from the overlapped patterns between Target 2 and 3 i.e. Pattern EC and NR, the strategy of making the EMG patterns be classified only after the EOG triggers i.e. LECT and RECT are set will reduced this error since LEC and REC moments can be jointly featured by transient EOG patterns (LECT and RECT) and steady EMG pattern (NR). This strategy will not bring extra time delay to EMG classification process as long as the transient triggers can be recognized within the EMG segmentation period i.e. 400ms in this experiment.

VI. CONCLUSION AND FUTURE WORK

This paper provides a solution for a new face movement based control method that combines features from both EMG and EOG signals. Different from previous research in [8][9][10], this control method allows the user to control the wheelchair without sharing extra attention to monitor the state of control, so that the user can operate the wheelchair and observing the surrounding environments at the same time. Moreover, facial motion noises such as eye blinks and random facial expression movements can be effectively removed by employing both transient and steady features

Our future work will include bringing more EMG channels from muscle group of different face regions and getting more accurate EOG signals. EMG classification methods such as support vector machine (SVM) and other neural network based algorithms can also be applied to improve the classification speed and accuracy.

Due to the slow respond speed of EEG based control, only EMG and EOG signals are employed in this experiment. However, EEG signals can be applicable in the future experiment due to its reasonable recognition rates and benefits to severely disabled users who can not even make recognizable face movement.

Furthermore, there are still inevitable noises, caused by heavy jerk frowning, heavy nose tilting and tight double eye closing movements that can trigger EOG events and generate EMG related patterns as well; in this experiment, these movements are intentionally avoided by the subject since they are unnatural and seldom made by user in ordinary occasion. Otherwise, these noises can be removed by fusing additional information from other sensors.

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