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Classifying Features of the Intrinsic Mode Functions Generated by Empirical Mode Decomposition of Isometric Force Response Using a Fuzzy Classifier

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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 verses unhealthy individuals. As a first step toward our long-term goal, we studied 24 healthy young adults ages 18 through 24 years, 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. Each times-series was decomposed into a set of Intrinsic Mode Functions using Empirical Mode Decomposition. Next, eight features were extracted and used to train a Fuzzy Set Classifier. The participants in this study were assigned to two categories: (1) high strength; and (2) low strength based upon the values of the eight extracted features. Even though the participants were all healthy and young, the features exhibited enough differences to successfully classify 99% of the participants. This finding suggests that, when clinical data become available, the features extracted from the Intrinsic Mode Functions and input into the Fuzzy Set Classifier may 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 analyzed using Empirical Mode Decomposition (EMD) into a set of Intrinsic Mode Functions (IMF). Eight features were extracted from the IMF and used as input into the Fuzzy Set Classifier (FSC).

In our previous work we have shown that the steady-state isometric force signal was non-linear and nonstationary [1]-[3]. By employing EMD, we also showed that the signal was corrupted by multiplicative noise [4].

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. Use of EMD to analyze the isometric force signal has shown that there are more than two resonant frequencies that need to be considered when classifying a participant's force response. 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 [5]. Our ultimate goal is to develop a diagnostic tool that can be applied in a physician's office for early detection and thereby more effective treatment.

The two well-known resonant peaks are characteristic of normal physiological tremor. The first, 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 [6]. The mechanical tremor is the second component of physiological tremor and is associated with the resonant properties of the joint segment [6]. Prior findings using isometric force experiments have been conducted on both healthy subjects and those afflicted with Parkinson's disease and suggest it is possible to discriminate between the two states [7].

Once the steady-state region of an isometric force response has been analyzed, the resulting features can be automatically classified using some form of pattern recognition algorithm. Fuzzy Set Theory (FST) is a generalized nonlinear approximator [8], [9], [10] and has been used to implement nonlinear dynamical systems [2], feed-back control systems [8]-[11], and as a pattern recognition method [12].

This paper describes the use of FST to implement an eight-feature classifier. Prior to extracting the eight features, an EMD algorithm was applied to the steady-state region of each participant's isometric force response decomposing the time series into a set of IMFs [13], [14]. This process was repeated for all five trials of the seven target force levels studied here. The number of IMFs comprising a given set depended upon the complexity of the force response. Next, a set of eight features was extracted from each of the first six IMFs that were generated by the EMD algorithm. This procedure resulted in six sets of features that were input into six independent FSCs. In theory, the six FSCs could process the eight IMF in parallel. Once the outputs of the six FSCs were calculated, they were combined to generate a single classification of the participant's force response into one of

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the two categories: (1) high strength; and (2) low strength.

II. Methods

The isometric force responses were acquired using the technique displayed in figure 1.

Fig. 1 – Schematic representation of the technique used to capture a participant's isometric force response. The horizontal lines drawn through the wrist and fingers imply that these areas were secured to the test platform to prevent accidental movements. The index figure applies an abductive force to a force detector (black circular object) in the direction shown by the arrow in the figure.

Twenty four healthy adults, half male and half female, ages 18 through 24 years 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 target force levels were presented to each participant in random order, and each subject completed five repetitions at each force level. At the beginning of each trial, no force was applied to the transducer. Next, the target force was displayed on a computer monitor and the participant responded by applying force to match the displayed target. The steady-state region of each trial consisted of the ten s. interval from 4 to 14 s. We excluded the first 4 seconds to avoid the dynamics of step-function transient response and the last second to minimize effects of fatigue. The sample rate for data collection was 100 Hz (i.e., T = 0.01 s). A second factor in the design involved dividing the participants into one of two categories based on the MVC, used as a measure of strength.

Figure 2 shows the plots of the steady-state isometric force and the corresponding six IMFs. The red plot is a time series showing the steady-region of a single participant's isometric force response. The six graphs located at the bottom of Fig. 2 are the first six IMFs following EMD analysis of the isometric force response.

Following the EMD step, a set of eight features are extract from each of the IMFs. The six sets of eight features were input into the appropriate six FSCs, one for each of the six IMFs. The extracted features and the use of FSCs allows for a clear interpretation by the perspective user of the system (e.g., physicians and kinesiology researchers).

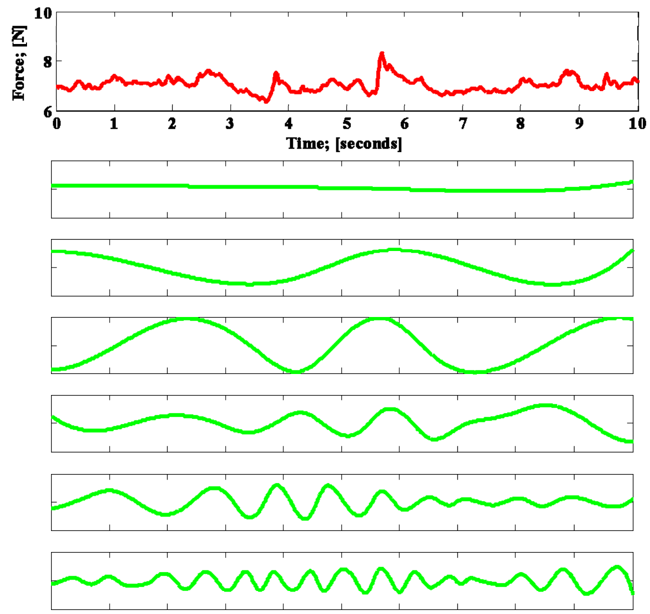

Fig. 2 – Plots of isometric force response (red) and the first six corresponding IMFs (green). The isometric force response was generated by participant number 1 in response to a target level of 25% MVC (MVC = 28.6 [N]).

The Table 1 contains a list of the eight features that were used as inputs to a given FSC. These eight features were selected to maintain consistency with classifiers used with other data sets that are part of our ongoing research, with the goal of discriminating between healthy participants and those exhibiting early stage neurodegenerative conditions. The other data sets have different categories than discussed in this paper. With the other data sets, all eight features were required in order to provide >95% correct classification. For example, in one of the data sets, the number of IMFs was dependent upon category.

Table 1: List of the initial eight features extracted from each IMF.

Feature Name:	Description:
Magnitude	Amplitude of sinusoid approximation
Frequency	Frequency of sinusoid
PhaseAngle	Initial phase angle of sinusoid
NumberOfIMFs	Number of IMFs after EMD
VectorNorm_IMFs	Vector norm of the IMF
IMF_std	The standard deviation of the IMF
VectorNorm_AM	Vector norm of the amplitude modulation of the IMF
SteadyStateError	The error between the trend of the IMF and the target force.

The participants were divided into 2 categories based upon the MVC that they were capable of generating. Figure 3 is a plot of the individual MVC and also indicates the gender of the participants. Two categories, low and high strength, were formed by placing half of the subjects into each category. Following the initial assignment into a strength-category, the features sets were divided into two subsets. The first subset was used as the training set for the FSCs and the second formed the test set.

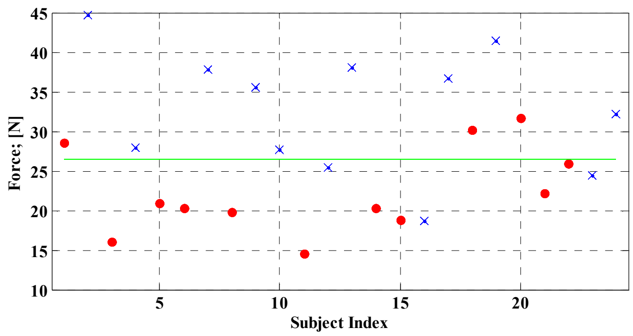

Fig. 3 - The plot of maximum voluntary contraction of the 24 participants. The MVC was used to divide the participants into low-strength (MVC below the green threshold line) and high-strength categories. The red dots indicate female participants and the blue x's denote male participants.

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 in the following discussion.

All components of the feature extraction and FSC implementation were programmed in Matlab, and the FSC was implemented using the Matlab Fuzzy Logic Toolbox [15]. The distributions of the MFs were optimized using the ANFIS function of the Matlab Fuzzy Set Toolbox.

Fig. 4 is a schematic representation of one of the six Sugeno-type FSCs used in the implementation. All six FSCs have the same configuration as shown in Fig. 4, however, the membership functions (MF) differed depending upon the IMF and the corresponding feature of the training sets. For a given IMF, each of the eight discrete-valued force-response features were transformed into degrees of membership in each of the seven MFs associated with the specific feature. The inputs were then mapped by a set of rules, referred to as the Fuzzy Associative Memory (FAM), to estimate the output category.

Prior to the training step, the seven Gaussian MFs were uniformly distributed across the domain of possible feature levels. Fig. 5 is a plot of the seven MFs related with the Magnitude feature of the second IMF after training the FSC.

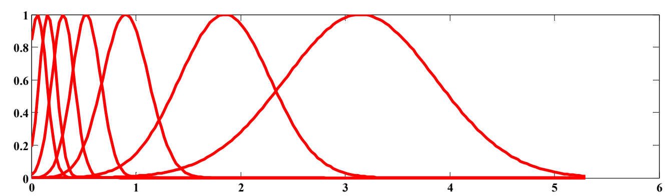

Fig. 5. – Plots of the seven Magnitude MFs following optimization.

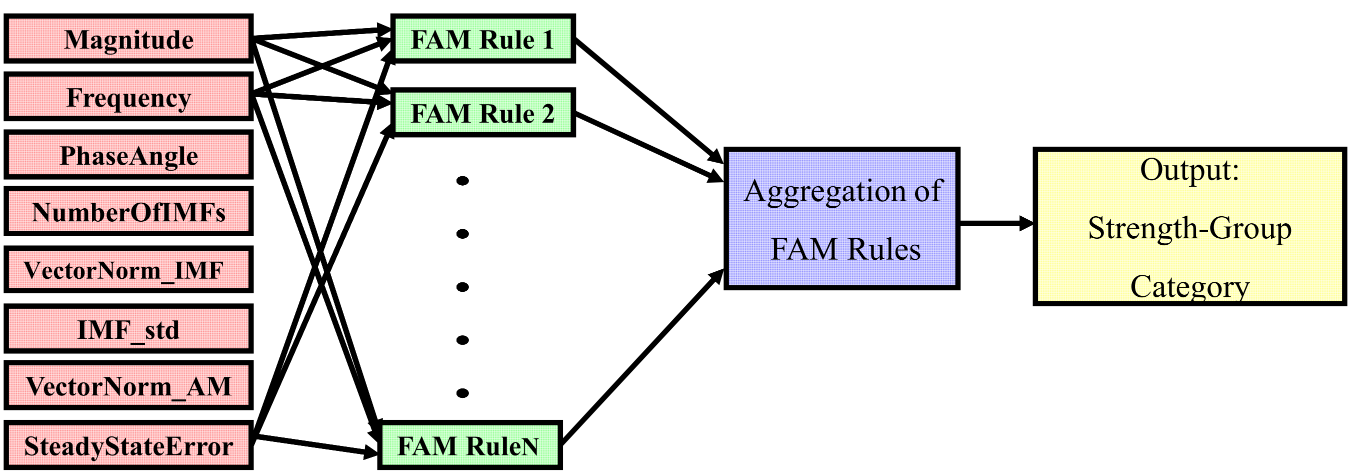

Fig. 4. - The schematic representation of the FSC associated with the second IMF. The eight red boxes on the left-hand side of the figure represent the MFs for the eight features that are input to the system. The green boxes represent the FST rules (FAM) associating input and output. The blue box on the right symbolizes the aggregation of the FAM rules and the yellow box denotes the process of assigning a discrete value to the aggregation of the rules which serves as the assignment of the strength-group category.

Each of the 8 features where converted to degrees of membership in all 7 of the corresponding MFs. The following is an example of one of the FAM rules:

If (Magnitude is High) and (Frequency is High) and (PhaseAngle is High) and (numberOfIMFs is High) and (vectorNorm_IMF is High) and (IMF_std is High) and (vectorNorm_AM is High) and (SteadyStateError is High) then (Strength Category is High)

Each of the rules that comprise the FAM received input from multiple antecedents. Each rule then calculated an intermediate class assignment in parallel. Once the results of all of the If-Then rules comprising the FAM were generated, all of the intermediate class assignments were aggregated to form the consequent. The consequent is defuzzified to estimate a singleton which is the FSCs assignment of a strength-group category.

When all six FSCs concluded estimation of the category of their input sets, the union of these six singleton outputs was used to assign the force response time series to either the high-strength or low-strength category.

III. Results

The strength study data set was divided into two subsets, each containing roughly equal numbers of low and high strength participants. The first half of the data set was used to generate and optimize the FSC. The second subset was used to validate the FSC performance.

Using the eight features previously described, the FSC correctly classified 99% of the test set. In addition to using the full eight feature set, the size of the feature space was reduced first by calculating all combinations of the eight features taken seven at a time. There were eight combinations of the seven-feature classifiers and all eight classified at least 90% correct, with four of the combinations correctly classifying 98%. Continuing to reduce the dimension of the feature space, the 28 combinations of the eight features taken six at time were tested. Of the 28 combinations only 2 combinations misclassified more than 10% of the test sets feature.

Continuing the process of reducing the dimension of the feature space, we were able to determine the five features, listed in Table 2 that resulted in consistently good classification.

Table 2: List of five best IMF features for the current data set.

Feature Name:	Description:
Magnitude	Amplitude of sinusoid approximation
vectorNorm_IMFs	Vector norm of the IMF
IMF_std	The standard deviation of the IMF
vectorNorm_AM	Vector norm of the amplitude modulation of the IMF
steadyStateError	The error between the trend of the IMF and the target force.

IV. Discussion

Even though all of the subjects were healthy young adults, the extracted features of the IMFs resulting from EMD of the isometric force responses were successful in classifying 99% of the participants into the correct category (i.e., high-strength or low-strength).

This finding suggested that the feature sets are robust and would be able to classify healthy individuals versus those with early stage neurological disorders. This is corroborated by the initial findings using this FSC paradigm on a dataset which included participants from three age groups and ranging from healthy young adults to older participants who showed signs of natural neural degeneration.

Our future work will involve applying the FSC to other datasets which include variation across age groups and health status.

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