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IMPROVEMENT OF MYOELECTRIC PATTERN CLASSIFICATION RATE WITH μ -LAW QUANTIZATION.

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Abstract − In order to realize a myoelectric-controlled multi-functional hand prosthesis, this paper proposes a method to improve the myoelectric pattern classification ability of a hand controller. By applying the proposed method of μ-LAW quantization, the pattern classification rate increased by 11.1\% (averaged for five subjects) and by 15.5\% (maximum), with a practical pattern classification rate of 97.8\% being achieved.

Keywords myoelectric, prosthesis, logic circuit

1. INTRODUCTION

In order to realize a myoelectric-controlled multi-functional hand prosthesis, this paper proposes a method to improve the myoelectric pattern classification ability of the hand controller.

Although the myoelectric control of electric-powered prosthetic hands has been researched since the early 1960s [1], and some prosthetic hands are already commercially available, most are single-function systems---only capable of performing a single function such as open-close---and are thus of limited usefulness in daily life. Accordingly, there have been calls to develop multi-function systems, capable of carrying out more than one function [2].

In response to this demand for greater prosthetic-hand functionality, recently, much research has been conducted on multi-function forearm prosthesis [3-7], applying pattern-classification methods, such as neural networks [3-6] or logic circuits [7], in order to determine the hand actions.

While neural network controllers are capable of highly-accurate pattern classification, size is a major obstacle to compact implementation, which is required in an application such as a prosthetic hand controller, where the prosthetic hand has to be implemented to be both smaller and lighter than a human hand. Therefore, we [7] have proposed utilizing a logic circuit for myoelectric-pattern classification, in order to realize a compact multi-function prosthetic hand.

However, because myoelectric signals vary among individuals and even for the same individual over time, it is not possible to determine in advance the exact specifications of the classification circuit. Accordingly, an evolvable hardware chip (EHW chip) [7, 8], which is capable of adapting its own circuit structure to specification changes, has been adopted for myoelectric pattern classification.

In the case of myoelectric pattern classification with a logic circuit, it is necessary to quantize the myoelectric signals into discrete numbers, which must then be coded as binary bit patterns. Efficient quantization and coding methods are, therefore, essential to realizing high-accuracy myoelectric pattern classification.

We have previously reported improvements to pattern classification rates by applying logarithm quantization and a redundant code [9]. However, the logarithm quantization, which was executed with a fixed algorithm, is not always effective for all myoelectric-pattern distributions, because the distribution characteristics of myoelectric patterns differ among individuals. Thus, it was only possible to achieve a 3.1\% increase in the averaged classification rate with a maximum increase of 10.5\% [9].

In order to overcome this quantization problem, in this paper, we propose employing μ-LAW quantization [10], where transformation characteristics can be adapted to the distribution characteristics in terms of a μ-value.

The effect of μ-LAW quantization is confirmed in the pattern classification of myoelectric signals, which are sampled from five subjects, including one experienced person, who has repeatedly participated in our experiments, and four new users joining our experiments for the first time.

By applying the μ-LAW quantization, the pattern classification rate increased by 11.1\% (averaged for the five subjects) and by 15.5\% (maximum). Furthermore, the classification rate for the experienced subject was 97.8\% (averaged over ten trials), demonstrating that skilled individuals are able to operate a multi-functional myoelectric hand with high-accuracy.

2. The EHW chip

Evolvable hardware is based on the idea of combining a reconfigurable hardware device with genetic algorithms [11] to execute reconfiguration autonomously [8]. This section briefly describes reconfigurable hardware and genetic algorithms before explaining how these are combined to realize evolvable hardware.

2.1. Reconfigurable hardware

The structure of reconfigurable hardware devices can be continuously changed by downloading to them a bit string called the configuration bit string.

A PLA (Programmable Logic Array, Fig. 1) is one of the simplest reconfigurable hardware devices, consisting of an AND-array and an OR-array. In Fig. 1, the black and white circles indicate switches, which determine the interconnections between the inputs and outputs (black circles indicate the connections). The rows of the AND-array form logical products for connected inputs, and the columns of the OR-array form logical sums for the connected row in the AND-array. We can specify these switch settings with a configuration bit string, as shown in Fig. 1.

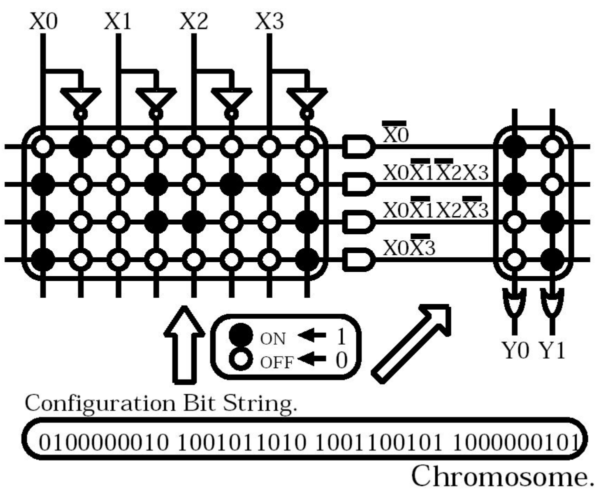

Fig. 1. The basic structure of the PLA.

2.2. Genetic algorithms

Genetic algorithms (GAs) are robust search algorithms loosely based on population genetics. They effectively seek solutions from vast search spaces at reasonable computation costs. Before a GA starts, a set of candidate solutions, in the form of binary bit strings, is prepared. This set is referred to as a population, and each candidate solution within the set is called a chromosome. A fitness function is also defined which represents the problem to be solved in terms of criteria to be optimised.

The chromosomes undergo a process of evaluation, selection, and reproduction. In the evaluation stage, the chromosomes are tested according to the fitness function. The results of evaluation are then used to weight random selections of the chromosomes in favor of fitter ones for the final stage of reproduction.

In the final stage, a new generation of the chromosomes is "evolved" through genetic operations that attempt to pass on better characteristics. Through this process of evaluation, selection, and reproduction which can be repeated as many times as required, less fit chromosomes are gradually expelled from a population giving fitter chromosomes a greater chance to emerge as the final solution.

The basic concept behind the combination of reconfigurable hardware devices and genetic algorithms in EHW is to regard the configuration bits for the reconfigurable hardware devices as chromosomes for the genetic algorithms. If a fitness function is properly designed for a task, then the genetic algorithms can autonomously find the best hardware configuration in terms of the chromosomes (i.e. configuration bits).

2.3. Hardware implementation of EHW; the EHW chip.

For most EHW research, genetic operations are executed by software running on either a PC or WS. This makes it difficult to utilize EHW in situations that need circuits to be as small and light as possible, such as a hand controller. One solution to this is to implement the GA on the hardware and to incorporate it in a single LSI chip together with the reconfigurable logic. The first version of the evolvable hardware LSI chip was designed by us in 1998 [7], in order to apply it to the hand controller.

3. The myoelectric hand controller

3.1. A Myoelectric pattern classifier with the EHW chip

The basic concept underlying our approach to myoelectric hand prosthesis is to control a multi-functional mechanical hand with the EHW chip for myoelectric pattern classification. The myoelectric hand system consists of a controller, a mechanical hand (Fig. 2), myoelectric electrodes and a battery (12V lithium-ion). In our latest system, two commercially available myoelectric electrodes (OttoBock; 13E125=50) provide two myoelectric-signal channels.

Fig. 2. The multi-functional mechanical hand.

The controller consists of (1) a myoelectric signal quantizer, (2) a myoelectric signal encoder, and (3) the myoelectric pattern classifier on the EHW chip. The quantizer and the encoder are required because pattern classification with the EHW chip is carried out using a logic circuit, where the input signals are binary bit patterns, on the PLA (Fig. 1). Therefore, the myoelectric signals have to be quantized to discrete numbers in order to encode them into binary bit patterns.

3.2. Myoelectric pattern quantization

Myoelectric signals were sampled during execution of the six following muscle contractions: (1) forearm supination, (2) forearm pronation, (3) wrist volar side flexion, (4) wrist dorsal side flexion, (5) hand closing and (6) hand opening, using surface electrodes attached to the forearm of the subjects. The sampled myoelectric signals were normalized to the values, which range from 0 to 7, before being quantized to discrete number, with linear quantization.

Fig. 3 shows an example of a myoelectric pattern distribution, where the x-axis represents the amplitude of signals detected from one electrode with the y-axis for the other electrode. In the worst case of quantizing for the patterns in this figure, three different actions--forearm supination (19 patterns), forearm pronation (20 patterns) and hand opening (2 patterns)--would all be are quantized as (0,0). This would lead to all the distinct patterns being classified as the same pattern, i.e., as being generated from the same action, and this kind of quantization error would hinder high-precision pattern classification.

This kind of quantization error is caused by the bias in the distribution of myoelectric patterns, which is not uniform over the distribution range, but is rather biased towards the low-value region.

3.3. Previous works for myoelectric quantization

In order to remove the biases in the distributions of myoelectric patterns, we have proposed employing a method of logarithm quantization [11], which provides transformations with high precision for the low-value regions, but with low precision for the high-value regions. By applying logarithm quantization, the correct pattern classification rate increased by 10.5\% (maximum) from 81.8\% (without logarithm transformation) to 92.3\% [11].

However, this method sometimes failed to increase the classification rate, and, consequently, the averaged rate only increased by 3.1\% [11]. This is because the logarithm quantization employs a fixed algorithm, and is not, therefore, effective for all myoelectric signal pattern distributions. In order to overcome this problem, in this paper, we propose utilizing μ-LAW quantization [10].

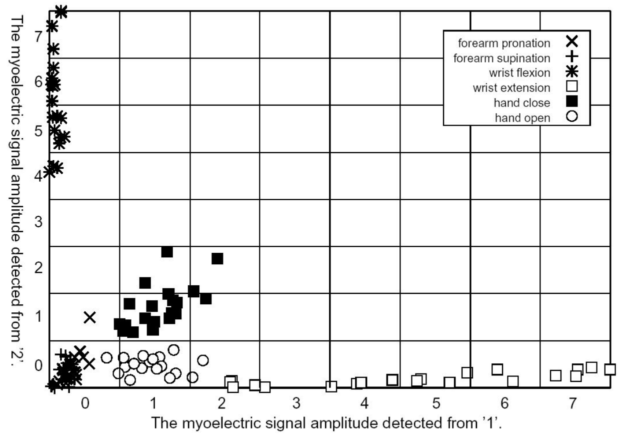

Fig. 3. An example of a myoelectric pattern distribution.

3. μ-LAW QUANTIZATION

The μ-LAW quantization is performed by applying the following transformation, before quantizing to discrete numbers.

$$v = \frac{V \log(1+(\mu e / V)}{\log(1+\mu)}, \quad for\ 0 \le e \le V \qquad (1)$$

where e is an input signal, v is an output signal, V is the maximum value of the input signals and μ is a transformation rate, which defines the transformation characteristics (Fig. 4). In this method, the transformation characteristic can be adapted to the myoelectric distribution in terms of a μ-value; therefore it can be applied to any exponentially-distributed myoelectric signal pattern.

Fig. 5 shows myoelectric signal patterns, which are transformed from the patterns in Fig. 3 by applying equation (1). In this distribution, the worst case of quantizing for the patterns with μ-LAW quantization is (2,3), where forearm supination (8 patterns) and forearm pronation (5 patterns) are both quantized to these values. This represents a large reduction in quantization error and, so, yields high-precision pattern classification. In this example, the μ-value is set to 100.

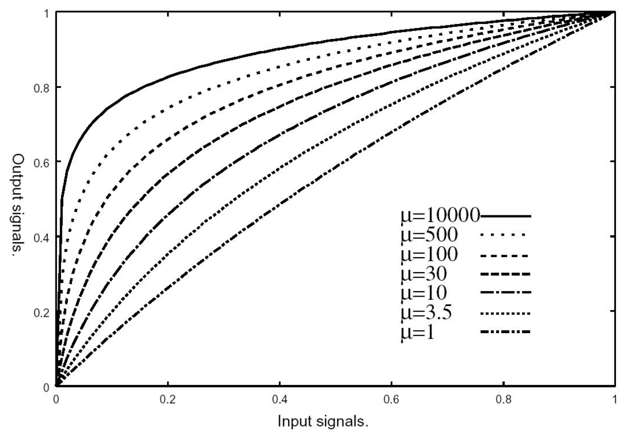

Fig. 4.The μ-LAW transformation characteristic.

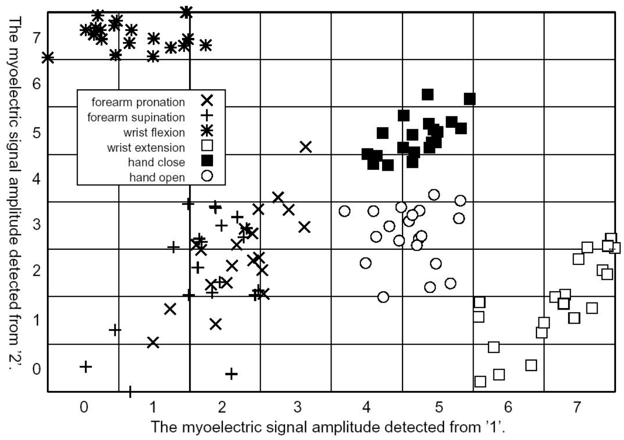

Fig. 5. An example of a myoelectric pattern distribution.

4. PATTERN CLASSIFICATION RESULTS

The effectiveness of μ-LAW quantization has been confirmed in a pattern classification experiment, using samples from five subjects, including one experienced person ('skilled' in TABLE I), who has repeatedly participated in our experiments, and four new users ('beginners' joining our experiments for the first time.

In these experiments, the parameters for GA operations were specified as follows.

- Number of populations: 32
- Crossover rate: 1.0
- Mutation rate: 2/256

TABLE I shows pattern classification rates with linear-quantization and with μ-LAW quantization. Applying μ-LAW quantization, the pattern classification rate increased by 11.1\% (averaged for five subjects) and by 15.5\% (maximum; subject 1). Furthermore, the classification rate for the experienced person increased to 97.8\% (averaged over ten trials), clearly demonstrating that experienced persons can operate a multi-functional myoelectric hand with high-accuracy.

TABLE I. Pattern classification results

		linear	μ-law	
	Subject ID	rate (%)	rate (%)	μ-value
Skilled	1	82.3	97.8	100
Beginner	2	78.7	84.7	500
	3	67.8	74.3	3.5
	4	69.0	83.4	10000
	5	75.5	88.8	10000

5. CONCLUSIONS

This paper has shown that applying μ-LAW quantization increases the pattern classification ability of the myoelectric hand controller. In the case of the skilled person, a practical pattern classification rate of 97.8% was achieved, which means that amputee persons can operate the multi-functional hand with high-accuracy, by undergoing rehabilitation training for myoelectric pattern generation.

Our developmental work into hand prosthetics is not limited to only the hand controller but also includes the development of a multi-functional mechanical hand (Fig. 2), which has a wrist function as well as a hand open-close function. The multi-functional hand with the EHW chip controller is currently in the clinical testing phase.

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