Human Tremor Analysis Using Particle Swarm Optimization

Russell C. Eberhart
Xiaohui Hu
Purdue School of Engineering and Technology
Indiana University Purdue University Indianapolis
799 West Michigan Street
Indianapolis, IN 46202-5160
eberhart@engr.iupui.edu

Abstract- This paper presents methods for the analysis of human tremor using particle swarm optimization. Two forms of human tremor are addressed: essential tremor and Parkinson's disease. Particle swarm optimization is used to evolve a neural network that distinguishes between normal subjects and those with tremor. Inputs to the neural network are normalized movement amplitudes obtained from an actigraph system. The results from this preliminary investigation are quite promising, and work is continuing.

1 Introduction

Tremor is defined as any involuntary, approximately rhythmic, and roughly sinusoidal movement (Elble and Koller 1990). The analysis and diagnosis of human tremor is a very challenging area. Two of the most common types of tremor affecting the U.S. population are essential tremor and Parkinson's disease (Elble and Koller 1990). Despite years of effort, relatively little seems to be known about these disorders.

Precise characterizations of these forms of pathologic tremor in terms of frequencies and amplitudes do not exist. Furthermore, differentiation between normal physiologic tremor and these pathologic tremors is often difficult, and precise characterization of the ranges of normal physiologic tremors have not been defined.

This paper presents the results of a preliminary study that used digital actigraphs to acquire data from normal and tremor subjects, and particle swarm optimization to evolve a neural network to discriminate between tremor and normal subjects.

2 Data Acquisition Using Actigraphy

Actigraphy is the measurement of movement. Wrist-worn devices for measuring movement called actigraphs have been available since the 1970s. These actigraphs have been widely used in medicine for theraputic, drug, and diagnostic studies. Analysis of data from a wrist-worn actigraph privides an inexpensive and non-invasive method of movement assessment.

Most actigraphs use a piezoresistive accelerometer as the sensor. Many actigraphs, however, do not provide the absolute value of acceleration as output. Rather, they provide the varying, or "AC," component, of acceleration as output. Additionally, although motion occurs in three dimensions, most actigraphs measure movement on only one axis. When worn on the wrist, this axis is generally perpendicular to the inside or outside flat surface of the wrist.

Until recently, available actigraph systems recorded only limited, summarized data. For example, typical measurements have been limited to the number of zero crossings (above some threshold) that occur each time epoch. Time epochs may be as brief as 4 or 5 seconds, or as long as a minute or more.

Recently, tri-mode actigraphs have become available from Precision Control Design, Inc. (PCD), in Ft. Walton Beach, FL, that record zero crossings, time above threshold, and integrated amplitude for each time epoch. These units still do not, however, provide the sampling frequency and amplitude resolution necessary to quantitatively characterize human tremor.

Within the past few months, however, digital signal processing (DSP) based actigraphs have been developed that provide the required sampling frequency and sensitivity. PCD's Tele-Actigraph system samples data at 27.3 Hz with a resolution of about 12 bits. It can sense a change in acceleration as small as about 10 milli-gravities (mGs). Data are telemetered real-time on a 300 megahertz carrier from the wrist-worn unit to an ambulatory unit that can be worn on the belt. The belt unit can acquire data autonomously for up to 5 hours 20 minutes, after which it is downloaded into a PC. Alternately, the PC can be connected directly to the belt unit to achieve continuous data acquisition. Using Labview on a PC, for example, data can be simultaneously acquired, viewed, and stored on the hard disk of the PC.

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For this preliminary study, data were acquired with the Tele-Actigraph (TAG) worn on the outside of the subject's non-dominant wrist. The data acquired were for what is known as postural tremor. The subject held his or her arm with the wrist and elbow unsupported. They were allowed to hold their arm in a comfortable position, with the elbow bent and the forearm approximately parallel to the floor. Data were acquired for approximately 60 seconds from each subject.

Figure 1 shows the three components of the Tele-Actigraph system. On the left is the TAG unit itself, which is usually worn on the wrist, but which may be attached to other parts of the body such as the leg. In the center of Figure 1 is the belt-worn unit that acquires the data from the TAG unit. On the right is the belt unit programmer that is used to load programs into the belt unit. In the current system configuration, the belt unit must be re-initialized by the belt unit programmer each time a new data session is started. In practice, the belt unit programmer is connected to a PC via the parallel port. The TAG unit can be programmed via a serial port on the PC.

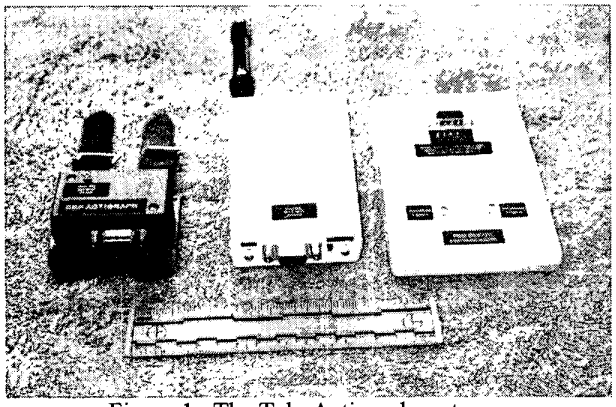

Figure 1. The Tele-Actigraph system.

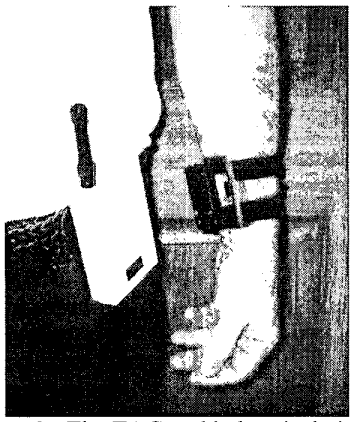

Figure 2. The TAG and belt units being worn.

Figure 2 shows the TAG unit being worn on the wrist, and the belt unit being worn on the belt. This is the usual configuration for ambulatory data acquisition sessions ranging up to five hours and twenty minutes in length.

3 Data Preprocessing

The raw data acquired from the TAG is in a columnar ASCII format, with the high nybble (4 bits) followed by the low byte (8 bits) for each data sample. The first preprocessing entails adding 16 times the value of the high nybble to the value of the low byte to obtain each data sample value.

The resulting raw data file is then viewed using a Matlab script, and the file is shortened to remove data received during the warm-up period of the TAG, which can be up to 30 seconds (but which is usually less than 15 seconds). The shortened raw data file is then analyzed using the Matlab power spectral density routine. Various spectral resolutions were tried, from 512 points down to 64 points. It was decided to use 128-point transforms for this study, resulting in an amplitude value for each of 64 frequency bins.

The upper and lower 2 values are stripped from the files, resulting in 60-point data vectors. The square root is taken for each power value, and the resulting amplitude vectors are normalized such that the maximum value for each vector is 1. These normalized 60-element amplitude vectors are then used as inputs to a neural network.

4 Analysis with Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary computation technique motivated by the simulation of social behavior. PSO was developed by Kennedy and Eberhart (Kennedy and Eberhart 1995; Eberhart, Simpson, and Dobbins 1996).

PSO is similar to a genetic algorithm (GA) in that the system is initialized with a population of random solutions. It is unlike a GA, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions, called *particles*, are then "flown" through the problem space. Rather than using traditional genetic operators, each particle adjusts its flight according to its own flying experience and its companions' flying experience.

PSO was used in this paper for evolving the neural network weights, and, indirectly, to evolve the network structure. This was accomplished by evolving, in addition to the network weights, the slopes of the sigmoidal transfer functions of the hidden and output processing elements (PEs) of a feedforward network. In other words, using the PE transfer function $output = 1/(1 + e^{-k*input})$, the slope k was evolved in addition to evolving the weights. For a

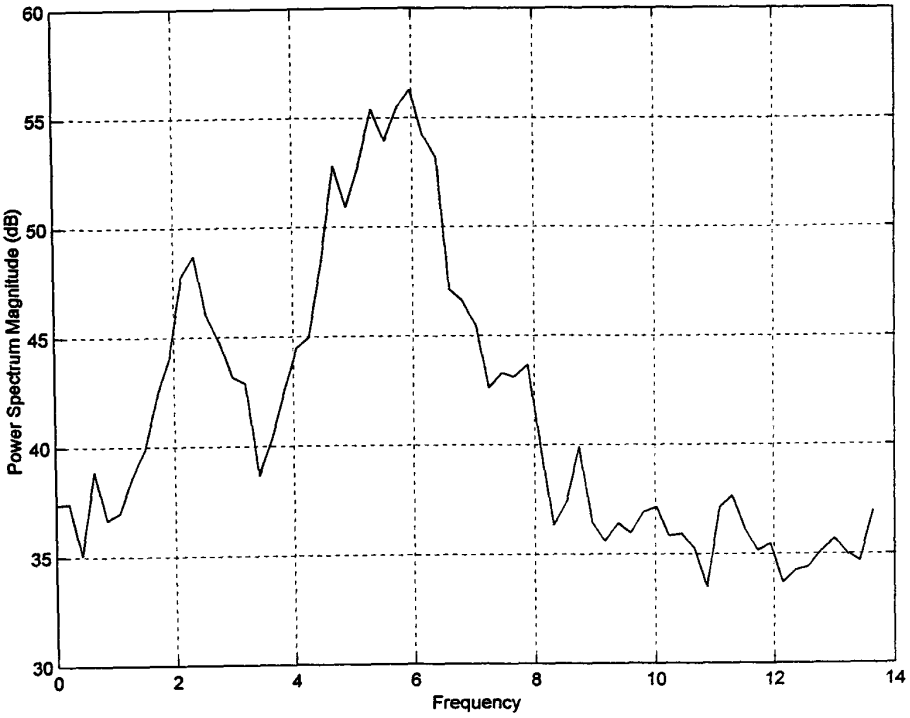

Figure 3. Power spectral density of wrist postural tremor of subject with Parkinson's disease.

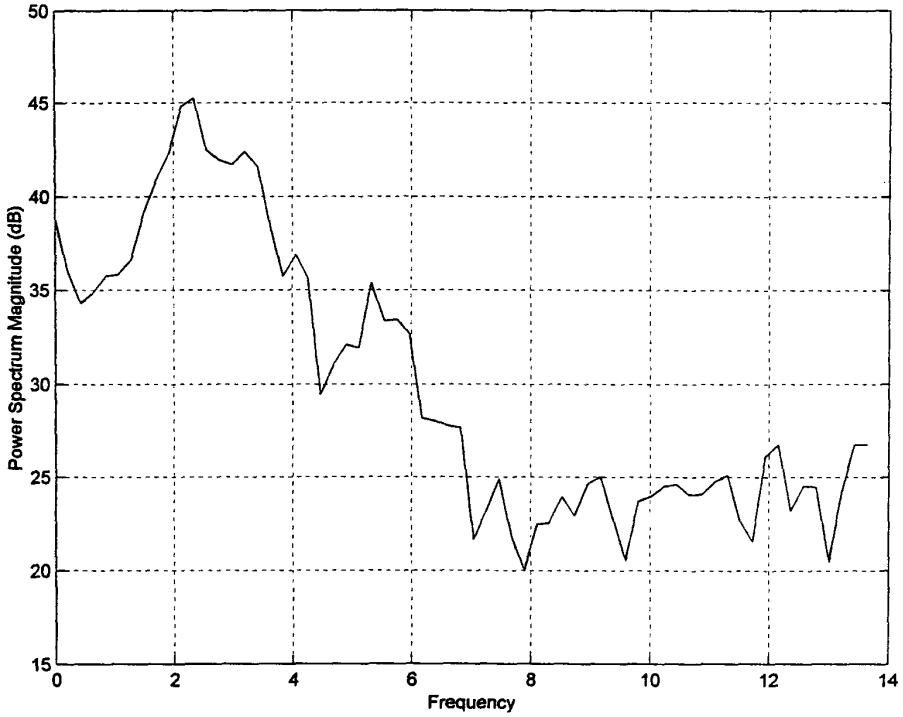

Figure 4. Power spectral density of wrist postural tremor of normal subject.

complete description of using PSO to evolve artificial neural networks, see Eberhart and Shi (1998).

The purpose of this preliminary study was to determine if pathologic tremor (essential tremor and Parkinson's disease) could be distinguished from normal physiologic tremor. No distinction was thus made between essential tremor and Parkinson's tremor subjects when evolving the neural network. A feedforward network with 60 inputs, 12 hidden PEs, and two outputs, was evolved. Sigmoidal transfer functions were used in the hidden and output layers.

Data sets were available from 12 subjects with tremor and 10 mornal subjects. The power spectral density plot for a subject with Parkinson's disease is shown in Figure 3, while Figure 4 depicts the spectrum for a normal patient. Neural networks were originally evolved using all 22 patterns; generalization was not the main object of this effort. However, subsequently, training on all but one pattern and testing on that remaining pattern has yielded an accuracy of 100 percent. Table I presents the outputs from a neural network evolved using all 22 patterns.

Table I. Classification results with a 60-12-2 feedforward neural network

Classification	Output 1	Output 2
Normal	0.053	0.948
Normal	0.027	0.973
Tremor	0.917	0.088
Tremor	0.981	0.019
Normal	0.181	0.813
Normal	0.025	0.975
Normal	0.038	0.962
Tremor	0.982	0.020
Tremor	0.932	0.067
Tremor	0.948	0.051
Tremor	0.968	0.036
Tremor	0.982	0.019
Normal	0.048	0.953
Tremor	0.986	0.015
Normal	0.066	0.935
Normal	0.070	0.930
Tremor	0.842	0.157
Tremor	0.944	0.058
Normal	0.028	0.972
Tremor	0.955	0.049
Tremor	0.990	0.011
Normal	0.038	0.961

The outputs for the first processing element show outputs greater than 0.8 for all tremor subjects, and under 0.2 for all normal subjects. Analogously, the second output has outputs greater than 0.8 for all normal subjects and under 0.2 for all tremor patients.

The particle swarm used to evolve the neural network had a population of 30 particles and a maximum velocity of 2.0. The initial damping weight was 0.9, and it was set to decrease to 0.4 over 2,000 iterations. However, only 38 iterations, or generations, were required to evolve the network. The process was thus extremely fast.

These results are very encouraging. Time has not permitted the evolution of other network topologies, but this is planned as part of the continuing work in this area.

Also planned are attempts to distinguish between essential tremor and Parkinson's disease, and between pathologic and physiologic tremor (at the early stages of pathologic tremor).

5 Conclusions

Particle swarm optimization has been successfully applied to evolve a neural network that classifies human tremor (Parkinson's disease or essential tremor) versus normal subjects. The method is extremely fast and highly accurate. The relatively small size of the data set indicates the need for further testing and development.

Acknowledgments

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