Cogn Comput manuscript No.
(will be inserted by the editor)

A Neuro-Fuzzy based Control System for Solar Powered Wheelchair based on Feature Extraction of Surface EMG signal

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Received: 30–10–2015/ Accepted: date

Abstract This paper presents the design and implementation of a low cost solar powered wheelchair for physically challenged people. The signals necessary to maneuver the wheelchair are acquired from different muscles of the hand using surface Electromyography (sEMG) technique. The raw sEMG signals are collected from the upper limb muscles which are then processed, characterized, and classified to extract necessary features for the generation of control signals to be used for the automated movement of the wheelchair. An artificial neural network based classifier is constructed to classify the patterns and features extracted from the raw sEMG signals. The classification accuracy of the extracted parameters from the sEMG signals is found to be relatively high in comparison to the existing methods. The extracted parameters used to generate control signals that are then fed into a microcomputer based control system (MiCS). A solar powered wheelchair prototype is developed and the above MiCS is introduced to control its maneuver using the sEMG signals. The prototype is then thoroughly tested with sEMG signals from patients of different age-groups. Also, the life cycle cost analysis of the proposed wheelchair revealed that it is financially feasible and cost effective.

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1 Introduction

With the advent of sophisticated and stand alone computing platforms, human-machine control (HMC) interfaces have found applications in diverse fields including design of technology for physically disabled people [1, 2, 3, 4, 5, 6]. The research on effective design of wheelchairs has been in the spotlight for over a decade now. During this period, the focus of the research has shifted from structural efficiency to ease of operation of the wheelchairs. The manual operations of wheelchairs require some forms of additional assistance-sometimes even from a care-giver which is not an option for everyone. The control systems for manually operated electric wheelchairs usually require a certain degree of external control inputs, such as in form of joystick or array of push buttons in order to provide required information (e.g., direction, speed, etc.) to the controller. Persons with marginal limbic ability are not expected to operate this kind of wheelchair by themselves. To overcome this problem, automated control based wheelchairs have been proposed and many research groups are still working on developing sophisticated and intelligent wheelchair control systems [7]. This kind of wheelchairs sample specific biological signals which are generated without extreme limbic movements, such as, Electromyogram (EMG) [8, 9, 10, 11], Electroencephalogram (EEG) [4, 5, 6, 12], Electrooculogram (EOG) [13, 14], etc., to provide the necessary control signals for maneuvering the wheelchair. Further existing wheelchair

This is a postprint of an article published in Cogn. Comput. The final version is available at: https://doi.org/10.1007/s12559-016-9398-4
Cite as: M.S. Kaiser, Z.I. Chowdhury, S. Al Mamun, A. Hussain, M. Mahmud. (2016). A Neuro-Fuzzy Control System Based on Feature Extraction of Surface Electromyogram Signal for Solar-Powered Wheelchair. Cogn. Comput., 8(5): 946–954. doi: 10.1007/s12559-016-9398-4.

control techniques include: eye gaze tracker method [15], eye blinking [16], tongue movement [17], speech recognition [18], and stereo omnidirectional system based gesture detection from images [19].

Due to the fact that these types of assistive devices (automatic wheelchairs) require very brief and impulsive signals (mentioned above) for their control systems to operate, they have been adopted by a wide range of physically challenged users. Since it is intended to use lesser degree of physical movements in controlling these assistive devices, the main challenge in designing such devices lies in the accurate and efficient extraction of all necessary information from the biological signals required to control those devices.

To this aim, intelligent systems have found to play a major role in design of wheelchair control systems. Specially, fuzzy logic controllers have been used in both microcontroller and field programmable gate array (FPGA) with ultrasonic sensors for controlling the wheelchair by taking dynamic timing information from the navigation environment [20]. Also, an FPGA based parallel fuzzy controller for wheelchair is proposed in [21]. The fuzzy system drives two H-bridges depending on the inputs provided by the disabled person.

In this work, a solar powered wheelchair is proposed which has it's control signals derived from a very common biological signal: the surface electromyogram (sEMG) signal. People with limited limbic abilities are the target users of this technology who have some abilities to produce certain level of muscular activation to generate the EMG signals and thereby to drive the wheelchair. An early prototype of such a wheelchair has been reported in [7].

2 Methods

Figure 1 shows the proposed solar powered wheelchair. The main components are: solar panels, battery charge controller, battery bank, sEMG signal acquisition and processing module (containing signal preprocessing, feature extraction, pattern classification), and wheelchair's motor control unit.

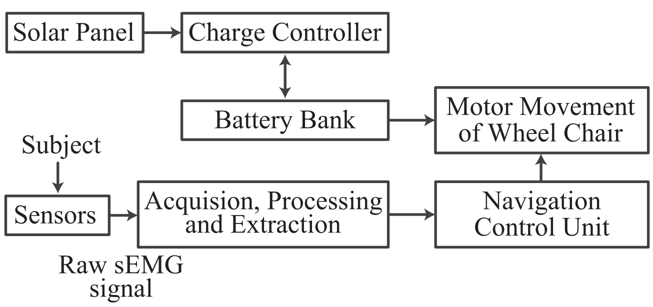

Fig. 1: Block diagram of the proposed wheelchair with it's various modules and communication flow among them.

2.1 Wheelchair with Solar Power

The custom-made wheelchair is seen in Fig. 2 with the design principles explained in the subsequent sections.

Fig. 2: Prototype of the proposed solar powered wheelchair.

Assembling of the Wheelchair The proposed wheelchair is a low cost one meaning that the designing and manufacturing of the wheelchair was carried out with locally available materials. Aluminum metal pipes which are considerably cheaper and lighter than steel were used. This type of material allowed the wheelchair to be light in weight, thereby reducing the required driving force. Also, it was designed as tilted-seat wheelchair facilitating the usability for patients with spinal cord injury.

The battery is housed just under the seat of wheelchair, utilized photovoltaic (PV) energy for charging which saved considerable amount of utility bill in comparison to the ones charged using the national grid.

Additionally, the control system was designed by means of a powerful Advanced RISC Machine (ARM) processor which allowed complex algorithms to be executed, thus, avoiding expensive hardware to be employed in the design.

In comparison to other existing automatic wheelchair systems, the attribute 'low cost' is justified considering the technological advantages in parallel with the price of the product. The average price of an automatic battery powered wheelchair is around US$2500. A vast majority of them are designed with a focus on structural privileges such as folding ability, light weight battery etc. as well as energy concerns such as low power consumption. The technological features of these wheelchairs are limited to providing external input via joystick or keypad. Considering those limitations, the

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flexibility provided by the proposed automatic wheelchair is greater with a manufacturing cost of around US$950.

Interfacing with the Solar Panel Solar panels (IM60, Motech Industries Inc., Taiwan) were used to convert solar radiation into electrical energy. Energy from sunlight was stored in battery bank, which was controlled by a commercially available charge controller (20A 12V/24V Auto Switch MPPT Solar Panel Battery Regulator Charge Controller KJ) to track the maximum power point (MPP). Lead acid battery (36B20L, Hamco Corporation, Dhaka, Bangladesh) was considered because of its low cost, reliability, tolerance to overcharge, low initial impedance, and the ability to deliver high current. The battery bank was utilized as backup energy provider because the PV system only generates enough electricity with sunlight.

2.2 Surface Electromyogram (sEMG) Signals

EMG signal is generated due to the rapid movement of ions across a cell membrane causing a charge imbalance between inside and outside of the membrane. Due to the diffusion of Na^+, K^+ and Cl^- ions, a potential difference is generated and propagates through the muscle fiber in form of an Action Potential (AP). This potential ranges from a resting value of -90 mV to a peak value of $+35$ mV and the instantaneous potential is directly proportional to the force produced by contraction of muscle fibers conducting the AP [22,23]. The sEMG is measured as the potential difference between a pair of electrodes with an additional electrode as reference. Since the measured potentials are very low in amplitude, the signals require amplification and preprocessing prior to be used in the control circuitry.

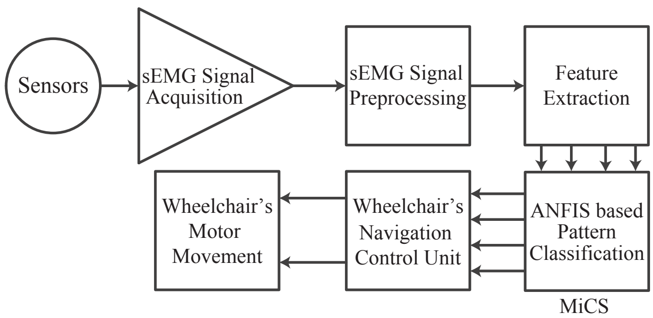

Fig. 3: Block diagram of the wheelchair's control system with sEMG signal.

The acquired sEMG signals (see sec. 2.3 for acquisition process) were preprocessed and some important features were extracted (see sec. 2.4 for feature extraction process) from its time and frequency domains. The time domain features were: mean absolute value (MAV) and slope sign change (SSC) [24,25]. Whereas, the frequency domain features were: zero crossing (ZC) and local minima (LM) [26]. These features were further classified using an Adaptive Neuro-Fuzzy Interface System (ANFIS) (see sec. 2.5) model for creating the control signals which were then fed into the driving circuit for the control of the wheelchair's motors. The control diagram of the wheelchair is shown in Fig 3.

2.3 Signal Acquisition and Processing

Hand muscle movements of a subject generate sEMG signals. The signals were taken during four different hand motions: wrist extension (WE), wrist flexion (WF), thumb movement (T) and finger movement except thumb (F). Appropriate positions for the lead electrodes were found using the trial and error method. The signals were collected for 1 minute at 1 kHz sampling frequency.

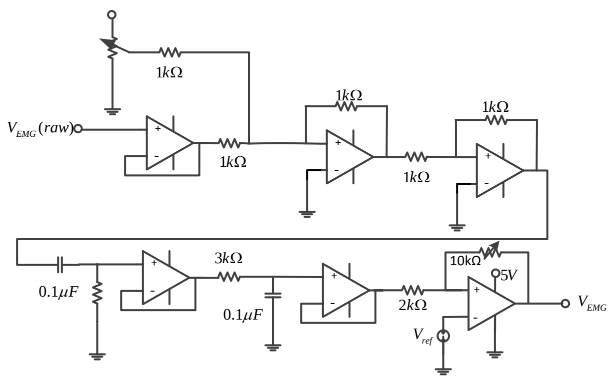

Fig. 4: Circuit diagram of sEMG signal acquisition.

The signal acquisition system front-end used in acquiring the sEMG signals is shown in Fig. 4. The acquired signals are preprocessed, filtered and amplified. Surface EMG sensor of identical electrical characteristics were used to acquire muscular signals, denoted by V_{EMG}. The frequency range of the sEMG signals lie between 7 and 500 Hz [27, 28].

Due to the fact that the sEMG signals are very often contaminated by noise from human body motion, electrode contact problems, power line, amplifier etc., they might not produce quality signals to be used to control the wheelchair. To mitigate the noise effects, a number of design issues were considered during the design phase of this work. Starting with placing the stimulation electrodes in proper places on the body with respect to recording electrodes. After acquisition of the raw sEMG signals, they are passed through a

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system which pre-processes those raw sEMG signals to improve the signal-to-noise ratio (SNR).

The motion artifacts were eliminated by the bandpass filtering the signals between 10 Hz and 20 kHz. The electrode noise, power line noise etc., were difficult to remove, however, the sEMG signals were denoised (rather the SNR was improved) by wavelet-based methods as described in [29,30]. These denoised and high SNR sEMG signals were further processed to extract important features.

2.4 Feature Extraction

In general, feature extraction from the sEMG signals is complex and very important for classification of the hand movements. Many researchers use time-frequency domain technique for feature extraction. Below is a list containing the heuristically selected features.

- Time domain (as suggested in [24,25]):
  - Mean absolute value (MAV): the MAV was calculated using the formula
    $$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n|^2 \tag{1}$$
  - Slope sign change (SSC): the SSC was calculated using the formula
    $$SSC = \sum_{n=2}^{N-1}[f[(x_n - x_{n+1}) \times (x_n - x_{n-1})]] \tag{2}$$
    $f(x) = 1$ if $x \geq$ $threshold$, else 0
- Frequency domain (as suggested in [26]):
  - Zero crossing (ZC): the ZC was calculated using the equation
    $$ZC = \sum_{N-1}^{n=1}[sgn(x_n \times x_{n+1}) \cap |x_n - x_{n-1}| \geq threshold] \tag{3}$$
  - Local minima (LM): if $x_{i-1} > x_i$ and $x_i < x_{i+1}$ where $1 < i < n-1$, index i is a local minima index and its local minimum value is x_i. If $(x_{n-1} < x_{n+1})$ it is right minimum, else if $(x_{n-1} > x_{n+1})$ it is left minimum.

The calculation of MAV, SSC, and ZC was performed as described in [31], and the LM was calculated as in [32]

2.5 Microcomputer based Control System (MiCS)

Fuzzy Inference System (FIS) was first introduced in 1965 [33]. Fuzzy logic can incorporate human decision making capability in the form of IF-THEN rules. The sEMG signals are non-stationary in nature, thus the pattern classifications are very difficult. Fuzzy logic system is able to classify the pattern of biological signals. In FIS, inputs are fuzzified to a value that lies in the interval $[0,1]$. Then it is interpreted by the IF-THEN rules [33].

The Adaptive Neuro-Fuzzy Inference System (ANFIS) for this control system was implemented in a Raspberry Pi 2 (`https://www.raspberrypi.org/`) and the necessary codings were done in python (v.3.4, `https://www.python.org/`).

The singular value decomposition method was used to determine the number of fuzzy rules. The membership parameters of the Sugeno type ANFIS were adjusted by using neural network [34]. Fig. 5 shows the ANFIS structure with five inputs, denoted by I_{ip}^j, where $p = [MAV, SSC, AR, ZC$ and $LM]$ and one output, denoted by O_i [34]. Bell shaped membership functions (MF) were used [34] and the required parameters for the input-output pairs were calculated using hybrid back propagation and LMS algorithms. Using membership functions, four fuzzy rules were derived. The output of the system can be written as in Eq. 4.

$$O = \sum_{i=1}^{L}\left[\frac{\prod_{j=1}^{n} MF_i^j(I_i^j)(Z_i)}{\sum_{i=1}^{L}\left(\prod_{j=1}^{n} MF_i^j(I_i^j)\right)}\right] \tag{4}$$

The output of each rule, denoted by Z_i, was given by Eq. 5.

$$Z_i = \alpha_{i_1}I_1 + \alpha_{I_2}I_2 + \alpha_{I_3}I_3 + \alpha_{I_4}I_4 + \alpha_{I_5} + I_5 + \alpha_{I_6} \tag{5}$$

where α_{ij} is the consequent parameters of input j. The linguistic variable of the inputs are $MF_i^1 = low$ $MF_i^2 = average$ and $MF_i^3 = high$.

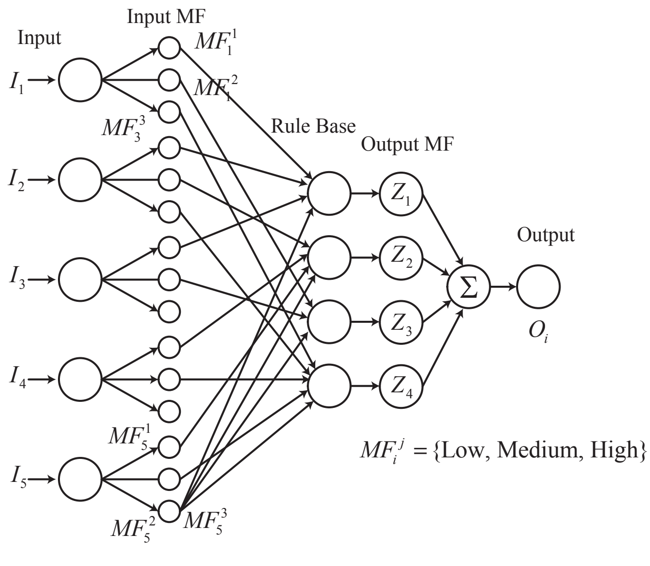

Fig. 5: Structure of adaptive neuro-fuzzy inference system with five input and 1 output. I: Input, MF: Membership Function, O: Output.

The multiplexed output MF's of the ANFIS were then fed to the direction control circuit for controlling the wheelchair's motors.

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2.6 Wheel Chair's Direction Controller

Fig. 6 illustrates control circuit for driving the wheelchair in a particular direction. Here D refers to diode (1N5400) and T refers to transistor (2SD1760). The diodes D_1 and D_2 were used to discharge the residual current when motors were in OFF state.

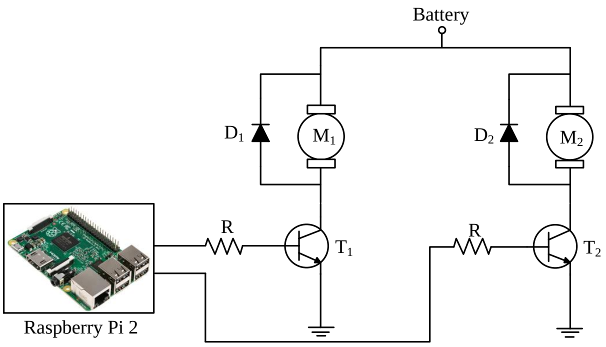

Fig. 6: Wheel chair direction control circuit

The direction control strategy for the proposed wheelchair is given in algorithm 1. Initially, the wheel chair was stalled in its position and waited for a control signal (CS). One of the four CSs were received from the MiCS: Forward CS (FCS); Left CS (LCS); Right CS (RCS); Stop CS (SCS).

When the received control signal was FCS, both T_1 and T_2 were switched ON. Thus motors (M1 and M2) moved the wheelchair in the forward direction. If the received control signal was LCS, T_1 and T_2 were switched OFF and ON, respectively, to move the wheelchair in leftward direction. Similarly, if the received control signal was RCS, T_1 was switched ON while T_2 was OFF, this caused the wheelchair to move in rightward direction. When the SCS was received, both T_1 and T_2 were switched OFF and the movement of the wheelchair was halted.

2.7 Financial Feasibility Matric: LCC

To evaluate the financial feasibility of the proposed wheelchair, the life cycle cost (LCC) analysis of the entire system was performed using Eq. 6. The LCC was computed on the capital cost, total operation and maintenance cost, and total replacement cost over the whole life time. Based on [7], LCC was used to find the optimal energy configuration of the system.

$$LCC = C_c + \sum_{n=1}^{N} C^n_{o\&m} + \sum_{n=1}^{N} C^n_r \tag{6}$$

where N is the life time of the system, C_c is the capital cost of the system, $C^n_{o\&m}$ is the annual operation and maintenance cost of year n and C^n_r is the replacement cost of the system.

Algorithm 1: Wheelchair direction control algorithm

Data: FCS, LCS, RCS, SCS
Result: Movement of Wheelchair
initialization of system parameters;
set $counter = 1$;
Acquire CS ;
while $counter = 1$ **do**
  if CS=FCS **then**
    Both wheels Move forward direction;
  else
    CS is low and Stop Both wheels;
  end
  if CS=LCS **then**
    Left wheel Stop ;
    Right wheel Move ;
  else
    CS is low and Stop Both wheels;
  end
  if CS=RCS **then**
    Right wheel Stop ;
    Left wheel Move ;
  else
    CS is low and Stop Both wheels;
  end
  if CS=SCS **then**
    Both wheel Stop ;
  else
    CS is low and Stop Both wheels;
  end
end

3 Results and Discussion

3.1 Feasibility of Wheelchair Maneuvering using sEMG Signals from Hand Movements

The wheelchair was tested with sEMG signals recorded from the hand muscles using sEMG sensors. Table 1 shows hand movements, sensor position on different muscles to extract sEMG signals and the corresponding functions for the wheelchair. The mean value of achieved accuracy was found to be high in comparison to the results presented in our previous work [7].

Table 1: Function classification accuracy by ANFIS.

Motion	Active Muscles	Function	Accuracy	
			Kaiser et al.	Proposed
WE	M_1	Break	91.0%	97.5%
WF	M_2	Move forward	94.0%	97.5%
T	M_3	Left/Right	93.1%	94.0%
T	M_4	Left/Right	93.1%	94.0%
F	M_5	Left/Right	93.2%	94.0%

M_1: Extensor carpi radialis longus, Extensor carpi radialis brevis, Extensor carpi ulnaris;
M_2: Flexor carpi radialis, Flexor carpi ulnaris, Palmaris longus;
M_3: Extensor/Flexor Pollicis Longus, Extensor Pollicis Brevis, Abductor Pollicis Longusi ulnaris;
M_4: Extensor/Flexor Pollicis Longus, Extensor Pollicis Brevis, Abductor Pollicis Longusi ulnaris;
M_5: Extensor/Flexor Digitorum Profundus, Extensor Carpi Ulnaris, Extensor Digitorum, Extensor Digiti Minimi

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The sEMG signals were successfully recognized for their related movements. Table 2 shows the confusion matrix of the identified and real movements of the hand obtained from MiCS. It can be appreciated that during the classification process, the MiCS could successfully distinguish between the movements from the wrist and the fingers. Also, the accuracy of identifying the wrist movements (97.5%) were higher than that of the finger movements (96%). The maximum recognition rate was found to be 97.5% with maximum error to be 4%.

Table 2: Recognition of hand movements by MiCS.

Identified Real	WE	WF	T	F
WE	97.5%	2.5%	0%	0%
WF	2.5%	97.5%	0%	0%
T	0%	0%	96%	4%
F	0%	0%	4%	96%

Table 3 shows accuracy comparison of hand movements' recognition among three studies:
1. From Nishikawa *etal*. [35],
2. From Kehzri & Jahed [26], and
3. From the system proposed in this work.

The achieved accuracy of the proposed approach is found to be better than that of the previous studies. Its worth mentioning here that this approach requires less amount of hand movements to achieve such high accuracy in comparison to other studies.

Table 3: Accuracy comparison of hand movements' recognition in different studies.

Selected Study	Hand movements	Average accuracy (%)
Nishikawa *etal*. [35]	10	92.10
Kehzri & Jahed [26]	6	96.70
Proposed system	4	96.85

3.2 Financial Feasibility

LCC is a useful tool for understanding the cost-effectiveness of different types of wheelchairs. For a wheelchair, LCC calculation is performed considering the expected lifetime of the system to be 20 years. Since the battery lifetime is five years, during the lifetime of the system the battery should be replaced at least three times (Non-recurring cost). Table 4 shows LCC analysis for different wheelchairs available in the global market. As evidentiated, the solar powered wheelchair proposed in this work is financially feasible.

Table 4: LCC analysis (in USD).

Type	Components	Cost	Total LCC
Solar Powered Wheelchair	PV Array	$ 100	
	Wheelchair	$ 77	
	Battery	$ 285	
	Converter	$ 64	$ 997
	Other Components	$ 50	
	Installation Cost	$ 26	
	Electricity Cost	$ 40	
	O and M Cost	$ 38	
	Non-recurring cost	$ 320	
Compass Sport GP605	Wheelchair	$ 3,399	$ 3907
	Electricity Cost	$ 150	
	O and M Cost	$ 38	
	Non-recurring cost	$ 320	
KD Smart Chair	Wheelchair	$ 1,995	$ 2503
	Electricity Cost	$ 150	
	O and M Cost	$ 38	
	Non-recurring cost	$ 320	
LiteRider PTC Portable	Wheelchair	$1,999	$2507
	Electricity Cost	$ 150	
	O and M Cost	$ 38	
	Non-recurring cost	$ 320	

4 Conclusion

A solar powered electric wheelchair was proposed and a prototype was developed in order to test the desired functionalities. The control sequences required to maneuver the wheelchair was derived from sEMG signals. The raw signals were carefully preprocessed to remove the artifacts present in the signals in order to improve the SNR. The improved signals were fed to MiCS, a powerful stand alone microcomputer based control system, which took the muscle activation information and applied a feature extraction algorithm to extract useful features representing the hand movements. Later, an adaptive neuro-fuzzy interface system was applied to classify and identify the hand movements and translate them to desired direction parameters. The MiCS yielded a satisfactory accuracy of above 97% in deciphering the hand movements from the sEMG signals. The direction parameters generated by MiCS were then used in driving the wheelchair. The design of the system was flexible enough, thanks to the functionalities performed by MiCS, for the integration of additional features such as global positioning system based location, usage of EEG instead of EMG, speech based emergency brake, etc., which are left to be implemented in the future.

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors and Contributors: This work was carried out in close collaboration between all co-authors. MSK, ZIC, SAM, and MM first defined the research theme and contributed an early design of the system. MSK, ZIC, and SAM further implemented and refined the system development. MSK, ZIC, SAM, MM, and AH wrote the paper. All authors have contributed to, seen and approved the final manuscript.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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