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EMG and Visual based HMI for hands-free control of an intelligent wheelchair

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***Abstract**: This paper presents a new human-machine interaction (HMI) method designed for hands-free control of electric wheelchairs. Both forehead electromyography (EMG) signals and color face image information is jointly used to identify winking and jaw clenching movements. Five winking and jaw clenching movement patterns are selected and classified, mapping into five control commands to drive a simulated wheelchair in an office environment. Six subjects participated in the experiments and the result shows that this new control method can work well and reliably.*

***Index Terms -** Wheelchair Controller, Face Detection, Eye Close Detection, Boosting, Adaboost, Haar Features, EMG, SVMs.*

I. INTRODUCTION

People with sever physical disabilities such as spinal cord injury, quadriplegia, hemiplegia or amputation cannot control an electric wheelchair using a traditional joystick by hand movements. Therefore, it is necessary to deploy alternative means such as face movement based control. Human face is a remarkable area for studying human machine interaction (HMI) methods. Facial image information plays a key role in understanding human intentions by a computer. The successful utilization of Haar feature based Boosting cascade face detection technique [14] [16] setup an essential foundation work for varies facial image based HMI methods such as eye moment interfaces [1] [3], head gesture interface [9], etc.

Recently, human muscle activity plays an important part in analyzing and understanding human intention too. Due to its fast responding performance, a number of EMG based controllers are developed by using different muscle groups of human body such as limb [5][13], neck [2][10], face[6][15], etc. This paper aims to develop a novel facial HMI which integrates both facial image information and facial EMG signals in order to recognize human control intentions for the real-time control of an intelligent wheelchair. The experiment result is tested by implementing designed control system onto a simulated mobile robot in MobileSim [7] simulator acting as a simulated electric wheelchair.

The rest of this paper is organized as follows. Section II gives a brief introduction of the system architecture and experimental settings. Section III introduces the selected human intentions for control and section IV states the designed control strategies. Section V shows the training process of support vector machines (SVMs) applied on classifying designed EMG movement patterns. Section VI explains Adaboost cascade based image searching technique used for detecting left and right eye close movements. Section VII gives the experiment results of the designed control strategy applied in a simulated office environment. A brief conclusion and further research prospective are given in section VIII.

II. EXPERIMENT SYSTEM

A. System Architecture

As shown in Fig. 1, the system architecture consists of three main parts. The first part is the data acquisition device Brainfinger Cyberlink^{TM} and Logitech^{TM} S5500 web camera. The second part is the human computer interface which is responsible for training and classifying facial movement features, mapping selected facial movements into wheelchair control commands. It has two sub blocks, which are namely data pre-processing block and pattern recognition and control block. The third part is an executable device which can be either a wheelchair or a simulated mobile robot, as shown in Fig. 2 (Left).

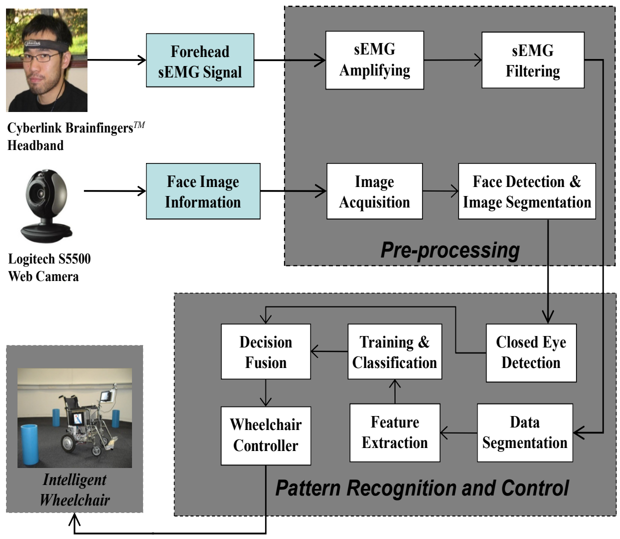


Fig. 1 Block diagram of the proposed system architecture

B. Data Acquisition and Mobile Wheelchair

As shown in Fig. 2 (Left), forehead surface EMG signal and facial image information are collected from subjects by attaching wearable skin surface EMG (sEMG) sensors and fixing camera pointing to user's face. Fig. 2 (Right) gives a close look of the EMG device which consists of a wearable headband and a data acquisition box (DAB). One channel EMG signal is obtained from the user wearing a headband attached with 3 flat EMG electrodes. The DAB contains a series of signal processing algorithms which can turn the amplified raw EMG signals (RES) into averaged EMG waveform (AEW) with a sampling rate of 100Hz.

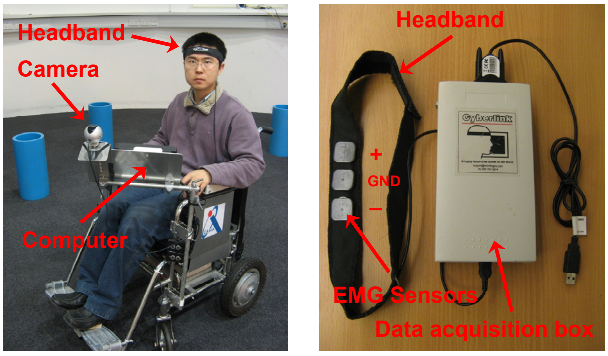


Fig.2 A subject sitting in wheelchair and wearing Cyberlink Brainfingers^{TM} headband (Left); The Cyberlink Brainfingers^{TM} data acquisition box and the headband (Right).

III. Human Intention Recognition

In this research, five facial movements are defined to control the simulated wheelchair, namely left eye close (LEC), right eye close (REC), continuous jaw clenching (CJC), single jaw clenching (SJC) and double jaw clenching (DJC). They are from either jaw clenching or eye close movements.

A. Jaw Clenching Movement:

SJC, DJC and CJC Movement Description

Three jaw clenching movements are generated by user contracting masseter muscle and buccinator muscle (indicated in Fig. 4) with a jaw clenching and chewing-like movement. Three specific jaw clenching movements are named as continuous jaw clenching movement (CJC), single jaw clenching movement (SJC) and double jaw clenching movement (DJC).

Fig. 4 shows the EMG signals sampled when a subject is making three jaw clenching movements i.e. SJC, DJC and CJC. As shown, CJC EMG waveform pattern is produced by making continuous gentle and fast jaw clenching movements. To produce SJC and DJC movements, the subject need to exert short and strong muscle contractions with jaw. Since heavy contraction is coming from the strongest muscle groups on the face, this action can cause a high spike waveform as shown in Fig. 4 and therefore SJC can be easily recognized by a threshold based strategy.

SJC, DJC and CJC Recognition

Torsten and Bernd [6] defined two "*contraction events*" and recognized them with adjustable thresholds applied on EMG waveform amplitudes. Similar to their work, here we pick up SJC and DJC evens based on adjustable waveform thresholds too. As indicated in Fig. 5, SJC is recognized by counting the number of overflows on a preset threshold value H within time ΔT, if the number of overflows exceed a preset value (3 in this experiment), then an EMG amplitude average within time ΔT will be calculated. If the averaged value is less than a set average value, then SJC is detected.

Similarly, DJC event can be detected as finding two successive SJC evens in a fixed time span $2\Delta T+\Delta t$, as depicted in Fig. 5. For recognizing CJC waveforms, we rely on a feature extraction and classification procedure by applying SVM based classification methods, the detailed procedure is discussed in Section V.

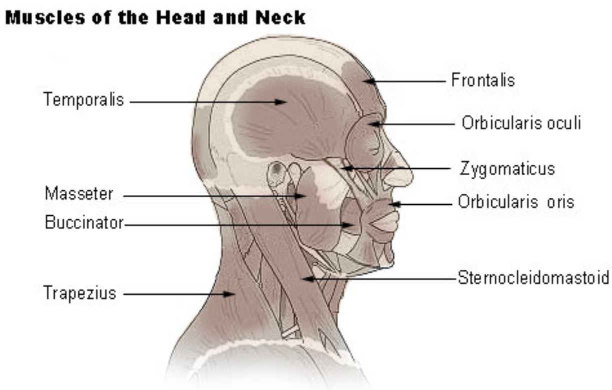


Fig. 3 Muscles of the head and neck [12]

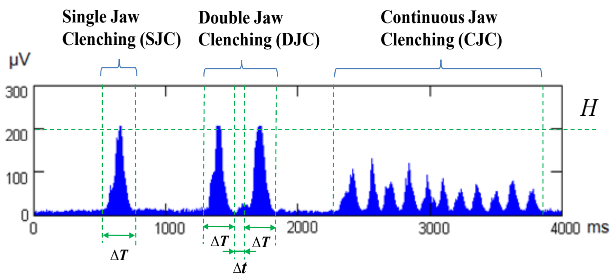


Fig. 4 SJC, DJC, CJC patterns in averaged EMG waveform

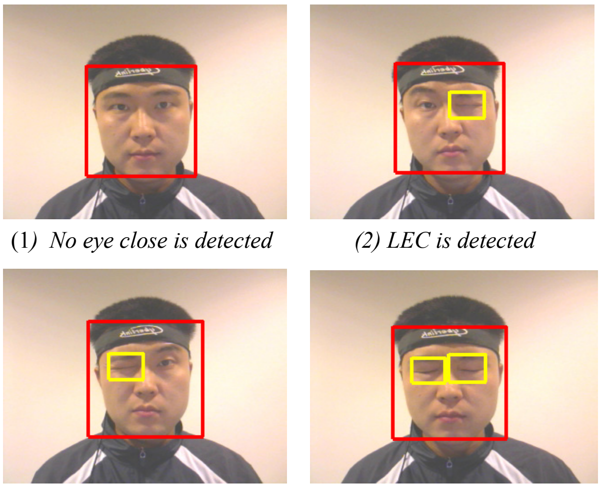
B. Eye Close (Winking) Movement:

LEC and REC Movement Description

The eye close movements employed in control strategy are called left eye close (LEC) and right eye close (REC), they are one eye open and one eye close (winking like) movements. Fig. 5 shows a subject making LEC and REC movements recognized by Adaboost cascade classifier. The eye close movements in this experiment are a class of heavy (squeeze) eye close movements that can be generated by closing and then squeezing the closed eye, and at the same time keeps the other eye open. The squeeze movement arouses a series of muscle contraction activities from 3 major muscle groups around eye which are frontalis, orbicularis oculi and tempolaris muscles.

LEC and REC Recognition

Since LEC and REC movements are featured by both EMG and image information at the same time, LEC and REC movements are identified by classifying features extracted from both forehead EMG waveforms and face image data. Fig. 5 shows the image classification result from Adaboost cascade classifier, and Fig.6 shows the EMG waveform patterns (Class EC) aroused by LEC and REC movements, the detailed classification and training are discussed in section V and VI.



(1) *No eye close is detected* (2) *LEC is detected*

(3) REC is detected (4) Both LEC and REC are detected

Fig. 5 Eye movements detected by Adaboost cascade classifier.

IV. CONTROL STRATEGY

So far, we have picked up five recognizable movements which are SJC, DJC and CJC from jaw movements and LEC and REC from eye movements. In order to apply these five designated movement patterns to an electrical wheelchair controller, a reference from manual joystick control method is taken, and a substitute control method comprising six control commands are designed, these control commands are: Go Forward (GF), Turn Left (TL), Turn Right (TR), Reduce Speed (RS), Stop (ST) and Go Backwards (GB). The logic connections between movement patterns and executable control commands are linked with parallel logic connections as follows:

If Left Eye Close pattern is detected then Turn Left;

If Right Eye Close pattern is detected then Turn Right;

If CJC pattern is detected then Go Forward;

If Single Click pattern is detected then Reduce Speed;

If Double Click pattern is detected then Stop;

If Double Click pattern is detected and the wheelchair has stopped then Go Backwards.

The selected movement pattern detection method can be logically expressed in parallel as follows:

If (Image) Left Eye Close is detected and (EMG) EC is detected then Left Eye Close pattern is detected;

If (Image) Right Eye Close is detected and (EMG) EC is detected then Right Eye Close pattern is detected;

If (EMG) PJM is detected then PJM Pattern is detected;

If (EMG) More than 3 and less than ten overflows over fixed threshold (H) are detected and the average over the period is less than a fixed value then Single Click pattern is detected (threshold based strategy);

If two successive Single Click patterns are detected within a fixed time span ($2\Delta T+\Delta t$*) then Double Click pattern is detected.*

The following paragraph will discuss the details about classification process of EMG (EX, EC and CJC classes) and image eye close patterns (LEC and REC).

V. EMG FEATURE EXTRACTION AND CLASSIFICATION

A. EMG Feature Extraction

Since SJC and DJC patterns can be recognized by the threshold based strategy stated in Section III, there are only two EMG waveform patterns, namely EC and CJC, left to be recognized. As shown in Fig. 6, the whole waveform patterns are divided into three classes which are class EX, class EC and class CJC. EC is an EMG pattern results from LEC or REC movements while CJC is from the periodic jaw clenching movement. Class EX contains all the other possible EMG waveform patterns including patterns from SC and DC movements, and other artefacts aroused by random facial expressions or frown, relax, etc.

As can be seen in Fig. 6, EC and CJC patterns are featured from a combination of time domain and frequency domain features. As evaluated and compared in [11], SVMs can give fast training performance and reliable classification accuracy on EMG data with simple time domain features, hereby we choose SVMs [4] as learning machines to separate CJC and EC from other waveform patterns and artefacts.

Before training SVM classifiers, the EMG data is divided into 200ms (20 samplings) disjoint data segments and a bunch of six features are extracted from each EMG data segment which makes a column of six feature values attached with a label representing designated data segment. The six features, four of which from time domain are mean absolute value (MAV), root mean square (RMS), waveform length (WL) and zero crossings (ZCs), and another two from frequency domain are the mean and median of signal frequencies (FMN and FMD).

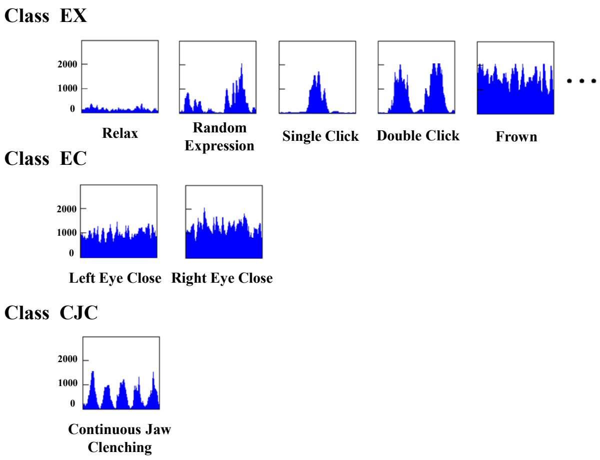


Fig. 6 Group of classes for SVMs EMG waveform classification displayed in 50 samplings (500ms).

B. SVMs Training and Classification Results

In the process of adopting sample data sets for training a SVM classifier, we propose the concept of a standard subject who is a well trained and experienced person. He or she can perform control movements and make control waveforms with little error, and can produce waveforms that well represent the differences between each waveform patterns in the feature space (good sample separability). The classifier is trained by sampling data from a standard subject only. Although this training method confines the classification result into fitting only one person, however, consider that humans have good adaptability by learning and imitating from others, we thereafter introduce a short training section introducing to new subjects about how to imitate standard control action and produce similar waveforms, and the result of this strategy are given in Section VII.

In this experiment, training data are sampled according to three classes displayed in Fig. 6; the sample data are recorded by a standard subject doing different movements for each divided class EX, EC or PCJ.

- For class EX, data are sampled when the subject is relaxing, frowning, making single or double clicking movements, making random face expressions (such as talking, smiling or peering etc.), all these actions are sampled for 160 seconds which makes 800 training vectors
- For class EC, waveform data are recorded when the subject doing LEC and REC movements for 80 seconds each, and the sampled data are mixed, making one eye close (EC) training set contains 800 training vectors.
- For class CJC, training data are sampled by the subject doing CJC movements for a total length of 56 second which makes 280 training vectors.

Notice that for making each sampling movement, the subject will keep the movement for only 8 seconds and have a rest after; this is to prevent the subject from muscle fatigue.

In this research, we apply RBF kernel as the machine kernel to give general quick and reliable classification result for implementing the proposed control strategy. A threefold cross validation are applied during training to validate the trained classifier. Fig. 7 shows the grid search results of the three classes in this 3D graph. The bottom two axes are the log(C) and log(γ) value of the SVM radial basis function (RBF) [8]:

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0. \quad (1)$$

where $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function.

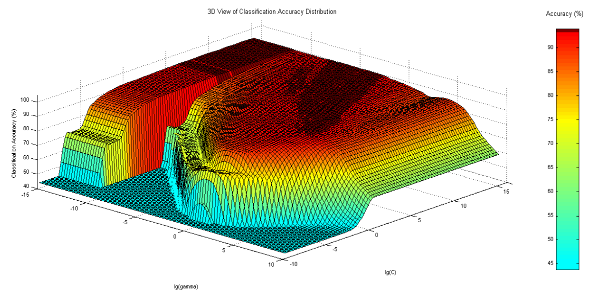


Fig.7 SVM Grid search results over EMG training data

Fig. 7 shows the grid search result with log(C) from -10 to 15, log(γ) from -15 to 10. The dark area shows the grid search result with classification accuracy above 93%. The best selected training result can be found at a log(C) value of 13 and a log(γ) value of -0.5 where the maximum classification accuracy is 93.75%.

VI. IMAGE PROCESSING

A Haar feature based Adaboost cascade classifier has good sample generalization ability, and can deal with minor rotation, scaling or illumination changes, which consumes a low computing power. These features can well satisfy this research as the closed eye detection needed here is dedicated to a group of six testing subjects in an indoor office environment.

A. Image search area segmentation

To simplify the image processing process for Haar feature based image searching, we make the size of the searching area (known as background) as small as possible. As depicted in Fig.8, the region of interest (ROI) for searching is designated to a configured area according to Adaboost face detection result (red frame), based on which the rough area containing left and right eyes are decided by geometry of human face and eyes position.

According to the parameters depicted in Fig. 8, the positive training image (eye close image) is produced by tailoring the closed eyes picture within black or yellow frame when the subject is making eye close movements. The negative training image is collected when subject is opening the eye. In this experiment, two Boosting classifiers for both left and right eyes are trained, and during recognition, the two classifiers are applied separately within yellow or black frame for detecting REC or LEC movements.

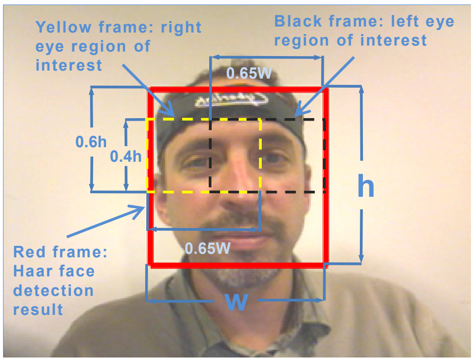


Fig. 8 Image segmentation for the region of interest (ROI)

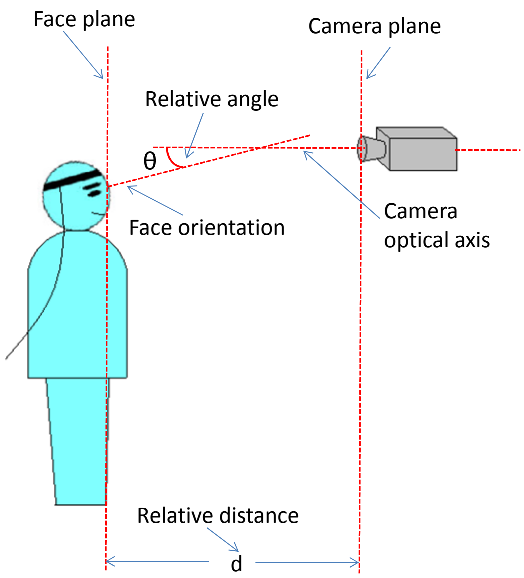


Fig. 9 Adaboost training image sampling setup

B. Positive and negative training image collection

As shown in Fig. 2(left), the wheelchair has a camera fixed at its front with a distance from 25 to 55 centimetres away from the subject's face where training images are acquired. In this experiment, three variable factors considered during image acquisition are relative angle θ, which is the relative angle between subject face orientation to camera optical axis, relative distance d, which is distance between subject face plane to camera plane (as shown in Fig. 9), and illumination condition, which is made variable by alternatively turning on or off six inset compact fluorescents fixed under room ceiling and changing the lighting position and angle of a filament lamp set in front of subject's face.

When sampling positive images, in the shooting range of 320 by 240 pixel resolution auto-focus camera, the subjects is sitting in front of a display screen observing their own image in an enclosed room (as shown in Fig.9), rotating his neck within 30 degrees of relative angle θ and moving his body forth and back within 25 to 80 centimetres at a same time.

For the designed task, six male subjects from 5 different ethics background (Italian, British, Chinese, Nigerian, Spanish and Iranian) are involved in the experiment. For each person, about 200 positive images and 800 negative images for each eye are acquired. In the end, the left eye positive images of all six subjects are mixed and trained with Adaboost cascade classifier using the mixed left eye negative images, and so does the right eye images are trained.

VII. Experimental Results

Six male subjects are randomly selected for the purpose of training Boosting cascade. We found that the strategy did not work well for three subjects after the entire control method is applied. Two subjects felled the difficulty in making one eye open and one eye close at the same time, one subject reported the difficulty in producing CJC movement. For the instance of this experiment, three subjects can use the control methods successfully and the simulation is based on these three subjects.

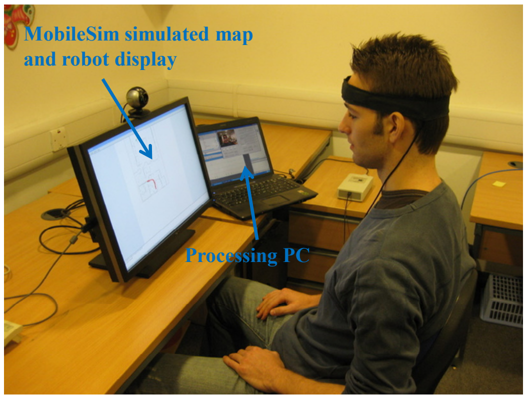
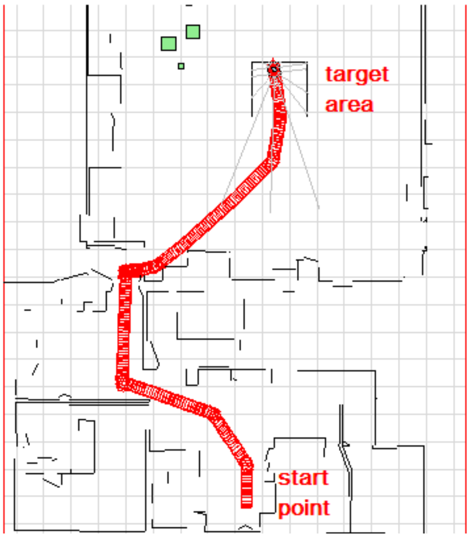
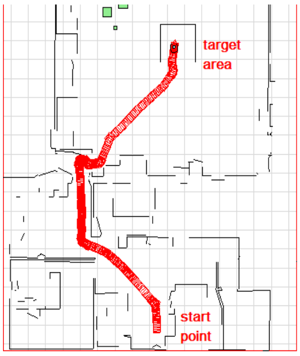


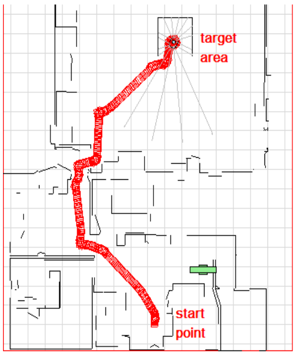
Fig. 10 Simulation environment setup

To test the designed control strategy, we use a simulated office map and apply the control strategy onto a simulated mobile robot in an enclosed room (as shown in Fig. 10). The processing PC is a laptop with an AMD Turion 64×2 TL50 CPU and 1GB memory, integrated graphic card running on 32bit Windows XP operation system. The processing speed is adequate as none of the subject has experienced latency during control. The map used in MobileSim [13] is an example map named <AMROffice.map> supplied with software. Fig. 11 shows the trajectory of three subjects operating robot goes through a series of indoor environments such as door way, corridor, wall, to a target area in open room. The maximum speed is 2 meter per second and the turning angle speed is set to 0.5 radian per second.



Subject A (2’30”)





Subject B (4’50”) Subject C (3’12”)

Fig. 11 Robot trails from the start point to a target area in a simulated indoor environment controlled by three subjects: Subject A, Subject B and Subject C and time used during control.

VIII. Conclusion and Future Work

In this paper, a new human-machine interaction method is proposed for disabled people to control the electric wheelchair without the need of hands. The developed HMI integrates both facial image information and facial EMG signals in order to recognize human control intentions for the real-time control of an intelligent wheelchair. The experiments are carried out by implementing the designed control system onto a simulated mobile robot operated in the MobileSim simulator. The experimental results demonstrate the feasibility and good performance of the proposed hybrid control system.

In the future, different combinations of muscle groups on the face will be investigated to form difference control strategies in order to suit individual needs. Also, this proposed control method will be implemented on a real wheelchair in the real-world in order to carry out further performance evaluations of this hybrid control method.

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