APPLYING GENETIC PROGRAMMING TO CONTROL OF AN ARTIFICIAL ARM

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INTRODUCTION

Robotics researchers at NASA's Johnson Space Center (JSC) and Rice University have made substantial progress in myoelectric teleoperation [1-5]. A myoelectric teleoperation system translates signals generated by an able-bodied robot operator's muscles during hand motions into commands that drive a robot's hand through identical motions. Farry's early work in myoelectric teleoperation used variations over time in the myoelectric spectrum as inputs to neural networks to discriminate grasp types and thumb motions; schemes yielded up to 93% correct classification on thumb motions [1,2]. More recently, Fernandez achieved 100% correct non-realtime classification of thumb abduction, extension, and flexion on the same myoelectric data using genetic programming to develop functions that discriminate between thumb motions using myoelectric signal parameters [3,4]. Genetic programming (GP) is an evolutionary programming method where the computer can modify the discriminating functions' form to improve its performance, not just adjust numerical coefficients or weights [4,6]. While the function development may require much computational time and many training cases, the resulting discrimination functions can run in realtime on modest computers. These results suggest that myoelectric signals might be a feasible teleoperation medium, allowing an operator to use his own hand and arm as a master to intuitively control an anthropomorphic robot in a remote location such as outer space.

These early results imply that multifunction myoelectric control based on genetic programming is viable for prosthetics, since teleoperation of a robot by an operator with a complete limb is a limiting or "best-case" scenario for myoelectric control. We hypothesize that myoelectric signals of traumatic below-elbow amputees can control several movements of a myoelectric hand with the help of a function or functions developed with genetic programming techniques. We are now testing this hypothesis with the help of NASA/JSC under a NASA/JSC - Texas Medical Center Cooperative Grant. In this study, five adult below-elbow amputees are performing two forearm motions, two wrist motions and two grasp motions using their "phantom" limb and sound limb while we collect myoelectric data from four sites on the residual limb and four sites from the sound limb. We will use a variety of myoelectric signal time and frequency features in a genetic programming analysis to evolve functions that discriminate between signals generated during different muscle contractions.

BACKGROUND AND THEORY

Farry focused on the time-varying spectrum of the myoelectric signal by studying the correlation between the myoelectric spectrum in the initial recruiting phase of a motion and the type of motion [5]. She examined the myoelectric signals for thumb flexion, extension and abduction by placing an electrode over the Extensor Pollicis Brevis/Abductor Pollicis Longus pair and an electrode over the Flexor Pollicis Longus/Flexor Digitorum Superficialis pair in a monopolar electrode configuration. In addition to myoelectric signal collection, Farry simultaneously recorded the motion of the thumb using an exoskeletal joint position measurement device as the subject performed one of the three thumb motions, a key grasp, or chuck grasp. Use of this device allowed her to determine to starting time of the actual motion, independent of the myoelectric signal, permitting a direct comparison among many test trials.

Farry demonstrated intuitive myoelectric discrimination between chuck and key grasps with a success rate of over 90% using a new spectral estimation approach, Thompson's multiple window method. This estimate has much lower bias and variance than traditional estimates, making it a better candidate to compute motion classification features. She also extended this method into a time-frequency analysis tool called the short-time Thompson transform, showing that the myoelectric signal may be more stationary than previously thought.

Fernandez continued this work by using genetic programming to analyze the myoelectric data collected by Farry. Genetic programming uses an evolutionary approach to problem solving by providing a way to search all possible programs composed of certain terminals and functions to find a computer program of unspecified size and shape which solves, or approximately solves, the problem. First, an initial, random population of programs composed of terminals and functions is created. Each program is then run and the result is assigned a fitness value according to how well it solves the problem. Next, a new population of programs is created from a predetermined reproduction technique based on the fitness of the results from the previous generation. The solution to the problem is the genetic program with the best fitness within all of the generations.

In this study, we continue to use the genetic programming methods of Fernandez, which followed the feature extraction method from Hudgins [7] and Saridis [8]. Hudgins developed a simple approach for the classification of four different motions or muscle contractions. His classification scheme used five different features from several windows or time segments of each of the signals. His five features were Mean Absolute Value, Mean Absolute Value Slope, Zero Crossings, Slope Sign Changes and Waveform Length. He used a multi-layer perception with back-propagation to classify myoelectric patterns from these features

Fernandez used more features than Hudgins as well as genetic programming instead of neural networks for classification. The first task of the GP implementation was the selection of the terminals for the genetic program. Fernandez began with Hudgins' features and defined five additional features to compose the terminal set:

1) *Average value* (AVG), defined by $\overline{X} = \frac{1}{N}\sum_{k=1}^{N} x_k$.

2) *Up slope* (UP), which counts the number of individual samples that have a positive slope, defined by $x_k - x_{k-1} > 0$. The rationale for this and the next feature, Down Slope, was differentiating between a gradual increase in the waveform and a steep increase.

3) *Down slope* (DOWN), a count of the number of individual samples which had a negative slope, as defined by $x_k - x_{k-1} < 0$.

4) The *ratio of mean absolute value (MAV) of channel 1 to channel 2*.

5) *The ratio of the MAV of channel 2 to channel 1*.

Note that the last two compound features (combinations of other features) gave moderately good results in the differentiation of the signals. In some of the solutions the genetic program used the first ratio, while in others it used the second one, even though one is the reciprocal of the other.

Fernandez' terminal set for the genetic program included several constants as well as the above features. This gave the genetic program the ability to manipulate the data with some consistency. The majority of the constants were a series of numbers which started at 0.7 and changed by an increment of 0.1 up to 1.3 (i.e., 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3).

The next task was defining the function set for the genetic program (Table 1), consisting of mathematical functions selected for their diverse properties. For example, Fernandez included trigonometric functions because the waveforms have sinusoid component features.

Name	Symbol
Addition	+
Subtraction	-
Multiplication	*
Division	/
Square Root	sqrt(abs(x))
Sine	sin
Cosine	cos
Tangent	tan

Name	Symbol
Natural Logarithm	ln(abs(x))
Common Logarithm	log(abs(x))
Exponential	exp
Power Function	x^y
Reciprocal	1/
Absolute Value	abs
Integer or Truncate	int
Sign	sign

Table 1 - Functions for the genetic program

The fitness function is the most important constituent of the GP method. The fitness function must always yield a value in the same small range for the same type of myoelectric signal and a value in a different range for another type of myoelectric signal. The value ranges corresponding to different classes of myoelectric signals must not overlap, i.e., the minimum of the range of one signal must be greater than the maximum of the range of another signal. Figure 1 illustrates a classification scheme's separation.

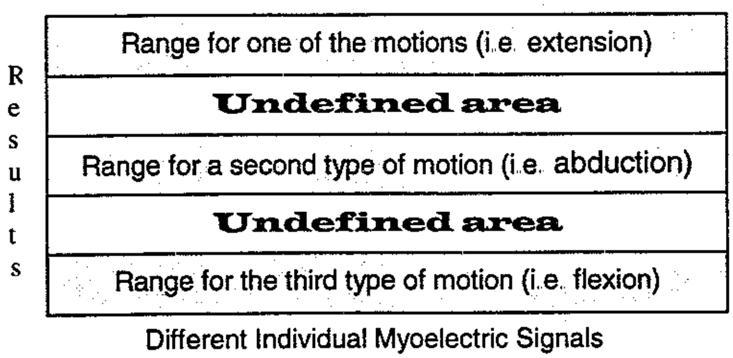

Figure 1 - A graphical representation of the classification scheme, where the signal type could be extension, abduction or flexion

The specific form of the fitness function was:

Fitness Function =

$$\mathrm{STD}(\mathrm{Signal}\,1) + \mathrm{STD}(\mathrm{Signal}\,2) + \mathrm{STD}(\mathrm{Signal}\,3) + \frac{\mathrm{Weight}}{\mathrm{MIN}\begin{bmatrix} |\mathrm{AVG}(\mathrm{Signal}\,1) - \mathrm{AVG}(\mathrm{Signal}\,2)| \\ |\mathrm{AVG}(\mathrm{Signal}\,1) - \mathrm{AVG}(\mathrm{Signal}\,3)| \\ |\mathrm{AVG}(\mathrm{Signal}\,2) - \mathrm{AVG}(\mathrm{Signal}\,3)| \end{bmatrix}}$$

where STD was standard deviation and AVG was average. The weight was a constant used to magnify the separation between the average values of the three signals.

Given the thumb motion data collected by Farry, Fernandez was able to achieve 100% discrimination of extension, flexion, and abduction of the thumb with a single discrimination function. Fernandez also achieved perfect discrimination of these thumb motions using slightly different strategies such as combinations of pair-wise discrimination functions. Consequently, we are beginning with Fernandez' GP approach in the current study with amputee data.

METHODS

Subjects

We have recruited five adult, unilateral below-elbow amputees for this study. Their average age is 34 years (range 23 - 50). There are three males and two females. All became amputees due to trauma, an average of 7.6 years (range 3 - 17) prior to this study. One subject currently uses a myoelectric arm exclusively while two subjects use both a myoelectric and a body-powered arm. Of the remaining subjects, one is a former myoelectric user now using only a body-powered arm, and the other has no myoelectric experience. All report the clear perception of a "phantom" hand.

Equipment

Myoelectric data is collected using a Fetrode electrode artifact reduction system (UFI, Morro Bay, California) consisting of disposable recessed silver-silver chloride electrodes, an amplifier and a signal conditioner. The Fetrode system has very high input impedance. It virtually eliminates induced motion artifact. The recessed, wet electrodes have low motion artifacts relative to those commonly used in prostheses; however, we want to initially test the GP on myoelectric signals rather than motion artifact.[1]

The myoelectric signals are routed from the Fetrodes through a BNC breakout board (National Instruments Corp., Austin, Texas) to an AT-MIO-16X data acquisition board (National Instruments Corp., Austin, Texas) located in a 133MHz Pentium personal computer (Gateway 2000, North Sioux City, South Dakota). Data collection is controlled using software written within the LabVIEW program development application (National Instruments Corp., Austin, Texas). We use MATLAB (MathWorks,

[1] Motion artifact is not necessarily a bad thing in prosthetics control. Physiologists frown on it, since it is, in fact "noise" to someone studying muscle physiology. It is also problematic to those prosthetics controllers which estimate muscle force; however, we have noticed that some myoelectric prosthesis users rely to some extent on the motion artifact (which is considerable with the stainless steel button electrodes in common use in prosthetics today) to operate their prostheses. Motion artifact may improve the performance of a classifier, to the extent that it is <u>motion-specific</u>.

Natick, Massachusetts) for preprocessing and feature computation, and Fernandez' custom software [4] for the GP implementation.

Procedure

The data collection from amputee subjects occurs at TIRR. Four pairs of surface electrodes are placed on the residual limb and four are placed at nearly identical sites on the sound limb using a monopolar configuration. Electrode site choices are initially based on muscles most likely to be active during the motions, but modified somewhat for each individual based on an assessment of where the most useful myoelectric signal is likely to be present given that person's residual limb anatomy. We place ground electrodes for each myoelectric channel on bony areas of the corresponding limb.

Data collection begins with the subject seated and their arm/hand in a neutral position. The subject is presented with a randomly selected image on a computer monitor showing one of the six intended final hand/arm positions: (1) open grasp, (2) close grasp, (3) wrist flexion, (4) wrist extension, (5) forearm pronation, and (6) forearm supination. They have been instructed to move both their sound limb and their "phantom" limb simultaneously to the given position using only the desired motion while not moving uninvolved joints. Data collection begins at the moment the picture first appears and continues for two seconds at a rate of 2400 Hz. The subject is then allowed a brief rest before the next motion is initiated (at their command). If the subject indicates that they may have made a mistake during a trial, then that data is discarded. Otherwise, that trial is added to our database, regardless of the opinions of the attending researchers. Our goal is to collect at least 100 trials for each of the six motions, for a total data set of 600 trials per patient. Our previous experience with GP and neural networks indicates that we need a large number of trails, which are randomly split between "training" or evolution, and testing.

Once we have a complete data set, we use Farry's rate of change of energy [1] algorithm on the myoelectric signatures to locate the motion start (sound limb) or motion command start (residual limb). This algorithm proved more accurate than several others in locating motion start where there was a motion-measuring exoskeleton to compare their performance. In this study, we are not using an exoskeleton (even on the subjects' sound limbs), since it will not be an option in clinical prosthetics fittings, which will focus entirely on the subjects' residual limbs. Locating motion start and aligning all of the myoelectric signatures relative to motion start makes all subsequent data manipulation easier.

Next, we compute features for input to the GP evolution and testing process. We are using a combination of the features from Hudgins [7], Farry [2], and Fernandez [3] as inputs to the GP evolution. We use approximately 35% of the trails in the evolution process and reserve the remainder for the final step, testing the resulting discrimination functions.

RESULTS

As of June 1997, we have completed the data collection system and are now testing the entire data path (from data collection through GP solution) with data from a research team member. We will begin collecting data from amputee subjects in July 1997.

CONCLUSIONS and FUTURE WORK

Farry's myoelectric teleoperation research began in 1991 with a search for an alternative to the fatiguing, non-intuitive three and four degree of freedom joysticks and bulky exoskeletons then commonly used for teleoperation of robot arms and hands [9]. While improvements and cost reductions in exoskeleton and other limb tracking devices have reduced the potential payoff of a myoelectric teleoperation system, we continue to explore this limiting case for myoelectric control. Consequently, we are collecting sound side data on the commanded motions simultaneous with the residual limb data. Myoelectric control remains a prime option for prosthetics control, however, and has become the main focus of our research in the NASA/JSC -- TIRR partnership. Our goal in the application of genetic programming to prosthesis control is multifunction myoelectric control that tailors itself to the individual prosthesis user, thus resulting in reliable multifunction performance that does not require the user's continual attention.

The study described in this progress report is a quick feasibility check of genetic programming to prosthetics control. We are focusing on identifying the particular motion, not determining its speed or magnitude. We are also not yet concerned with simultaneous combinations of motions. If GP continues to show promise after these initial trials, we will explore speed, magnitude, and combinations of motions. We will also pursue GP extensions that allow the discrimination functions to continue evolving based on realtime performance. For example, after the initial training or evolution process, the user could "discipline" the prosthesis when it makes a mistake in interpreting the user's myoelectric signals. The prosthesis controller can then use that error feedback to refine its discrimination functions.

Beyond the genetic programming effort, however, we plan to make the data sets collected in this study available to other researchers via the World Wide Web. Lack of access to subjects and appropriate myoelectric measurement equipment has kept many researchers from applying innovative control algorithms on myoelectric prosthesis control. In addition to lowering the cost of entry into myoelectric research for others, we hope to gain insight into the performance of our approach versus that of other approaches.

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