Hand Sign Classification Techniques Based on Forearm Electromyogram Signals

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***Abstract*— This paper describes classification techniques to distinguish hand signs based only on electromyogram signals of a forearm. Relationship between finger gesture and forearm electromyogram is investigated by two signal processing approaches; an empirical thresholding method and meta heuristic method. The former method judges muscle activity according to the criteria experimentally determined in advance, and evaluates activity pattern of muscles. The latter learns the electromyogram characteristics and automatically creates classification algorithm applying genetic programming. Discrimination experiments of typical hand signs are carried out to evaluate the effectiveness of the proposed methods.**

Keywords- electromyogram(EMG); muscle; criterion; genetic programming; estimation; finger; gesture; sign; motion; forearm

I. Introduction

When one bends or stretches his joints of fingers, electromyogram (EMG) signals are induced in muscles according to their contraction. EMG signals suggest some information on muscular motions such as muscle torque or joint angles, and they can be measured from a skin surface with noninvasive electrodes. It is expected to realize an intuitive human-machine interface using EMG signals, instead of conventional interfaces such as joysticks, data-glove devices, motion capture systems. Although various interfaces using EMG signals have been proposed to control robot hands [1-8], they require troublesome procedures and not a little calculation time.

The authors have studied the classification methods of finger motion based only on electromyogram of forearm muscles [9, 10]. An EMG measurement system is constructed first to obtain finger activity in terms of myoelectric signals. Then we focus on the facts that forearm muscle activity is related to finger motion and individual hand sign has its distinctive EMG pattern. Two types of classification techniques are described in this paper. One of them is an empirical thresholding method which determines criteria of muscle activity by preliminary experiments and deduces its hand sign from the activity pattern. The other is a meta-heuristic approach. Genetic programming technique is applied to produce hand sign classification algorithm. These proposals are finally applied to experiments to distinguish three typical hand signs.

II. Hand Sign Classification

Fig. 1 illustrates three forearm muscles which generate EMG signals associated with hand motion, as well as the positions of three electrodes attached on the skin above the muscles. Two of them, *extensor pollicis brevis* and *extensor digitorum* are involved in finger extension. The other, *flexor digitorum profundus* is involved in finger flexion.

We are interested in the phenomenon that not only finger muscles but forearm muscles work while the knuckles displays hand signs. This paper is concerned with the relationship between hand signs and forearm EMG signals, and the implementation of hand sign classification based on the forearm EMG.

The figure also expresses the transformation of a hand game, "rock-paper-scissors," which is adopted as a test bed of hand sign classification.

Anatomical investigations suggest that only proper muscles work when one forms each hand sign, and our myoelectric experiments supports it as shown in Table 1 which indicates contribution of muscles to gesticulation by hands [9]. *Extensor pollicis brevis* contributes only to form "paper" among three signs. *Extensor digitorum* does its part in indicating "scissors" and "paper." *Flexor digitorum profundus* works when displaying "rock."

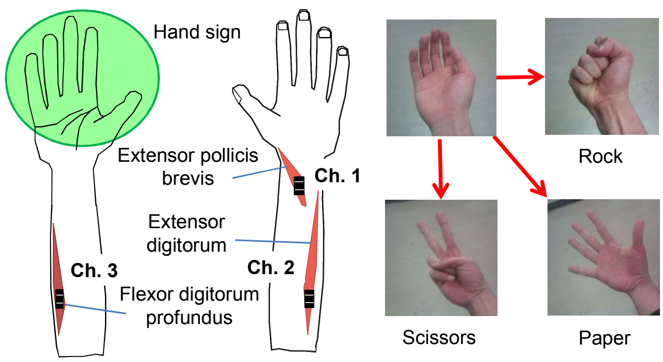

Figure 1. Measured muscles and electrodes attached on forearm.

TABLE I. MUSCLE ACTIVITY PATTERN FOR HAND SIGN

Muscle		Rock	Scissors	Paper
Ch.1	Extensor pollicis brevis	×	×	○
Ch.2	Extensor digitorum	×	○	○
Ch.3	Flexor digitorum profundus	○	×	×

○: active ×: inactive

An EMG measurement system is constructed to detect surface EMG signals of a forearm as shown in Fig. 2. The signals are measured with bipolar surface electrodes which contains two parallel silver bars. An EMG measurement instrument (Oisaka development Ltd.) amplifies and transforms the EMG into integrated EMG (IEMG) signals with rectification smoothing whose cutoff frequency is 2.4 Hz using a differential amplifier. They are sampled at 10 kHz through a 16-bit A/D converter.

We next evaluate the correlation between the forearm EMG signals and finger motions with signal processing PC. We obtain the activity pattern of each forearm muscle corresponding to specific hand sign. Fig. 3 illustrates a block diagram of our EMG measurement system. The EMG measurement instrument catches surface EMG signals by three electrodes attached on a forearm, preprocesses them, and converts them into IEMG signals. Exercise physiology often uses the IEMG signal as an activity level index of muscles [5].

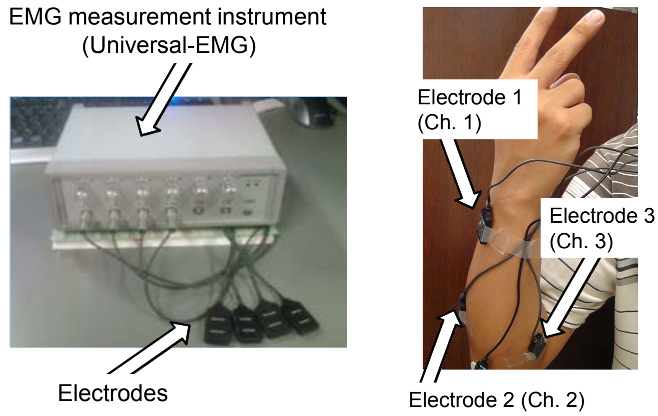

Figure 2. EMG measurement system.

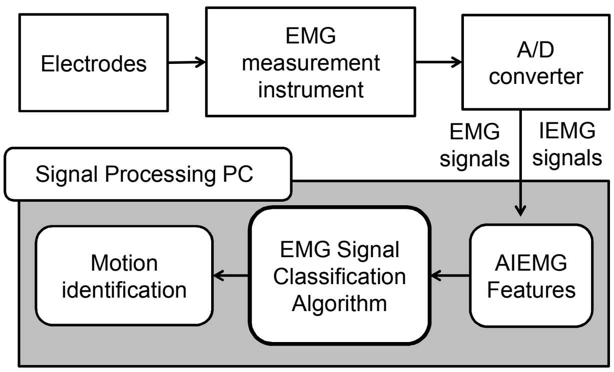

Figure 3. EMG measurement block diagram.

Both EMG and IEMG are introduced into a PC to evaluate AIEMG features. The AIEMG feature represents an average of EMG signals during a designated interval [3]. An EMG signal classification algorithm of hand sign is installed in the PC. The following sections discuss a couple of methods to discriminate finger motion based on AIEMG features. The proposed system eventually indicates the identified hand signs according to the classification method.

Note that signals detected by the electrode are not necessarily induced only by the corresponding muscle. It is important to differentiate desired information from noisy signals to identify muscle motion in high accuracy.

III. EMPIRICAL THRESHOLDING METHOD

We designed an algorithm to classify hand signs by comparing combination of muscle activity to designated patterns shown in Table 1. As it is necessary to judge whether each muscle is active or inactive, we establish the criterion in terms of myoelectrical intensity on the basis of preliminary experiment data according to the following principle.

Forearm EMG signals are measured and evaluated at first to determine the criterion that divides active and inactive signals. Fig. 4 indicates output voltage of EMG signals detected by electrodes channel 1, 2, and 3, respectively, regarding each hand sign, where the horizontal axis denotes time and the vertical represents magnitude of the EMG signals. The IEMG signals are transformed as shown in Fig. 5. Those waveforms suggest that only channel 3 is inactive with respect to "paper" for example.

We obtain AIEMG feature after all by converting IEMG signals as shown in Fig. 6, where the vertical axis represents the peak magnitude of the AIEMG signal when the subject made gestures of "rock," "scissors," and "paper." We have tried 30 tests to display each of three hand signs, and all the

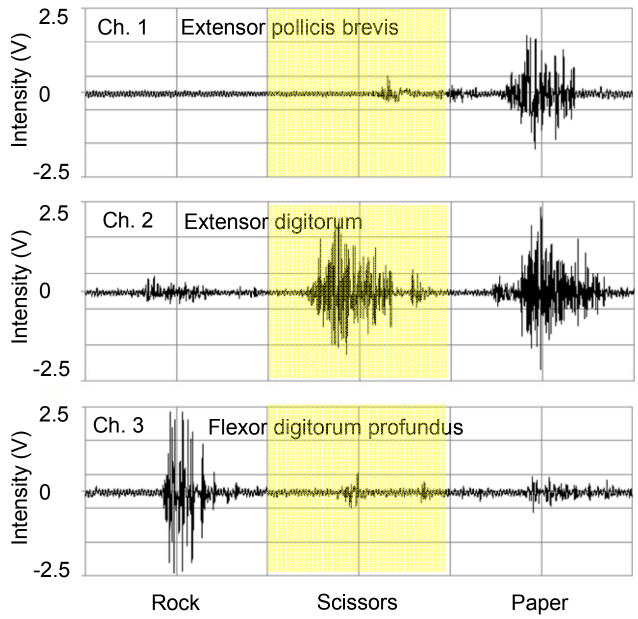

Figure 4. Detected EMG signals.

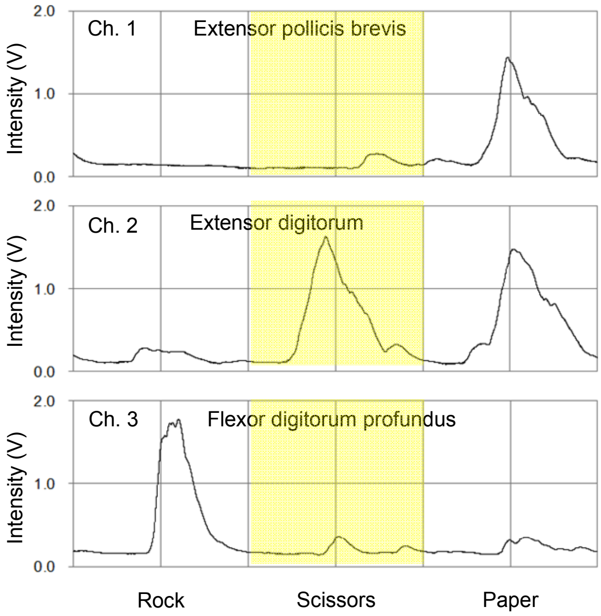

Figure 5. Converted IEMG signals.

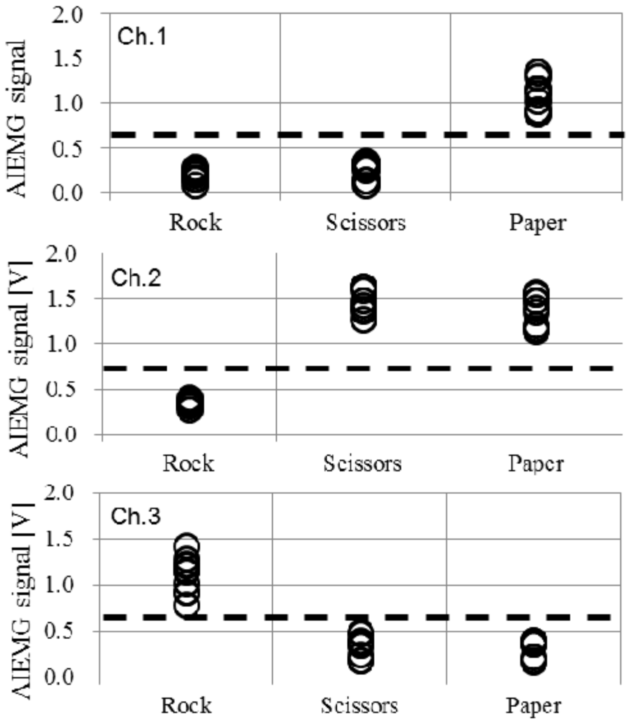

Figure 6. Criteria in terms of AIEMG signals.

data can be clearly assorted into low or high intensity. A border of intensity is assigned to each channel as its criterion.

The upper part of Figure 6 shows the output of channel 1, which receives EMG signals of *extensor pollicis brevis*. We decided the criterion index, CI_1 for channel 1 as 0.60 V, which is illustrated by a broken line in the figure. All the data concerning “rock” and “scissors” lie lower than the line, while those for “paper” were higher. That is why we could find that *extensor pollicis brevis* was active only for “paper.” The activity of muscles can be estimated according to the criterion as follows. Provided that the magnitude of a measured signal is smaller than the criterion, the corresponding muscle is considered to be inactive. Otherwise it is presumed to be active.

In the same way, the output AIEMG signals of channels 2 and 3 are arranged in the lower part of Fig. 6. The criterion index, CI_2 for channel 2 was determined as 0.78 and CI_3 for channel 3 was 0.62 V. By acquired EMG signals of *extensor digitorum*, channel 2 suggested the muscle was active for “scissors” and “paper.” Channel 3, expressing the activity of *flexor digitorum profundu*s, disclosed that the muscle was active only in the case of “rock.”

We finally establish a flowchart of the gesture estimation algorithm as shown in Fig. 7. This process checks the combination of the measured AIEMG signals against the activation patterns of muscles corresponding to the hand signs shown in Table 1.

We finally carried out the experiments of hand sign estimation based on the algorithm. Identification rate was evaluated after 25 trials were conducted for each hand sign. Experimental results reveal that entire score of identification rate is 93 % as shown in Table 2.

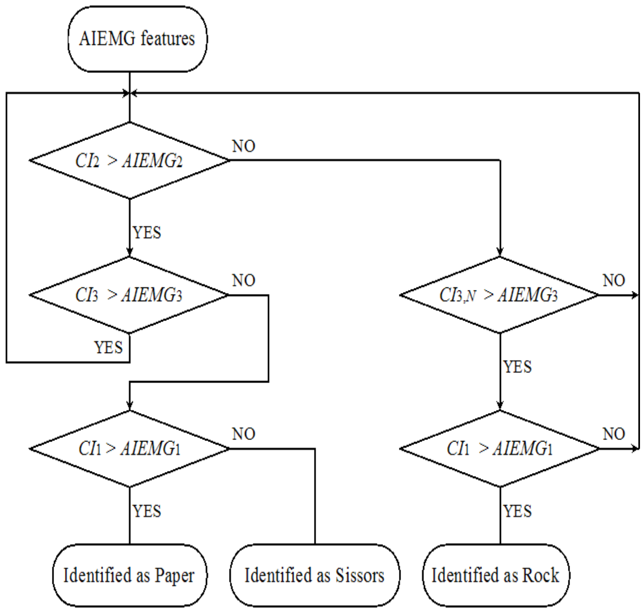

Figure 7. Thresholding hand sign estimation algorithm

TABLE II. IDENTIFICATION RESULTS BY EMPIRICAL METHOD.

Rock (%)	Scissors (%)	Paper (%)	Total (%)
100	92	88	93

IV. META HEURISTIC METHOD

Another hand sign identification algorithm is designed as a classification tree created by genetic programming [11]. The evolutionary process composes hand sign classification program based on numerous myoelectric data of finger shapes. The program provides an index number representing each hand sign as calculation output.

The hand sign classification system is designed as shown in Fig. 8. This diagram expresses both the configuration and the procedure of EMG measurement and hand sign estimation based on forearm EMG. Left side indicates the preprocess part of the system, where genetic programming technique learns and obtains characteristics of EMG pattern for each hand sign to produce a classification tree. Right side shows the real time process part, where a hand sign classification program is installed according to the classification tree and it indicates the conjecture of hand sign in real time based on the measured forearm EMG.

While hand keeps forming any shape, subject's EMG is measured as shown in Fig. 9. This figure represents examples of waveforms regarding the EMG, IEMG, and AIEMG detected by channel 1, 2, and 3, respectively when a subject displays "rock." Signals are also obtained with regard to the other hand signs in a similar way.

Then the AIEMG values are digitized by sampling every 1.67 ms for 0.5 seconds, and we obtain 30 discrete data from each electrode. A sequence of the hand sign data is integrated by arranging AIEMG values of three electrodes in the order of time series. Fig. 10 exemplifies the AIEMG value sequences of "rock," "paper," and "scissors", respectively. The integrated data of 90 values is introduced to the genetic programming procedure as an instance for learning.

The instance also contains a numerical index of hand sign, *index_i*, which stands for the type of the shape. In this paper, a rock, a paper and a scissors are expressed by 0, 1, and 2, respectively.

Consequently, the instance, *f_i*, regarding a single hand sign is described as

$$f_i = (V_{1\_1}, V_{1\_2}, V_{1\_3}, \ldots V_{j\_1}, V_{j\_2}, V_{j\_3}, \ldots V_{30\_1}, V_{30\_2}, V_{30\_3}, index_i)$$

where i is the number of individual hand sign, and V_{j_1}, V_{j_2}, V_{j_3} represent the j-th voltage value of the electrode 1, 2, and 3, respectively.

Next we prepared the set of primitive functions. Each computer program is a composition of functions from the function set and terminals from the terminal set. By choosing any functions, a logical equation is composed to make hierarchical sequence evermore. The sequence stops extending when a terminal is selected.

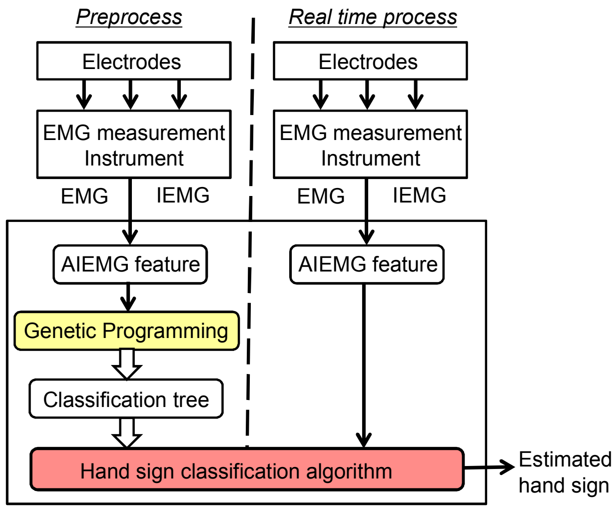

Figure 8. Meta heuristic hand sign classification system.

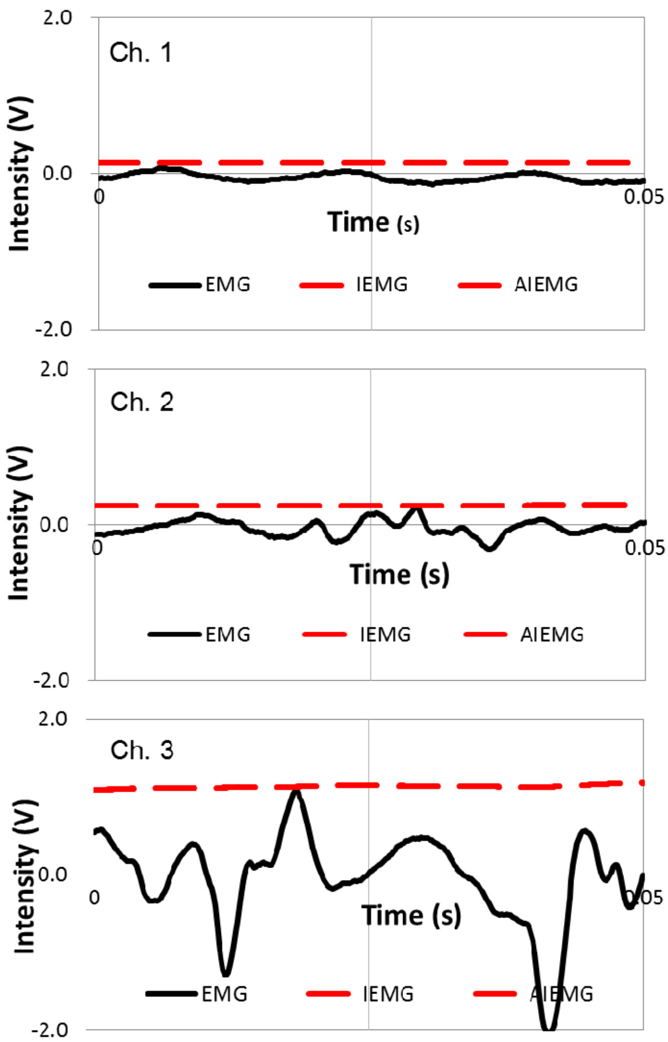

Figure 9. Real time electromyogram regarding "rock.

We actually applied 50 instances for each of three hand signs for learning, and then determined the values of parameters to control the runs. The population size and the maximum number of generations were 3000 and 300, respectively. Every computer program is modified by genetic programming, and evaluated its faculty of classification by applying the myoelectric data. Each computer program in the population returned a numerical index value representing the type of hand sign in the problem. The fitness measure of the problem was defined as accuracy score of the programs that successfully answered the type of sign. It is desirable that the program obtains 1 for the fitness value.

We began a run of genetic programming with the creation of a population of 3000 random computer programs on condition that the maximum tree depth is 20, the maximum program size is 20, crossover rate is 1.0, and mutation rate is 0.9. The individual program was randomly created in the initial generation of the population. The blind random search was carried out in the space of computer programs to represent possible solution. After selecting the designated number of parents, both the genetic mutation and crossover were executed to breed a new population of programs. The reproduction operation was conducted the designated times to individuals selected from the population in terms of their fitness.

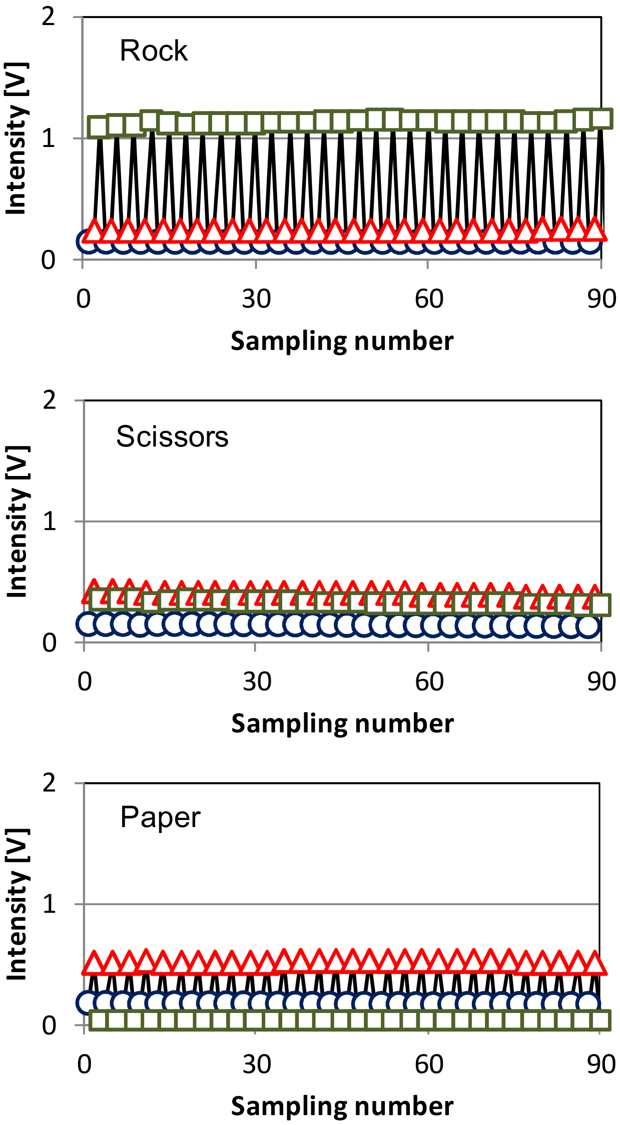

Figure 10. Sampled electromyogram data

Experimental results suggest that the solution program is evolved rapidly until 20 generations for fitness values reach their maximum. We decided the individual program of the highest score as the result of a run of genetic programming. The best-of-run program is represented by the classification tree represented in Fig. 11 (a). It is possible to be translated to a computer program as shown in Fig. 11 (b) for instance. It calculates an index value denoting a type of hand signs. The preprocess results in establishing the hand sign classification algorithm.

Real time experiments were finally conducted according to the real time process in Fig. 8 to estimate hand sign using the classification algorithm established by the preprocess in Fig. 11. This optimum program tried to classify 75 samples of gesturing one of three hand signs. Fig. 12 indicates a part of the identification results. Five among 25 identification trials are displayed for each hand sign. A circle represents the index value obtained by each trial. An index value between 0 and 1, between 2 and 3, between 1 and 2 stands for “rock,” “paper,” and “scissors,” respectively. Thus, the figure expresses all the 15 trials are successful in discrimination of three hand signs.

Total identification rate is evaluated in Table 3, which shows percentages of correct answers of finger sign estimation. Results have revealed that the proposed system successfully

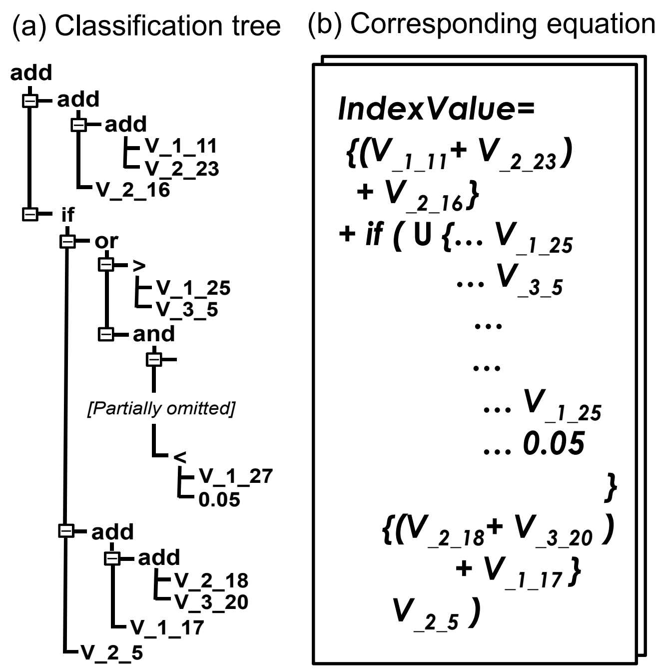

Figure 11. Optimum classification tree and program.

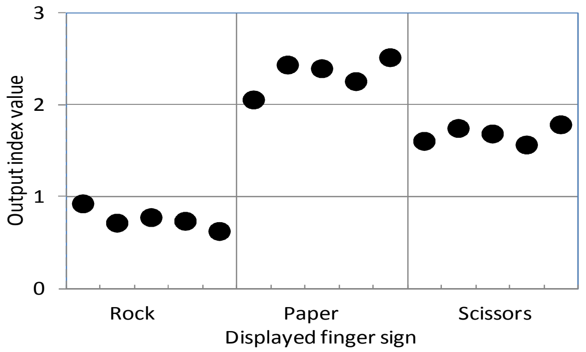

Figure 12. Index values provided by classification tree.

TABLE III. IDENTIFICATION RESULTS BY META HEURISTICS.

Rock (%)	Scissors (%)	Paper (%)	Total (%)
100	96	100	99

categorized all the hand signs into three candidates except one.The accuracy rate of the program was eventually estimated at 99 %.

V. CONCLUSION

This paper studied classification systems of hand sign based on the forearm electromyogram. We made physiological and anatomical investigations on the relationship between finger motion and myoelectric response of forearm muscles. It was confirmed that hand sign was reasoned from activity pattern of the forearm EMG. The EMG measurement system was designed to detect myoelectric signals from the surface skin of forearms and to extract the features of IEMG and AIEMG signals.

Two methods for hand sign classification were investigated next. The empirical thresholding method was proposed first by designing fractionation flowchart in terms of electromyogram intensity of forearm muscles. This method distinguish whether each muscles is active or not, based on the criteria obtained by experiments on the relationship between hand signs and muscular signals. Some experiments were conducted to classify gestures of "rock-paper-scissors." Three typical hand signs are demonstrated to be identified in a total accuracy of 93 %.

Meta heuristic technique was applied next to the same problem as for genetic programming. Genetic evolution procedure generated the optimum classification algorithm to distinguish hand signs by automatically extracting the characteristics of forearm EMG signals caused by finger motion. The typical hand signs were also experimented to discriminate in accordance with the classification algorithm, and results proved that the definitive algorithm successfully identified the hand signs in accuracy of 99 %. The entire investigations manifested that our proposed techniques is valid and effective in estimating hand sign only on the basis of forearm myoelectric signals.

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