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Modeling of the steady-state disturbance term in isometric force using components of the Power Spectrum.

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Abstract— **The analysis of isometric force may provide early detection of certain types of neuropathology such as Parkinson's disease. Our long term goal is to determine if there are detectable differences between model parameters of healthy and unhealthy individuals. The participants in this study were twenty four healthy adults ages 18 through 24, both male and female. The experiments involved the participants exerting isometric force over a range from 5% to 65% of maximal voluntary contraction. The analysis involved the steady-state portion of the recorded time series. Five components of the power spectral density were extracted and used as features to classify the participants into two categories: (1) high strength; (2) low strength based upon the values of the five extracted spectral components. Even though the participants were all healthy and young the features exhibited enough differences to successfully classify 80% of the subjects into the proper category. This finding suggests that the 5-component model should be capable of discriminating between healthy individuals and those who are in an early stage of neurodegenerative disease.**

I. Introduction

This study is part of on-going work involving the modeling of isometric force exerted by the index finger. All of the subjects were young healthy adults, and the datasets are a reference point for future comparisons across age and across a range of neuropathologies. The steady-state portions of the datasets were used to parameterize models. In our previous work we found that single linear time-invariant (LTI) model was not adequate to characterize the isometric force range of an individual; instead non-linear modeling techniques were required [1, 2, 3].

To date, our modeling results agree with previous studies that identified two resonant peaks present in the power spectral density (PSD) of isometric force recordings. Physiological tremor can explain both of the resonant peaks that appear in sub-regions of the PSD. Deviations from the normal resonant frequencies may indicate pathological tremor, which in turn can provide for earlier diagnosis of neurological disorders such as Parkinson's tremor [4]. Our ultimate goal is to develop a diagnostic tool that can be applied in a physician's office for early detection and more effective treatment.

The two resonant peaks are characteristic within the physiological tremor distributions. The first is thought to originate from a number of central and peripheral mechanisms, consistently falls within the range of 8-12 Hz, is termed neuronal tremor, and is resistant to change [5]. The mechanical tremor is the second component of physiological tremor and is associated with the resonant properties of the joint segment [5].

Isometric force experiments using the index finger have been conducted on both healthy subjects and those afflicted with Parkinson's disease. Prior findings suggest the possibility of discriminating between the two states [6].

The change in dynamical complexity in the steady-state region of the isometric force response has been analyzed using the approximate entropy statistic [7, 8]. In addition, piece-wise linear stochastic maps have been used to model the isometric force response of the index finger [9, 10]. More recently the isometric force steady-state region has been modeled using a nonlinear dynamical system approach [1-3, 16]. These results showed that a fourth-order, pole-zero nonlinear difference equation was adequate to characterize a subject across the target force range, but that one set of coefficients was not adequate for modeling all subjects, even within a single age category [1, 3, 16]. In an attempt to reduce the complexity of the equations, we explored the use of Volterra series and Hammerstein systems [11-13, 15]. While the Hammerstein model overcame the need to parameterize 10 separate ARMA models for the 10 strength conditions we study, it required a nonlinear (peace-wise linear) mapping consisting of 10 sections.

These nonlinear dynamical system models provided acceptable results; the mathematical representations are not readily interpretable by professionals in kinesiology and medicine, the fields with the greatest interest in these phenomena. Despite the more complex nature of non-linear methods, their study may provide insight in the complexities of the human neuromuscular system. In this paper we expand our non-linear model by applying concepts from non-linear system theories involving Methods.

In this study we generated models of the isometric force response in the steady-state region by extracting

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specific features of the power spectral density (PSD) [17].

Twenty four healthy adults, ages 18 through 24, both male and female, participated as subjects after providing informed consent. The task was to produce a constant level of isometric flexion force using the index finger so that the force output on a computer screen matched the target force levels, i.e., 5, 15, 25, 35, 45, 55, and 65% maximal voluntary contraction (MVC). Data on the task-related normal forces and on tangential force were collected with a 3-dimensional load cell. The trial length was 15 s. The force levels were presented to each subject in random order, and each subject completed five repetitions at each force level. The steady-state region of each trial consisted of the ten second interval from 4 to 14 s. The sample rate for data collection was 100 Hz (i.e., T = 0.01 s). A second factor of this study involved dividing the participants into one of two categories based on the MVC, used as a measure of strength.

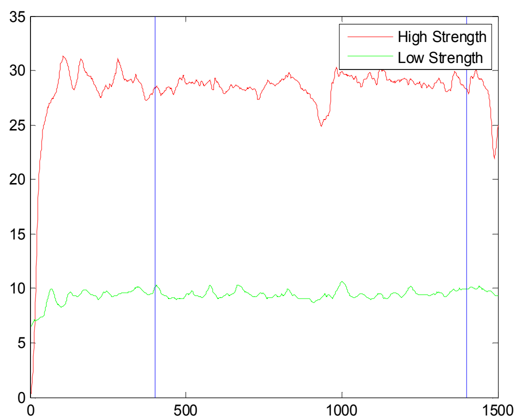

Fig. 1 – Plot of two time-series recorded form at 65% MVC. The red graph was generated by the strongest participant while the green plot was generated by the lowest strength participant. The blue vertical line delineate the steady state region that was subsequently analyzed

In order to study the characteristics of the disturbance term of the total isometric force response, we developed models of the steady-state response.

As an example, Fig. 1 shows the plot of two trials which were recorded from two different individuals at the 65% MVC force level. The red line shows the isometric force of the highest strength participant and the green plot for the lowest strength individual. The two vertical blue lines enclose the region of the steady-state response that was subsequently analyzed.

Previously we modeled the stochastic component of the steady-state response as a set of autoregressive moving average (ARMA) random process [1, 3]. Several model categories were evaluated and the ARMA (4, 4) model family was determined to be the best low-order model of the disturbance term [1, 16]. In addition, a Hammerstien model, using a ten-section piece-wise linear static nonlinearity cascaded with a fourth order linear dynamic term was successfully used to model the steady-state region of the isometric force response [15].

While both of these approaches yielded good results, there were difficult to interpret by the perspective user of the system (e.g., physicians and kinesiology researchers).

To overcome the confusion associated with interpreting parametric models of the isometric force response we have chosen to use a nonparametric approach by extracting components of the PSD thus providing a visual analysis of the steady-state response to non-mathematicians.

Our initial approach was to extract four components from the PSD which included the two physiological tremor resonant peaks, the 1/f-like fractional Gaussian noise (fGn) region, and the white noise level [17]. Here we refine this approach by using the extracted components as the initial conditions to a nonlinear regression algorithm to provide a more accurate model of the PSD.

II. METHODS

The participants were divided into 2 categories based upon the MVC that they were capable of generating. Fig. 2 is a plot of the individual MVC and gender of the participants. Two categories, low and high strength, were formed by placing half of the subjects into each category.

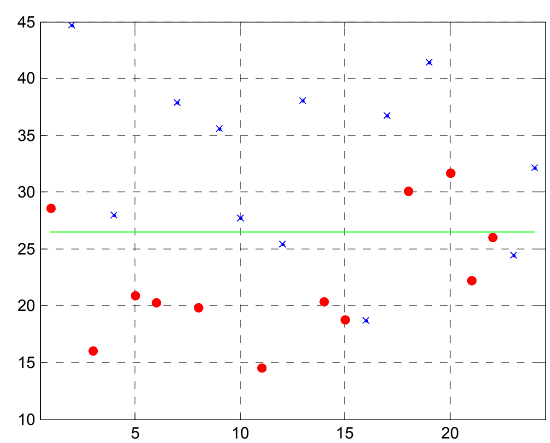

Fig. 2 – Plot of maximal voluntary contraction of the 24 participants. The MVC was used to divide the participants into low-strength (MVC below the green threshold line) and high-strength categories. The red dots indicate female participants and the blue x's denote male participants.

The MVC and corresponding target force levels differed across subjects. To standardize the responses across individuals we used an integer index corresponding to increasing target force level. This index was termed the condition index and is used as the independent variable on the following figures.

Fig. 3 is the plot of PSD associated with the steady-state region of isometric force response.

The five subregions, or components, are indicated on the figure. Region A is the low frequency line which can vary in slope and y-intercept. Regions B and D are the two resonant peaks associated with physiological tremor. Region C is associated the 1/f-like neural noise while region E is used to estimate the base-line white noise level. Parameters associated with theses five components are extracted and used as initial condition to the non-linear regression algorithm

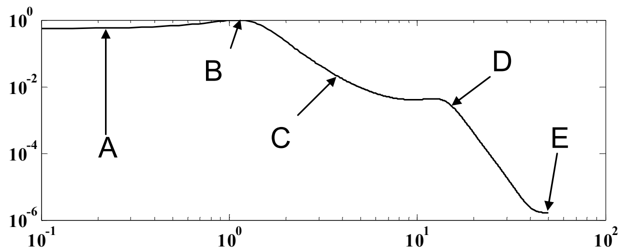

Fig. 3 – Plot of a PSD estimated from the steady-state region of isometric force response.

Two PSD estimation techniques were used to generate the set of features that were later used to classify the participants. The first method was Welch's method with a 512 sample Hamming window and 50% overlap between the periodograms. Second we employed a spectral estimation technique that emphasized the resonant frequencies that were present within the time series [18].

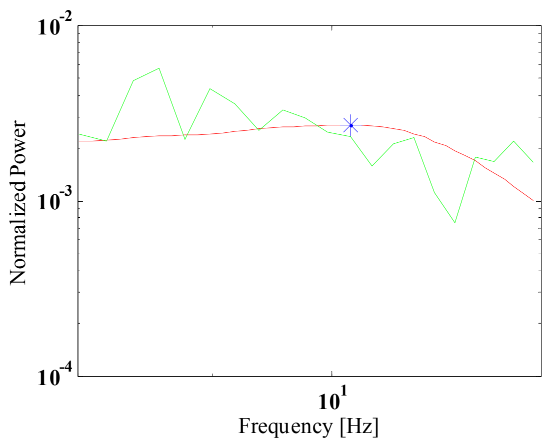

Fig. 4. The blue star indicates the location of the resonant frequency of the second sinusoidal component in the 8 to 12 Hz range of the frequency spectrum. The red plot is the eigenfunction spectral estimate whose maximum value was used to estimate the resonant frequency. The PSD, plotted in green, was used to estimate the amplitude of the second sinusoidal component.

This technique is one of the subspace methods known as eigendecomposition of the autocorrelation matrix which was estimated using the observed data. Fig. 4 shows the overlay of the Welch periodogram (green) and the eigendecomposition (red) in the region of the 8 to 12 Hz resonant peak (Region D). The blue star shows the location of the peak value which was used to estimate the magnitude and frequency of the resonance.

Estimates for the low frequency resonant peak (region B) were obtained in a similar manner. The estimates of the slope and y-intercept for the two linear region (Regions A and C) were obtained by linear regression. The mean and variance of the PSD in the 30 to 50 Hz range were used as estimates of the baseline white noise. Eq 1.is the Lorentzian function that was used to model to two resonant peaks [19].

$$y = \mathrm{abs}\left(y_0 + (2 \times a/\pi) \times \left(w/(4 \times (x - x_0)^2 + w^2) \right) \right) \quad \textbf{Eq. 1}$$

In Eq. 1 $\mathbf{y_0}$ is DC offset (set equal to 0); **a** is the amplitude of the function; **w** is the width (set equal to 3); $\mathbf{x_0}$ is the peak position, and **x** is a vector containing the frequency range.

III. Results

Following the analysis of the PSD into the five regions shown in Fig. 3, the estimation procedure generated the parameters which served as initial condition to the non-linear regression algorithm. The nonlinear regression further refined the parameters by iteratively minimizing the differences between the components and the Welch PSD estimate.

Fig. 5 shows the final fit of the five components. The Welch PSD of the raw data was plotted in red on Fig. 5. The green plot shows the curve that resulted from the superposition of the five components.

After all of the PSDs for all subjects were optimized by the nonlinear regression algorithm, the parameter space was reduced from ten dimensions to three by performing principle component analysis (PCA) and selecting the three components that were associated with the three largest eigenvalue. The final step was to generate a classifier based on the Mahalanobis distance metric [20].

Using the approach described above, 80% of the subjects were properly classified as belonging to either the low-strength or high-strength category.

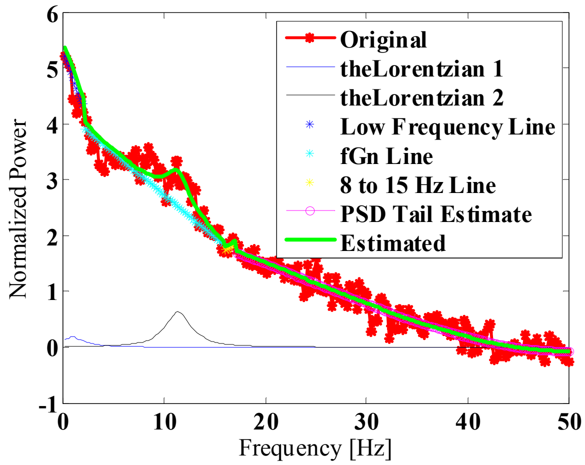

Fig. 5. Plots of the Welch PSD of a typical steady state disturbance term (red) and the estimated fit using the 5 components of the (green). The estimated PSD was the linear combination of the two Lorentzian estimates of the resonant peaks and estimates of the low frequency and fGn lines plus the estimate of the region of the tail from 15 Hz to 50 Hz.

IV. DISCUSSION

Using a nonparametric approach to modeling the steady-state region of isometric force response provides a visually intuitive interpretation of the time-series across many subjects. Further reducing the PSD to 5 components, provides a clear method for diagnosing subjects based on intuitive parameters thus providing clearer understanding for physicians and researchers who do not have extensive training in complex mathematics.

Even though all of the subjects were healthy young adults, the extracted components of the PSD were successfully used to classify 80% the participants in either a high-strength of low-strength categories. This finding suggested that the features should be able to classify healthy individuals from those with early stage neurological disorders.

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