Two-Wheel Vehicle Control using the Hand Gesture Signal Recognition

Mohammad `Afif B Kasno[1], Kyungkwon Jung[1],
Yonggu Lee[2], and Kihwan Eom[1]

[1] Department of Electronic Engineering, Dongguk University,
26, Pil-dong 3-ga, Jung-gu, Seoul, Korea
[2] Department of Medical Instrument and Information, Hallym College, Chuncheon City, Gangwond-do, Korea
kihwanum@dongguk.edu

Abstract

In this paper, a real-time experimental of Hand Gesture SEMG signal using Spectral Estimation and Linear Vector Quantization for Two-Wheel Vehicle Control is proposed. The raw SEMG signals been captured from SEMG amplifier, up to 4 channels of Auto Regressive (AR) power spectral density (PSD) responses data will be combined and a fine tuning step by using LVQ will then incorporate for pattern classification. The database then been build and use for real-time experimental control classification. Captured data will send through serial port and Two-Wheel Machine will receive and move accordingly. The detail of the experiment and simulation conducted described here to verify the differentiation and effectiveness of combined channels PSD method SEMG pattern classification of hand gesture for real-time control.

Keywords: *Two-Wheel Vehicle Control, SEMG pattern classification, LVQ, Spectral Estimation, Human-Computer Interaction*

1. Introduction

Since the past three decades ago, biomedical myoelectric signal control has becoming more popular for its application in rehabilitation and human-computer interfaces (HCI). Surface electrode sensors use for capturing Surface electromyography (SEMG) signal which will be useful to measure the activities of the musculature system [1]. The application of SEMG varies in term of the various acquired signals from different tissue, organ, or musculature. Various approach for the use of SEMG has been presented and such approaches are extremely valuable to physically disable persons like unvoiced speech recognition and the hands-free SEMG mouse [2].

There are many useful pattern recognition method has been proposed recently to help identify and distinguish each different hand gesture SEMG signals. Kyung Kwon Jung et. al [3] proposed the SEMG Pattern Classification using Spectral Estimation and Neural Network and 4^{th}-order Yule-Walker algorithm is been proposed to estimates the power spectral density (PSD) of the SEMG signals. This method gives the success rate of the proposed classifier about 78 percent. Furthermore, M. A. Kasno proposed the experimental improvement of [4] by using 100th –order merged Covariance AR data and LVQ and the proposed classifier reach 99 percent of success rate.

In order to make each hand gestures well distinguish from each other is of crucial importance [5]. The hand gesture figure should be more attentive so the surface electrode sensors area which the musculature placed on could react and gives the sufficient distinguish information for each of the hand gesture. There are several of hand gesture figures been experiment like Korean Hand Gesture [3] [4], Punch Movement Hand Gesture [2], and Thumb-up Rotation Hand Gesture [5].

In this paper, the Real-Time Hand Gesture SEMG 100th order merged Covariance AR and LVQ to control two-wheel vehicle simultaneously is proposed. Different of Hand Gesture approach as well as SEMG captured signal channels is been experiment and discussed.

2. SEMG Measurement Tool

Electromyography (EMG) is the biomedical signal which measures the electrical impulses of muscles at rest and during contraction. The way SEMG-based attached to the musculature for measuring makes HCI the most practical because of conveniently and safely compare to the other neural signals [6]. Referring to [4], the SEMG Measurement Tool was built and test with similar set of measurement. Figure. 1 shows the SEMG Measurement Tool. It is consists of SEMG electrodes, SEMG amplifier circuitry and A/D converter for computer interfacing.

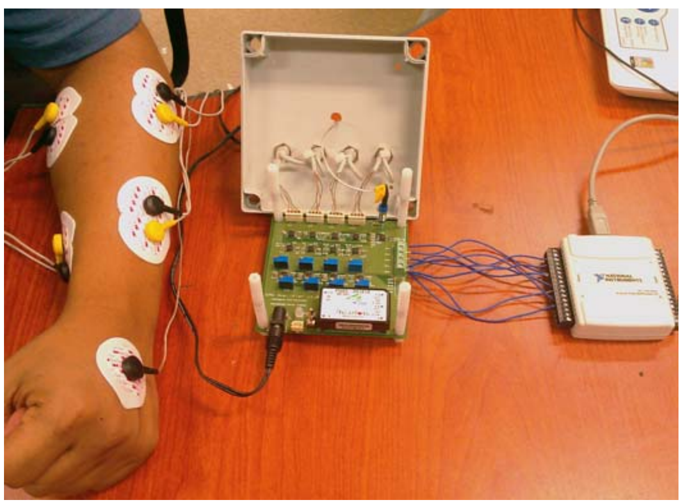


Figure 1. SEMG measurement tool.

The 3M™ Red™ wet gel monitoring electrodes are been used for the SEMG electrodes. Instrumentation Amplifier usually provides excellent accuracy because it provides high bandwidth even at high gain. Therefore, The SEMG amplifiers are instrumentation amplifier, namely INA2128 chip for the preamplifier and OPA2604 for body reference circuit [7]. The ADC used is NI-DAQ USB 6009. The NI-DAQ USB 6009 is a bus-powered for high mobility, built-in signal connectivity, OEM version, compatible with LabVIEW™ and Measurement Studio for Visual Studio .NET and provided NI-DAQmx driver software for interfacing with other computing software like MATLAB™. It has 8 analog input channels with 14-bit and up to 48 sample rates (kS/s) [8].

During contraction, the electrode picks up an SEMG signal and the preamplifier boosts the signals high enough to prevent electrical interference. The preamplifier also filters the noise. After that the additional amplifier increases the amplitude of signals to the TTL level and offset will be adjusted. The National Instrument (NI DAQ USB-6009) will then convert the signals into digital form to allow the NI-DAQmx program to read and store SEMG data. The device has four input channels connected to the PC through NI-DAQmx interface.

3 Two Wheel Vehicle System

Two-Wheel Vehicle System is made by microprocessor, DC Stepping Motor and also circuitry. A microprocessor is a multipurpose, programmable, clock driven, register based device that takes input and provides output of the system. A microprocessor incorporates most or all of the functions of a computer's central processing unit (CPU) on a single integrated circuit (IC, or microchip) [9]. In this project, Atmega128 microprocessor is been used as CPU system. The ATmega128 is a low-power CMOS 8-bit microcontroller based on the AVR enhanced RISC architecture. By executing powerful instructions in a single clock cycle, the ATmega128 achieves throughputs approaching 1 MIPS per MHz allowing the system designer to optimize power consumption versus processing speed [10].

Sanyodenki 103H5205-0480) Stepping Motor has been used for the wheel control. The stepping motor is DC 24V-1.2A input voltage, 1.8°/step [11], and it been controlled by SLA7024 High-Current PWM, Unipolar Stepper Motor Controller / Drivers which are designed for high-efficiency and high-performance operation of 2-phase, unipolar stepper motors. The packaging combined with power FETs and monolithic logic/control circuitry advances power multi-chip modules (PMCMs™) toward the complete integration of motion control [12].

The Figure. 2 shows the Two-Wheel vehicle system and Table 1 shows the details about wheel movement direction.

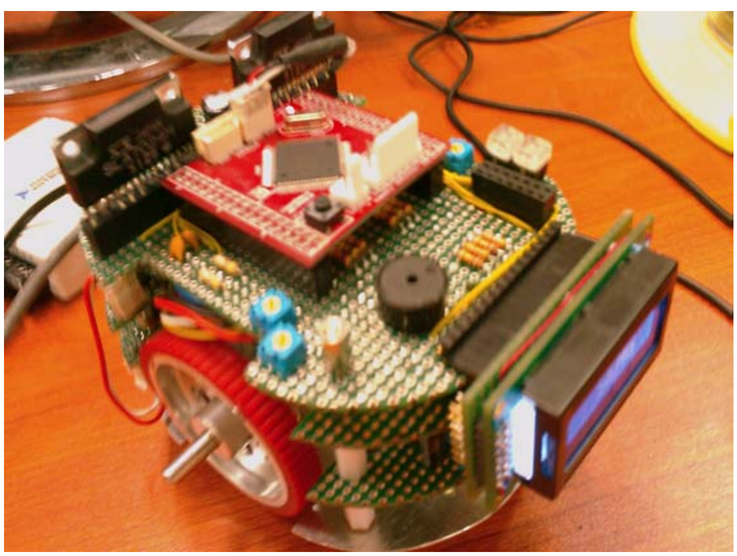


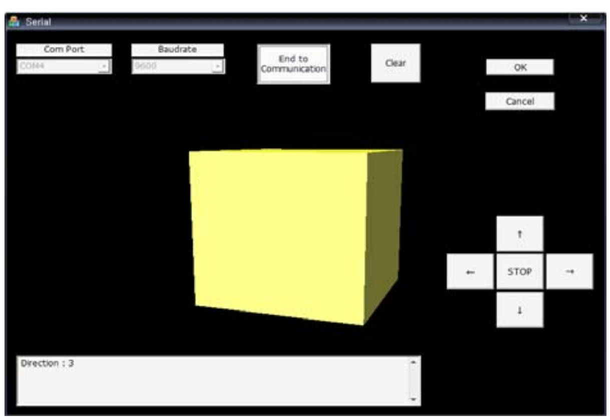
Figure 2. Two-Wheel Vehicle System

Table 1. The details of wheel direction movement. It is consists of 2 stepping wheel and 3 different movements, forward, reverse and stop.

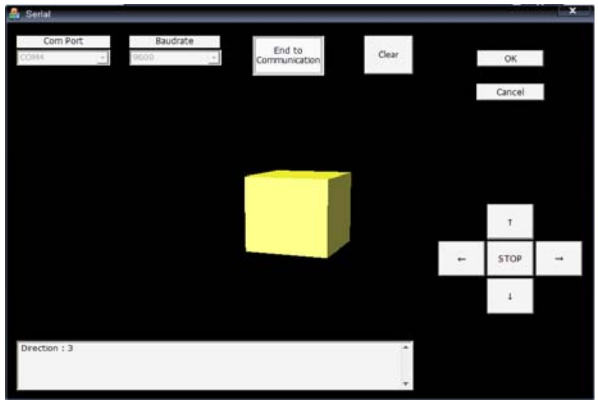
Action(Flag)	**Wheel**	
	Left	**Right**
Forward(w)	○	○
Reverse(x)	●	●
Right(d)	○ ○	- ○
Left (a)	- ○	○ ○
Stop(s)	-	-

○: On Forward, ●: Turn Reverse, - : Stop

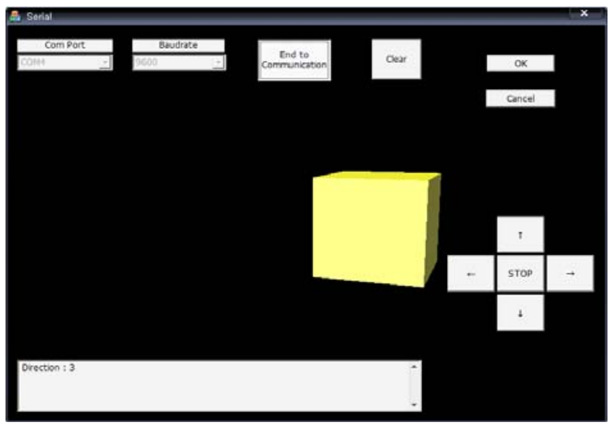
For computer interfacing, MFC program is been used to take the output result from SEMG Measurement Tool, translate using file descriptor and transmit data-flag to Two-Wheel vehicle system via serial communication. MFC program is developed referring to [13] and OpenGL Library. The MFC program also provides GUI in 3D simulation. The GUI is showed in Figure. 3.



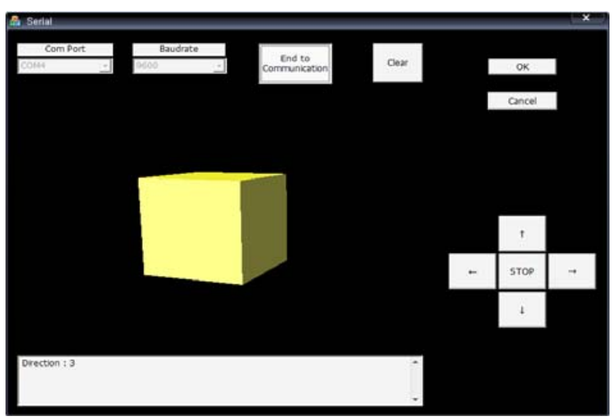
(a) Forward state



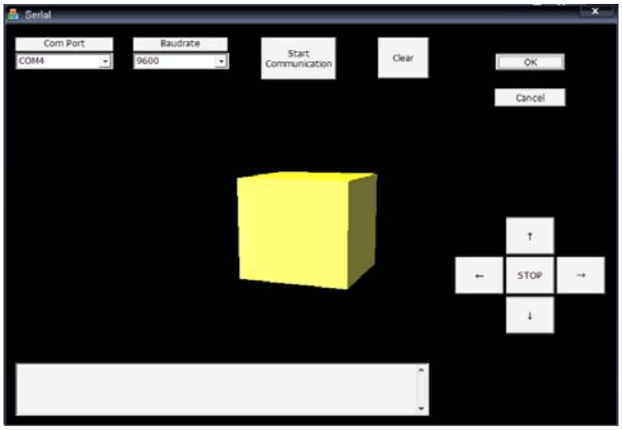
(b) Reverse state



(c) Right state



(d) Left state



(e) Stop

Figure 3. MFC GUI 3D simulation

4 Pattern Classification

4.1 Covariance Method

The Covariance method is a technique for estimating the AR parameters [14]. The Covariance equations are written as

$$\begin{bmatrix} r(0) & r(-1) & \cdots & r(-n) \\ r(1) & r(0) & \cdots & \vdots \\ \vdots & \vdots & \ddots & r(-1) \\ r(n) & \cdots & \cdots & r(0) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sigma^2 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{1}$$

Where *r(k)* is autocovariance a_n is AR parameter, σ^2 is variance. If $\{r(k)\}_{k=0}^{n}$ were known, equation (1) could be solve for $\theta = [a_1, \dots, a_n]^T$.

To explicitly stress the dependence of θ and σ^2 on the order *n*, (1) can be written as

$$R_{n+1} \begin{bmatrix} 1 \\ \theta_n \end{bmatrix} = \begin{bmatrix} \sigma^2 \\ 0 \end{bmatrix} \tag{2}$$

4.2 LVQ

Learning vector quantization (LVQ) is one of the earliest and most powerful machines learning method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors. The LVQ network architecture is shown in Figure. 4.

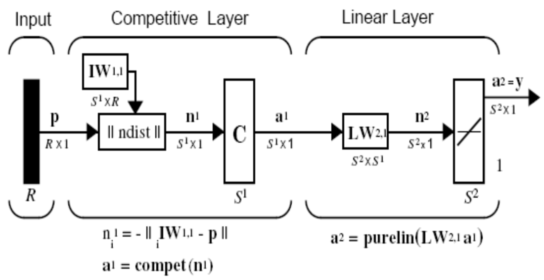


Figure 4. LVQ network architecture.

LVQ network has a first competitive layer and a second linear layer. The competitive layer learns to classify input vectors. The linear layer transforms the competitive layer's classes into target classifications defined by the user. The net input of the first layer of the LVQ is written as

$$n_i^1 = -\|\, {}_i w^1 - p \,\|, \tag{3}$$

Or in vector form as

$$n^1 = -\begin{bmatrix} \|\, {}_1 w^1 - p \,\| \\ \|\, {}_2 w^1 - p \,\| \\ \vdots \\ \|\, {}_{S^1} w^1 - p \,\| \end{bmatrix} \tag{4}$$

Where n is neuron, w is weight and p is the input. The second layer of the LVQ is represented by W^2 matrix where the columns represent subclasses and rows represent classes. The row in which the 1 occurs indicates which class the appropriate subclass belongs to is written as

$$(w_{ki}^2 = 1) \Rightarrow \text{Subclass } i \text{ is a part of class } k \tag{5}$$

The classes learned by the competitive layer are referred as subclasses and classes of the linear layer as target classes [15].

5 Proposed Method

The system built is been showed in Figure. 5. The proposed of Real-Time Hand Gesture SEMG control using Spectral Estimation and LVQ for Two-Wheel method configuration is shows on Figure. 6. The simulation coding on how the real-time will operate is described with a flow chart in Figure. 7.

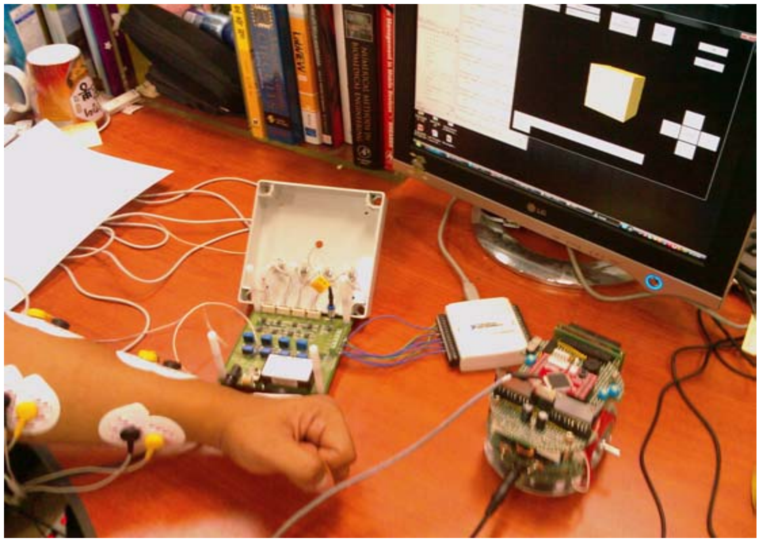


Figure 5. The full system of Real-Time hand gesture SEMG

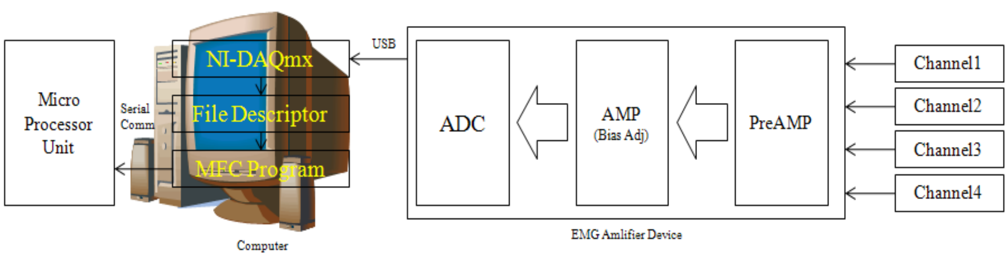


Figure 6. Block diagram of proposed system

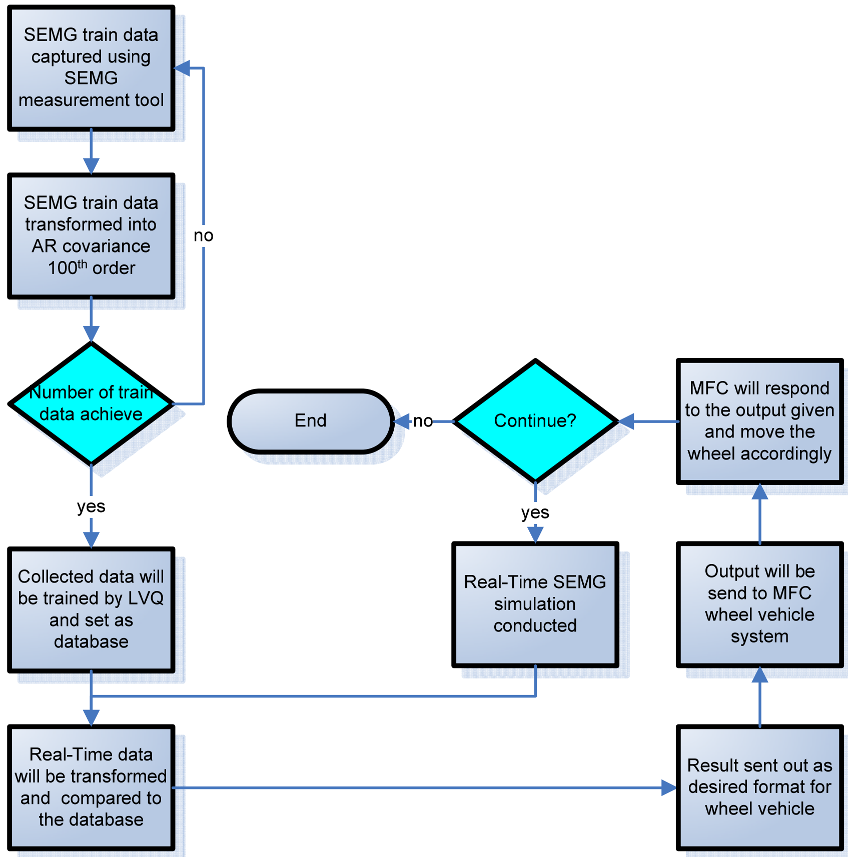


Figure 7. Flow chart of real-time simulation coding

First, the SEMG train data will be captured using SEMG measurement tool. The required channels are depending on the simulation needed. The data will be sampled at 10 kHz in 2 seconds. Then, the SEMG train data will transformed into AR Covariance 100th order by using spectral estimation covariance. Until the number of required data train is achieved, the simulation will keep continuing data train captured loop.

After the number of required data train is achieved, the simulation proceeds to pattern classification and the trained data will be conducted to LVQ training phase. The LVQ neural network has 4 neurons on the input layer, and 6 neurons on the output layer. The initial step size in interval location step has been set to 0.01, learning rate is set to 0.9, and the learning rate is decreased in the course of time.

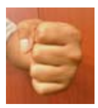
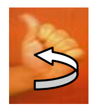
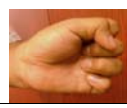
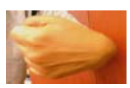
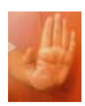
The trained data will be set as database, and Real-Time simulation will be conducted. As the train data is sampled at 10 kHz in 2 seconds, the real-Time simulation will also be conducted in the same duration. The captured real-time data will be transformed into AR covariance 100th order and will be compared with the database. Result will be sent out as desired format for wheel vehicle system.

Result from SEMG measurement tool will be read as input for MFC two-wheel vehicle system. The result then been compared with the setting and the MFC two-wheel will move the wheel accordingly

6 Experimental Result

The experiment conducted to showed the differentiation of each hand gestures for single, double, triple or quadruple channels setting in terms of successful recognition are described below.

Table 2 shows the hand gestures for real-time simulation.

Korean Hand Gesture	Punch Hand Gesture	Thumb up Hand Gesture	Control Direction
 ㄴ			Forward (w)
 ㄱ			Back (x)
 ㄷ			Left (d)
 ㅅ			Right (a)
 ㅂ			Stop (s)

The real-time experimentation was conducted by 20 samples for training and 10 samples for testing. Results for different hand gestures are showed in Table 3. It is showed the differentiation of each hand gestures for single, double, triple or quadruple channels setting in terms of successful recognition. The successful rate is low due to the inefficient SEMG electrodes during simulation, which been slipped off from arm.

Table 3. The Korean hand Gestures for real-time simulation. The table consists of the Korean Hand Gesture figures, Time presented for train data and real-time simulation classified time for different channels combination.

Korean Hand Gesture	*Time presented for train data*	*Time presented for testing data*	*Real-time simulation classified times*			
			Ch1	Ch1 and Ch2	Ch1, Ch2 and Ch3	Ch1, Ch2, Ch3 and Ch4
	20	10	7 (70%)	7 (70%)	8 (80%)	8 (80%)
	20	10	1 (10%)	2 (20%)	3 (30%)	3 (30%)
	20	10	1 (10%)	2 (20%)	3 (30%)	3 (30%)
	20	10	3 (30%)	3 (30%)	4 (40%)	5 (50%)
	20	10	0 (0%)	0 (0%)	2 (20%)	3 (30%)

Table 4. The Punch Movement hand Gestures for real-time simulation. The table consists of the Punch Movement Hand Gesture figures, Time presented for train data and real-time simulation classified time for different channels combination.

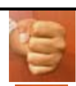
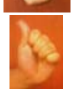
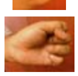
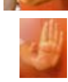
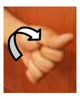
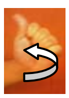
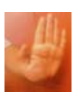
Punch Movement Hand Gesture	*Time presented for train data*	*Time presented for testing data*	*Real-time simulation classified times*			
			Ch1	Ch1 and Ch2	Ch1, Ch2 and Ch3	Ch1, Ch2, Ch3 and Ch4
	20	10	5 (50%)	5 (50%)	6 (60%)	6 (60%)
	20	10	0 (0%)	0 (0%)	1 (10%)	2 (20%)
	20	10	0 (0%)	0 (0%)	3 (30%)	3 (30%)
	20	10	2 (20%)	2 (20%)	2 (20%)	2 (20%)
	0	10	0 (0%)	1 (10%)	2 (20%)	2 (20%)

Table 5. The Thumb-Up Rotation hand Gestures for real-time simulation. The table consists of the Thumb-Up Rotation Hand Gesture figures, Time presented for train data and Real-time simulation classified time for different channels combination.

Thumb-Up Rotation Hand Gesture	*Time presented for train data*	*Time presented for testing data*	*Real-time simulation classified times*			
			Ch1	Ch1 and Ch2	Ch1, Ch2 and Ch3	Ch1, Ch2, Ch3 and Ch4
	20	10	3 (30%)	4 (40%)	6 (60%)	7 (70%)
	20	10	1 (10%)	2 (20%)	3 (30%)	3 (30%)
	20	10	2 (20%)	2 (20%)	3 (30%)	3 (30%)
	20	10	1 (10%)	2 (20%)	2 (20%)	2 (20%)
	20	10	2 (20%)	2 (20%)	4 (40%)	4 (40%)

The results showed that the hand gestures response to each of the SEMG electrodes channels differently. Some of the hand gestures did not response well with only one channel and need other channels in order to distinguish the hand gestures preferably. The more channels used for the simulation, the more accurate pattern recognition can be done in order to distinguish the hand gestures. During real-time experimentation, Korean Hand Gestures showed the best results with high successful rate compared to the other hand gestures. It was because of more flexion happen during contradiction of muscle movement when most of finger muscles involved compare to the other hand gestures.

7 Conclusion

In this paper, real-time simulation of Hand Gesture SEMG using Spectral Estimation and LVQ for two-wheel machine control is proposed. Proposed method is combining of SEMG measurement tool and MFC Two-Wheel vehicle system. The use of the Covariance Method is to estimates the power spectral density of the signal. The spectral estimate returned is the magnitude squared frequency response of AR model. The pattern classification used LVQ Neural Network and once the database is set up as training data, the real-time simulation taken place in order to give the instruction control for two-wheel MFC control system.

In order to verify the effectiveness of the proposed method, the experimental of 3 different SEMG hand gesture has been conducted. Experimental results showed the differentiation of each hand gestures for single, double, triple or quadruple channels setting in terms of successful recognition.

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Authors

Mohammad `Afif b Kasno was born in Terengganu, Malaysia on December 4, 1985. He received the B.Eng. degree in electronic engineering from the University of Technology Malaysia in 2008, and worked as a researcher at the same university for more than one year before he further his study at Dongguk University, Seoul, Korea in Master of Electronic Control. His interest fields are Electronic Control, Neural Network and Human-Computer Interaction.

Kyung Kwon Jung was born in Korea. He received the B.S., M.S., and Ph.D. degrees in Electronic Engineering from Dongguk University, Seoul, Korea in 1998, 2000 and 2003, respectively. He is currently working as research engineer in Electronic Engineering at Dongguk University and U-embedded Convergence Research Center at Korea Electronics Technology Institute. His research interests are in intelligent systems, digital signal processing and sensor network applications.

Yong Gu Lee was born in Korea. He received the B.S. and M.S. degrees in Electric Engineering and Ph.D. degree in Electronic Engineering from Dongguk University, Seoul, Korea in 1987, 1993 and 1997, respectively. He is currently working as a full professor in Radiological Technology at Hallym College. His research interests are in digital image processing and neural network applications.

Ki-Hwan Eom was born in Seoul, Korea in 1949. He received the B.S. and Ph.D. degree in electronic engineering from Dongguk University, Korea in 1972, and 1986, respectively. He was a visiting professor from 1989 to 1990 at Toho University and from 2000 to 2001 at University of Canterbery. Since 1994, he has been with Dongguk University, where he is currently a professor in the Division of Electronics and Electrical Engineering. His research interests are in electronic application and convergence system