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A MATLAB-Based Interactive Environment for EMG Signal Decomposition Utilizing Matched Template Filters

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ABSTRACT

An interactive software package for analyzing and decomposing electromyographic (EMG) signals is designed, constructed, and implemented using the MATLAB high-level programming language and its interactive environment. EMG signal analysis in the form of signal decomposition into their constituent motor unit potential trains (MUPTs) is considered as a classification task. Matched template filter methods have been employed for the classification of motor unit potentials (MUPs) in which the assignment criterion used for MUPs is based on a combination of MUP shapes and motor unit firing pattern information. The developed software package consists of several graphical user interfaces used to detect individual MUP waveforms from raw EMG signals, extract relevant features, and classify MUPs into MUPTs using matched template filter classifiers. The proposed software package is useful for enhancing the analysis quality and providing a systematic approach to the EMG signal decomposition process. It also worked as a very helpful environment for testing and evaluating algorithms developed for EMG signal decomposition research.

Keywords: EMG signal decomposition, feature extraction, interactive systems, matched template filters, motor unit potential classification, user interfaces.

1. INTRODUCTION

Biological one-dimensional signals are used in medicine and biology. Recording of the electrical activities of the heart muscle, called electrocardiogram (ECG) [1], [2], is considered as the diagnostic signal in the assessment of the cardiovascular system. Electroencephalogram (EEG) [3], [4] is a signal that records the electrical activities of the brain and is used in the diagnostics of the central nervous system. Electromyographic (EMG) [5]-[12] signal is the recording of the electrical activity associated with muscle contraction and is used to assist in the diagnosis of the muscle or nerve disorders and for the analysis of neuromuscular system. In this paper, we will present an interactive environment for EMG signal analysis.

EMG signal analysis takes the form of signal decomposition and motor unit potential (MUP) classification into group of similar shapes. The developed interactive system exhibits a style of control and works as an environment for the classification task required for EMG signal decomposition. The system is a MATLAB-based interactive software package and it is useful for enhancing the analysis quality and providing a systematic approach to the EMG signal decomposition process. It worked as a very helpful environment for testing and evaluating algorithms developed for EMG signal decomposition research. From the users' side, it relieved them from the boring and painful efforts associated when dealing with the extensive textual information associated with the MUP classification task and provided them with a full control on the process.

Interactive MUP classification environments have been developed based on certainty criteria for classification. Stashuk [5] had developed an interactive EMG signal decomposition system called DQEMG (decomposition-based quantitative EMG). DQEMG consists of a series of algorithms for estimating motor unit (MU) firing pattern statistics, clustering based on MUP shape and MU firing pattern characteristics, and certainty-based supervised MUP classification. Rasheed et al. [6] had modified the certainty criteria used in DQEMG and developed adaptive certainty criteria for MUP classification and employed it in the interactive environment presented in [7]. To achieve improved classification performance, Rasheed et al. [8] had investigated another kind of classifiers based on fuzzy nearest neighbor (NN) assertion rule. They developed fuzzy *k*-NN classifiers for MUP classification based on assertion criteria and employed it in developing an interactive environment presented in [9]. In this paper, the developed system used for classifying MUP waveforms is using matched template filter classifiers and based on similarity criteria. The results of the matched template filter classifiers reported in [10-12] have been generated using the developed interactive environment presented in this paper. The purpose of computer interaction in the developed system is to facilitate the use of a computer for MUP classification and to enhance the user's power to accomplish this task.

The developed MUP classification interactive environment consists of tasks involving the user and the interactive system. These tasks can take place in a sequential fashion. The inputs and outputs of the interactive MUP classification system are modeled as languages. The language goals are to provide methods for describing the user interface and the programs that model the interface in the developed interactive system. In the interactive world, two interfaces to the computer are distinguished. The first between the user and the computer called the user interface. The second between the programmer of the system and the computer called the program interface. The user interface provides a means to communicate with the computer by using the dialogue language. The dialogue language is handled by its counterpart on the programmer side: the programming language.

The developed software package provides graphical user interfaces (GUIs) to detect individual MUP waveforms from raw EMG signals, extract relevant features, and classify MUPs into motor unit potential trains (MUPTs) using different versions of matched template filter classifiers. The criterion for grouping MUPs is based on a combination of MUP shape and MU firing pattern information.

2. EMG SIGNAL COMPOSITION AND DECOMPOSITION

An electromyographic (EMG) signal is the detection of the electrical activity associated with muscle contraction and reflects the electrical depolarization of excitable muscle fiber membranes that create electrical signals called muscle fiber potentials (MFPs). It can be detected by employing concentric needle electrodes that are inserted through the skin into the muscle. The signal recorded by the tip of an inserted needle electrode is the superposition of the individual electrical contributions of anatomical compositions called motor units (MUs), that are active

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during a muscle contraction, and background interference. Background interference includes noise and artifacts.

A single motor neuron and all the muscle fibers innervated by its axon constitutes a motor unit. All the muscle fibers in a MU contract at the same time as they are all activated by the same nerve cell. The EMG signal originates from the electrical discharges generated by the MUs, i.e., when a MU is recruited, its motor neuron fires a train of electrical impulses such that their muscle fibers contract causing a muscle twitch. The summation of the spatially and temporally dispersed potentials due to one firing impulse of individual muscle fibres belonging to a MU results in a signal called a motor unit potential (MUP) waveform. Each time an impulse occurs, the associated MU muscle fibres contract and a MUP waveform is generated such that, during a constant force contraction, a train of impulses are sent down the motor axon at fairly regular intervals resulting in a train of MUPs called a motor unit potential train (MUPT). A MUPT is the collection of MUP waveforms generated by one motor unit and positioned attheir times of occurrences or separated by their inter-discharge intervals (IDIs). The summation of the MUPTs of all recruited MUs constitutes the observed EMG signal.EMG signal decomposition considers a composite EMG signal to be resolved into its constituent MUPTs such that a classification of the MUPs to their MUPTs is performed. MUP classification into groups of similar shapes is mainly used to assist in the diagnosis of muscle or nerve disorders and for the analysis of neuromuscular systems. The actual firing times of individual MUs can be compared with those of other MUs to test for the existence of synchronous behavior and may also be used to estimate MU firing rates.

The objectives of EMG signal decomposition are:

a) The detection of possible MUP waveforms.
b) Dividing (classifying) detected MUPs into groups such that each set of grouped MUPs represents the activation of a single MU and through which the activation of each active MU can be discriminated for subsequent processing.
c) The extraction of relevant clinical information from individual MUPs and MU firing patterns. The shapes of MUPs waveforms and MU firing patterns are important sources of information for use in the diagnosis of neuromuscular disorders where they are used for the assessment of neuromuscular disorders from which clinically relevant information can be extracted in the form of MUP and MU parameters. Diagnosis is then facilitated by an analysis of the characteristics of these measured parameters.

3. MATCHED TEMPLATE FILTERING CLASSIFICATION

The basic MUP matched template filtering algorithm consists of sliding MUPT templates over the EMG signal detected MUPs and calculating for each candidate MUP m_j a distortion, or correlation, measure estimating the degree of dissimilarity, or similarity, between the template and the MUP m_j. Then the minimum distortion or maximum correlation position is taken to represent the instance of the template into the EMG signal under consideration with a threshold on the similarity/dissimilarity measure allowing for rejection of poorly matched MUPs. We used correlation measures as estimates of the degree of similarity between a MUP m_j and MUPT templates.

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The correlation between two signals represents the degree to which signals are related and cross correlation analysis enables determining the degree of waveform similarity between two different signals. It provides a quantitative measure of the relatedness of two signals as they are progressively shifted in time with respect to each other.

Consider an EMG signal decomposed into *M* mutually exclusive sets, $\omega_i \epsilon \Omega = \{\omega_1, \omega_2, \ldots, \omega_M\}$. Each set ω_i represents a MUPT into which MUPs will be classified and set Ω is the set of corresponding integer labels defined such that $\Omega = \{\omega_1 = 1, \omega_2 = 2, \ldots, \omega_M = M\}$. Set Ω provides all possible integer labels for the valid MUPTs. As some of the MUPs may not be assigned to any of the valid MUPTs, the MUPs decision space set can then be extended to include $\Omega \cup \{\omega_{M+1}\}$ where ω_{M+1} designates the unassigned category for when by some established criteria the classifier decides to not assign the input MUP.

Two matched template filters have been investigated for supervised MUP classification during EMG signal decomposition. The first is the normalized cross correlation which is the most widely used correlation measure [13]. It is given by formula (1):

$$NCC^{j}_{\omega_i}(x) = \frac{\sum_{k=1}^{n} m_j(x+k).\ T_i(k)}{\sqrt{\sum_{k=1}^{n} m_j(x+k)^2}\ .\ \sqrt{\sum_{k=1}^{n} T_i(k)^2}} \quad (1)$$

The second is the pseudo-correlation [14], [15] measure given by formula (2):

$$pC^{j}_{\omega_i}(x) = \frac{\sum_{k=1}^{n}(T_i(k).m_j(x+k) - \left|T_i(k) - m_j(x+k)\right| .max\left\{|T_i(k)|, \left|m_j(x+k)\right|\right\})}{\sum_{k=1}^{n}(max\left\{|T_i(k)|, \left|m_j(x+k)\right|\right\})^2} \quad (2)$$

Denote ρ to be the matched template filter correlation coefficient such that:

$$\rho^{j}_{\omega_i}(x) = \begin{cases} NCC^{j}_{\omega_i}(x) & \text{when choosing normalized cross correlation,} \\ pC^{j}_{\omega_i}(x) & \text{when choosing pseudo correlation.} \end{cases} \quad (3)$$

where, m_j is the candidate MUP feature vector, T_i is the MUPT ω_i template feature vector, and $x = 1, 2, \ldots, n$ is the time-shifting position between the MUPT ω_i template and the candidate MUP m_j with n being the dimension of the feature vector. Figure 1 shows the similarity between a candidate MUP, drawn in a solid line, and a MUPT template, drawn in a dashed line, along with the degree of similarity in terms of the normalized cross correlation, *NCC* = 0.992, and the pseudo correlation, *pC* = 0.997, measures.

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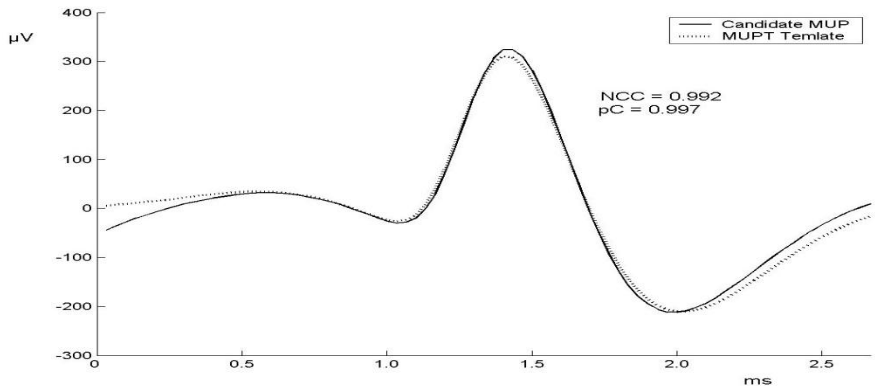

FIGURE 1. Similarity between a candidate MUP and a MUPT template.

The candidate MUP m_j is assigned to the MUPT ω_i that has the maximum degree of similarity and whose class label is given by:

$$\omega(m_j) = \arg\ max_{i=1}^{M} \left(\rho_{\omega_i}^{j}(x)\right) \qquad (4)$$

3.1 MATCHED FILTER CLASSIFIER FOR MUP CLASSIFICATION

For the purpose of MUP classification, we developed classifiers based on MUPs similarity measures that take into account the MUP shapes and MU firing pattern information. These classifiers follow an adaptive nature for train-wise setting of the MUPT assignment threshold based on firing pattern consistency statistics.

The matched template filter (MTF) classifier for MUP classification estimates a measure of similarity between a candidate MUP m_j and the MUPT templates expressing the confidence in the decision of classifying a MUP to a particular MUPT. It determines for each candidate MUP m_j a normalized cross correlation value calculated from (1) or a pseudo correlation value calculated from (2) representing the strength of resemblance of the MUP m_j with the MUPT templates.

The MTF classifier also determines for MUP m_j a firing time similarity decision function $S_{FS_i}^{j}$ with respect to the established firing pattern of the MUPTs, i.e., the MUPTs that are not fully recognized yet. The firing pattern information is represented by the firing similarity decision function S_{FS}. For candidate MUP m_j, $S_{FS_i}^{j}$ is evaluated by:

$$S_{FS_i}^{j} = S_f\left(I_{bi}^{j}, \mu_i, \sigma_i\right).\ S_f\left(I_{fi}^{j}, \mu_i, \sigma_i\right) \qquad (5)$$

where, $S_f(I, \mu, \sigma)$ is a firing time function based on the deviation of an IDI, I, from the estimated mean IDI, μ, of a MUPT that has an estimated standard deviation, σ. I_{bi} and I_{fi} are the IDIs that would be created by assigning a MUP m_j to MUPT ω_i; I_{bi} is the backward IDI, the interval between MUP m_j and the previous MUP in the MUPT; I_{fi} is the forward IDI, the interval between MUP m_j and the next MUP in the

MUPT and as shown in Figure (2). $S_f(I, \mu, \sigma)$ is evaluated using a multi-modal Gaussian model that takes into consideration missed-firings given by:

$$S_f(I, \mu, \sigma) = \sum_{n=1}^{K} p_I^{(n)}(I) \quad (6)$$

where, $p_I^{(n)}(I)$ is based on a Gaussian probability density distribution:

$$p_I^{(n)}(I) \propto N(n\mu, n\,\sigma^2) \quad (7)$$

$$p_I^{(n)}(I) = \frac{1}{\sqrt{n}}\, e^{-\frac{1}{2n\,\sigma^2}(I - n\,\mu)^2} \quad (8)$$

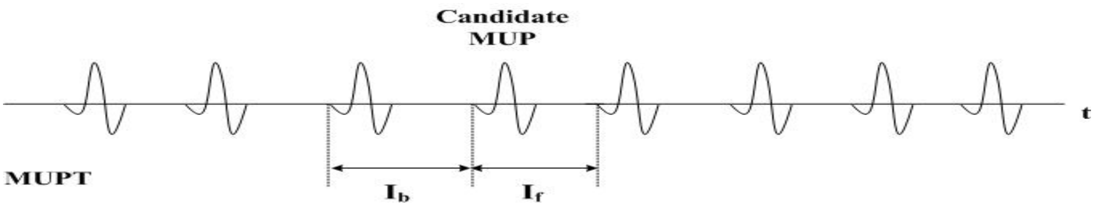

FIGURE 2. Candidate MUP with its forward IDI and backward IDI in a MUPT.

The modes become broader and smaller as n increases. In the current implementation of the MTF classifier, K is set to a value of 40. Figure 3 shows the firing timing similarity function S_f for three MUPTs having detection probability of $P_d = 0.5, 0.7, and\ 0.9$. P_d is assumed to be the same for all MUPs within a MUPTs. In (7) and (8), σ corresponds to the estimated standard deviation of the IDIs in the major mode (n = 1) from the major mode IDI mean μ.

The decision of assigning a MUP m_j to a MUPT ω_i is based on the value of the overall similarity S_i^j associated with the classification of MUP m_j to MUPT ω_i. The overall similarity S_i^j is determined from the multiplicative combination of $\rho_{\omega_i}^{j}(x)$ and $S_{FS_i}^{j}$ given by:

$$S_i^j = \rho_{\omega_i}^{j}(x) \,.\, S_{FS_i}^{j} \quad (9)$$

Candidate MUP m_j belongs to the MUPT ω_i for which its overall similarity S_i^j is the greatest and if it is greater than the minimal similarity threshold (S_m) for which a classification is to be made:

$$\omega(m_j) = \arg\ max_{i=1}^{M} \left(S_i^j\right) \quad (10)$$

Otherwise MUP m_j is left unassigned.

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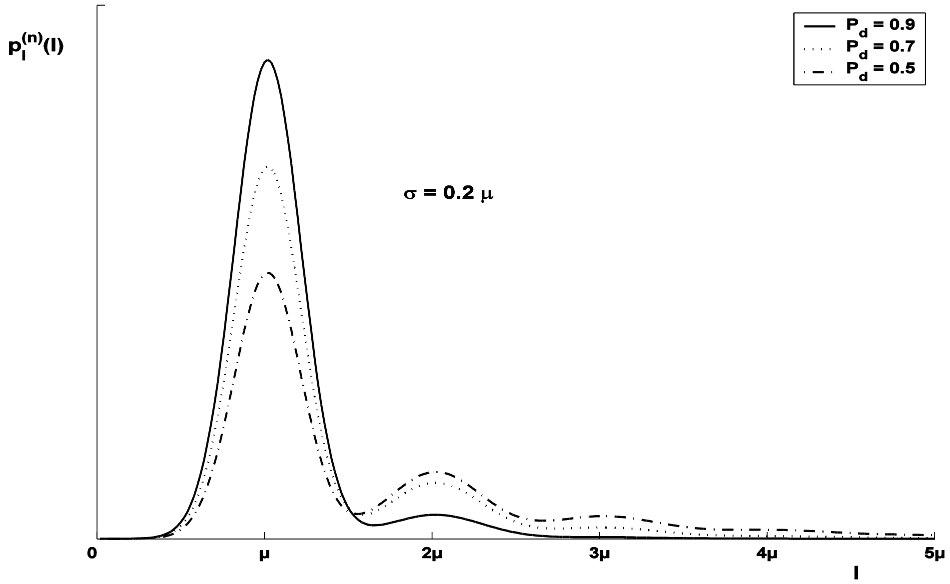

FIGURE 3. IDIs density distribution for MUPT with missing firings, mean μ = 50 ms, standard deviation σ = 0.2 μ, and detection probability $P_d = 0.5, 0.7, and\ 0.9$.

The value of similarity measure $\rho^j_{\omega_i}(x)$ and the firing time similarity decision function $S^j_{FS_i}$ is restricted to the interval [0, 1] and it corresponds to the confidence in the classification given the information of each function. A value of 1 corresponds to the ideal situation (maximum similarity) with respect to the information relevant to that function. However, for a classification that is certainly incorrect with respect to any source of information the corresponding similarity function yields a value approaching 0.

3.2 THE ADAPTIVE MATCHED TEMPLATE FILTER CLASSIFIER

The adaptive matched template filter classifier (AMTF) uses an adaptive similarity approach for assigning MUPs to MUPTs. The similarity criterion for grouping MUPs is based on a combination of MUP shapes and an active and passive use of MU firing patterns.

The adaptive nature of MUP classification is related to the adjustment of the minimal similarity threshold for each MUPT based on train firing pattern statistics and it follows the algorithm described in [6], [8], [10]. A complete description of the AMTF classifier is given in [10].

4. INTERACTIVE ENVIRONMENT STRUCTURE

User-computer interaction takes place in the form of a dialogue and to design interactive systems, two closely-interrelated languages are designed to deal with a single conceptual model of the processes being performed by the computer. With one language, the user communicates with the computer and operates on the conceptual model. With the other language, the computer communicates with the user depicting the state of the conceptual model.

Program architecture for the MUP classification interactive environment is needed for enabling the user to control interactively to a certain extent the flow of activities during program execution. Normally, the user can exercise influence on a program's control flow only at points where the program is ready for it. The user interface of the program represents the means by which the program allows the user to influence the flow of control during execution. The user interface consists of certain media for user-computer communication and a dialogue language in which the user formulates commands and other messages to the system.

The interactive MUP classification environment model has the structure shown in Figure 4. It consists of the following basic phases:

a) **INITIALIZE**: This phase is activated when the interactive environment software package starts running. It reads values for the parameters and initializes conditions, variables, and procedures. Then it displays a main user interface page, from which the user can navigate to other user interfaces. Each displayed user interface contains a list of control objects that the user can use interactively.

b) **RUN**: This is the main phase of the program, where the program equations and procedures are used for MUP classification. For a specific EMG signal, the digitized raw signal data is read; isolated MUP waveforms are detected; relevant features are extracted; classifier seeding MUPs are specified; and finally MUPs are classified based on similarity criteria. The classification criteria are based on a combination of MUP shapes and motor unit firing pattern information employed by the similarity-based classifiers to perform the classification. The classifier generates individual MUP assignment decisions based on the overall similarity, S_i^j, associated with classifying a MUP to its assigned MUPT evaluated using (9).

c) **CONTROL**: This phase is responsible for the dialogue between the user and the computer via the user interface control objects. It controls the navigation across the set of user interfaces and controls the sequence of execution jobs by deactivating the specific control object once a job is done and subsequently activating other control objects in the execution pipeline.

d) **POSTPROCESSING**: This phase depends considerably on the purpose of the interactive environment. Typical functions that may be required are: listing classifier performance indices once the classification of MUPs is completed; plotting a decomposition summary for the EMG signal; plotting a MUP trace for a specific interval of decomposition results; plotting a specific MUPT raster; mapping the classified feature space into a two-dimensional plane or a three-dimensional space.

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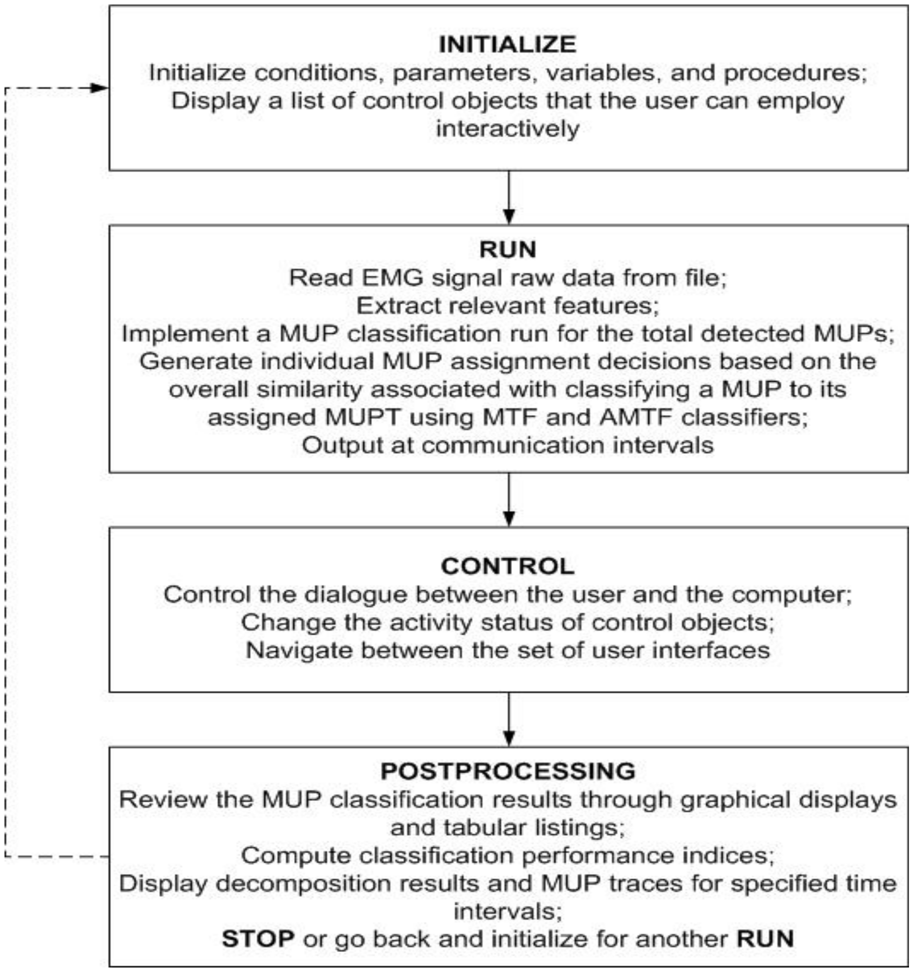

FIGURE 4. Major operations in the interactive MUP classification environment.

Features employed in the classification task of EMG signal decomposition are extracted using the **Feature Extraction** user interface shown in Figure 5.

MUPs classification is performed using the **Template Matched Filter Classification** user interfaces shown in Figure 6 for time-domain features and in Figure 7 for wavelet-domain features.

e) FEATURE EXTRACTION

The first task in EMG signal decomposition is the segmentation and MUP detection task. It is concerned with locating the main positive peaks or spikes found in an EMG signal. The detected spikes or MUPs should have rapid rising edges, which indicate that the electrode is close to active muscle fibers. MUs that were active during signal acquisition generate these MUPs. Conversely, MUPs that have slow rising edges and small amplitude were generated from MUs with fibres that are far away from the electrode.

The EMG signal is divided into segments of possible MUP waveforms and searching for time intervals containing these MUPs comprises the MUP detection operation. A segment can either contain one MUP or superimposed MUPs (compound segments). Time intervals with low energy are without MUPs and represent signal baseline. Detected spikes within windows of sampled raw, first-order, or second-order discrete derivatives data form the MUP waveforms. For the developed system a window of 80 sample points representing MUP intervals of 2.56 ms at a sampling rate of 31.25 kHz formed a MUP pattern feature vector. The collection of feature vectors forms the feature space data set necessary for subsequent pattern recognition operations.

Features employed in the classification task of EMG signal decomposition are extracted using the **Feature Extraction** user interface shown in Figure 5. This user interface allows users to decompose real EMG signals detected during slight to moderate levels of contraction; and simulated EMG signals of different complexities.

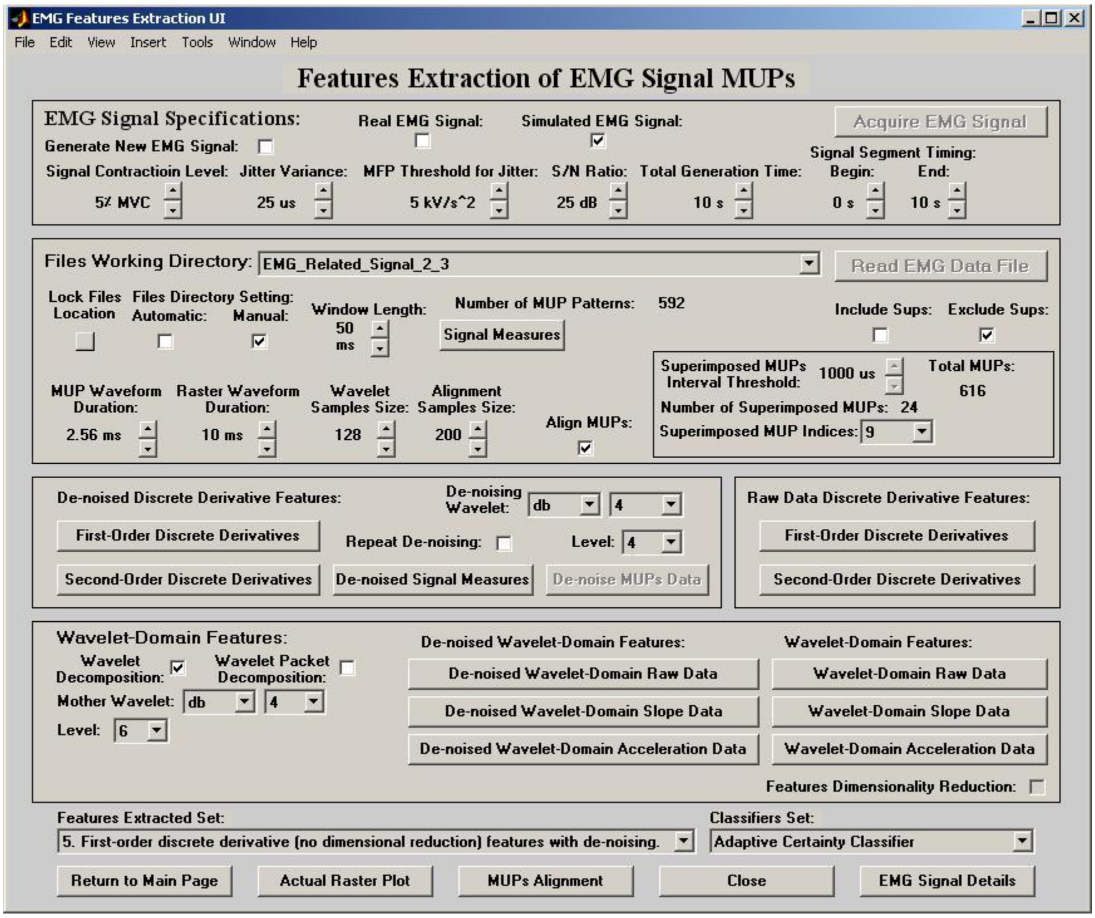

FIGURE 5. MUPs Feature Extraction user interface.

Once, analog EMG signals are acquired from subjects in a clinic, they are digitized and stored in data files. For evaluating the MUPs classification task with the similarity-based classifiers, the real EMG signals are decomposed manually by an experienced operator using a computer-based graphical display algorithm and the manual decomposition results are considered to be the reference for evaluation. The manual decomposition results are stored in a golden standard file containing the following information: the estimated number of MUPTs, the estimated number of MUP patterns, the firing time of each MUP pattern, the file offset of each MUP pattern necessary to extract the MUP samples from the raw EMG data, and the MUPT assignment of each MUP pattern. These files, i.e., the EMG signal data file and the golden standard file should then be transferred to the computer running the

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developed system and saved in specific file folders so that the system can access them for subsequent operations.

The developed system is integrated with an EMG signal simulator that is based on a physiologically and morphologically accurate muscle model [16]. The simulator enables us to generate EMG signals of different complexities with knowledge of the signal intensity represented by the average number of MUP patterns per second (pps), the numbers of MUPTs, and which MU created each MUP pattern. Furthermore, the amount of MUP shape variability represented by jitter and/or inter-discharge intervals (IDI) variability can be adjusted. Within the EMG signal simulator, the user is able to set and change other relevant parameters.

The simulator outputs a data file containing the raw EMG discrete data samples and a golden standard file containing the following information: the number of MUPTs, the number of MUP patterns, the firing time of each MUP pattern, the file offset of each MUP pattern necessary to extract the MUP samples from the raw EMG data, and the MUPT assignment of each MUP pattern.

After acquiring the EMG signal, the user can decide either to use the whole signal or specify a segment of it. Based on information contained in the golden standard file, the EMG data file is read and for each MUP waveform the MUP samples are extracted from the raw EMG data file using the file offset within the data. This offset represents the firing time position of the MUP pattern and is considered as the middle sample, and then from this position we read backward half the size of the MUP samples and the other half forward. The read samples represent the MUP pattern feature vector. Repeating this reading for all the MUP patterns in the signal, we get a collection of MUP feature vectors to form the time-domain raw data feature space data set. The user interface allows using this data set to form time-domain discrete derivative and wavelet-domain feature spaces.

6. SUPERVISED CLASSIFICATION OF MUPS

The task of supervised classification during the process of EMG signal decomposition is involved with the discrimination of the activation patterns of individual MUs, active during contraction, into distinguishable MUPTs. Therefore, MUPs most likely belong to the same MUPT if their shapes are closely similar and if their IDIs are consistent with the discharge pattern of the considered MU. This means that two kinds of information: the MUP shapes and the times of occurrences of MUPs should be considered for classification.

In this paper, MUPs classification is performed using the **Template Matched Filter Classification** user interface shown in Figure 6 for time-domain features and in Figure 7 for wavelet-domain features. The developed interfaces use both the MTF classifier and its adaptive variant: the AMTF. Both classifiers have been integrated within the developed software package. The classification interfaces allow the user to use any of these classifiers.

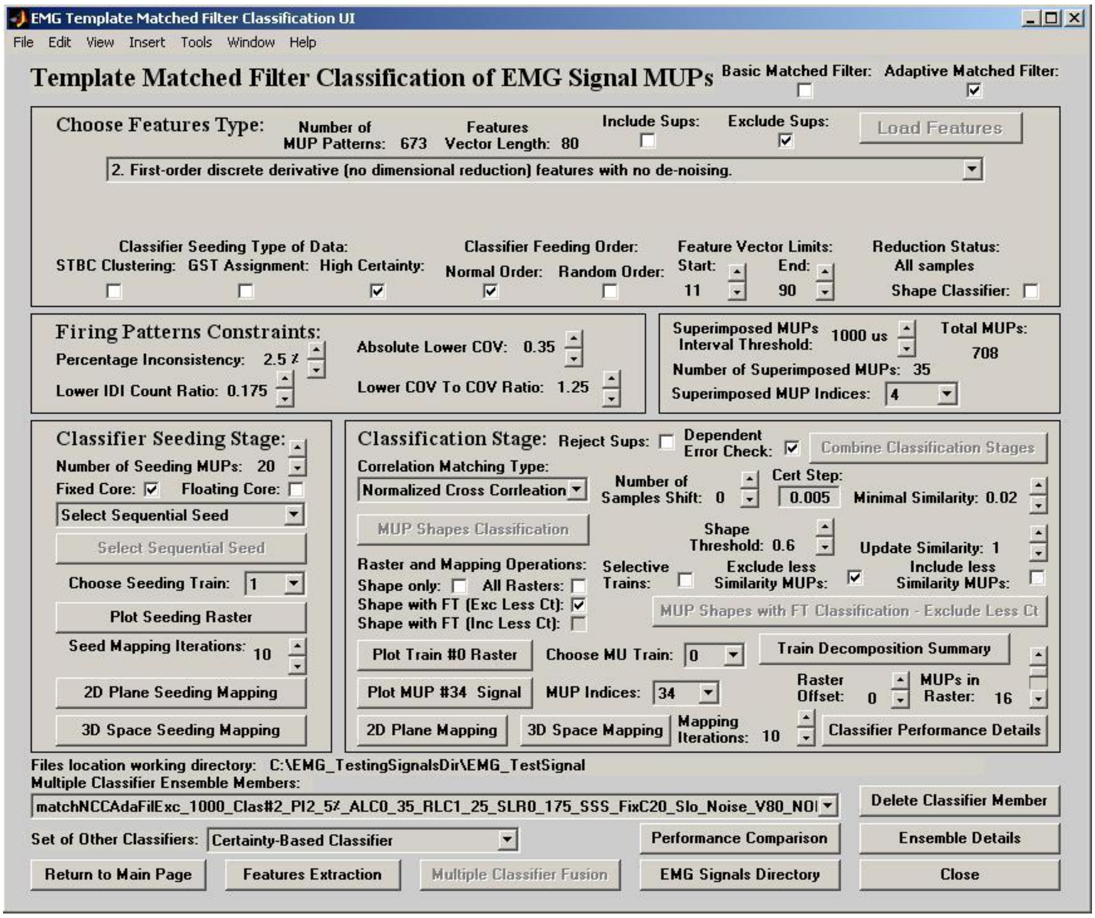

FIGURE 6. Matched Filter Classification interface with time-domain features.

The supervised classification task of MUPs for MTF and the AMTF classifiers relies on a labeled reference MUP set that contains correctly classified MUPs. The reference set of MUPs are those MUPs used to calculate initial MUPT templates to seed the classifiers.

After specifying each MUPT labeled reference set, we make sure that we chose isolated MUPs to avoid, as much as possible, choosing superimposed MUPs. The isolated MUPs have occurrence times that are separated by more than 3~ms from any other MUP occurrence times.

A set of firing pattern consistency statistics had been formulated for detecting erroneous MUP classifications [6], [8] such that following each classification pass through the MUP data, the firing pattern consistency statistics for each MUPT are calculated to detect classification errors in an adaptive fashion. This firing pattern analysis allows the algorithm to modify the threshold of similarity required for the assignment of a MUP classification and individually for each MUPT based on an expectation of erroneous assignments.

The classification performance of the classifiers was evaluated and compared in terms of their assignment rate $\mathbf{A_r}$, error rate $\mathbf{E_r}$, and correct classification rate $\mathbf{CC_r}$ performance indices.

The assignment rate $\mathbf{A_r}$ is defined as the ratio of the total number of assigned MUPs, which is equal to the total number of MUPs detected minus the number of MUPs unassigned, to the total number of MUPs detected:

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$$A_r = \frac{\textbf{number of MUPs assigned}}{\textbf{total number of MUPs detected}} * \mathbf{100} \qquad (11)$$

The error rate $\mathbf{E_r}$ is defined as the ratio of the number of MUPs erroneously classified to any valid MUPT to the number of MUPs assigned:

$$E_r = \frac{\textbf{number of MUPs erroneously assigned}}{\textbf{total number of MUPs assigned}} * \mathbf{100} \qquad (12)$$

The correct classification rate $\mathbf{CC_r}$ is defined as the ratio of the number of correctly classified MUPs, which is equal to the number of MUPs assigned minus the number of MUPs erroneously classified, to the total number of MUPs detected:

$$CC_r = \frac{\textbf{number of MUPs correctly classified}}{\textbf{total number of MUPs detected}} * \mathbf{100} \qquad (13)$$

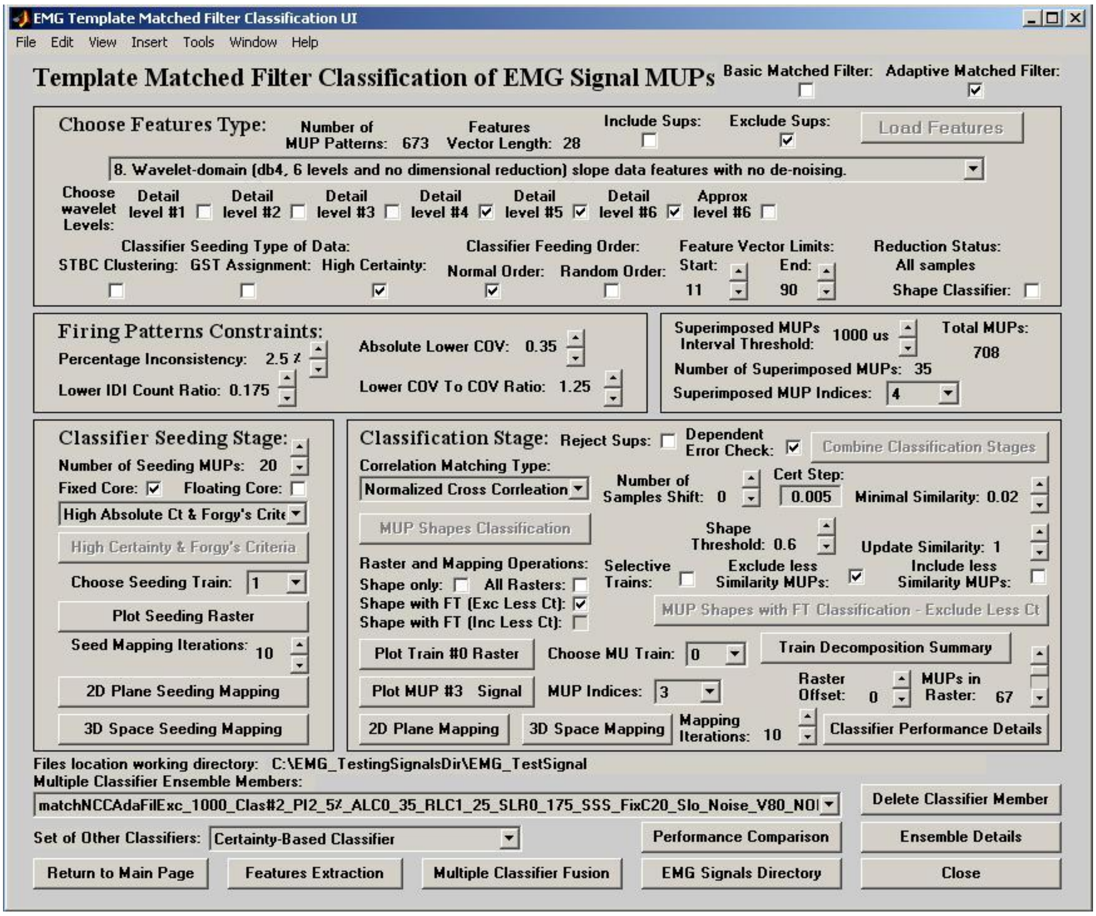

FIGURE 7. Matched Filter Classification interface with wavelet-domain features.

7. DECOMPOSING A TEST EMG SIGNAL

In this section, the results of decomposing a test EMG signal are presented. The test EMG signal is a simulated signal generated by the EMG simulator, which is integrated within the developed system. The test EMG signal used has 7 MUPTs and was simulated to have an intensity level of 70.7 MUP patterns per second, jitter value of 100 µs, and inter-discharge variability with coefficient of variation of 0.15.

Figures (8) and (9) demonstrate the AMTF decomposition summary results for the tested EMG signal in terms of shimmer plot, inter-discharge intervals (IDIs) histogram, MU firing patterns, and IDI mean and standard deviation statistics.

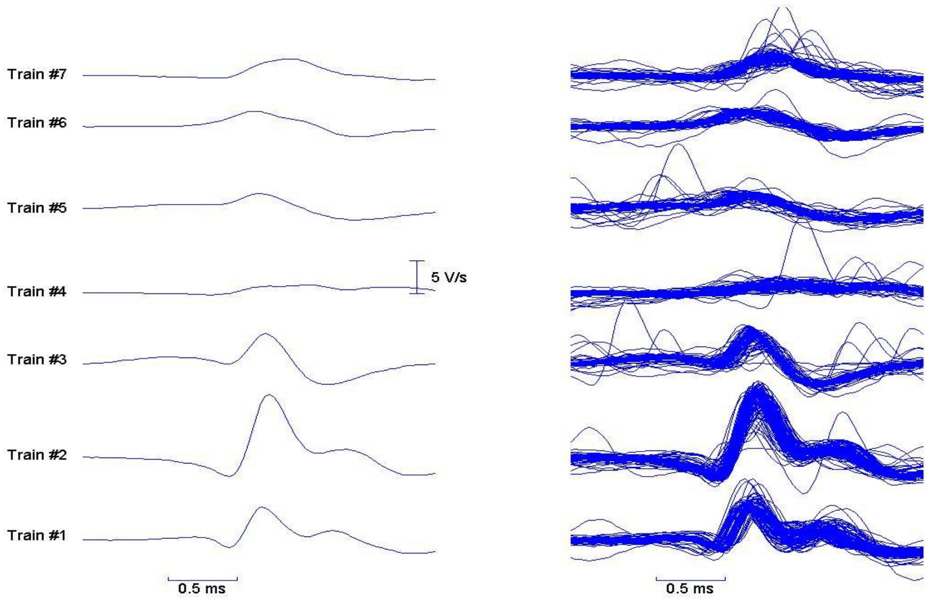

FIGURE 8. Tested EMG signal MUPT templates and shimmer plot.

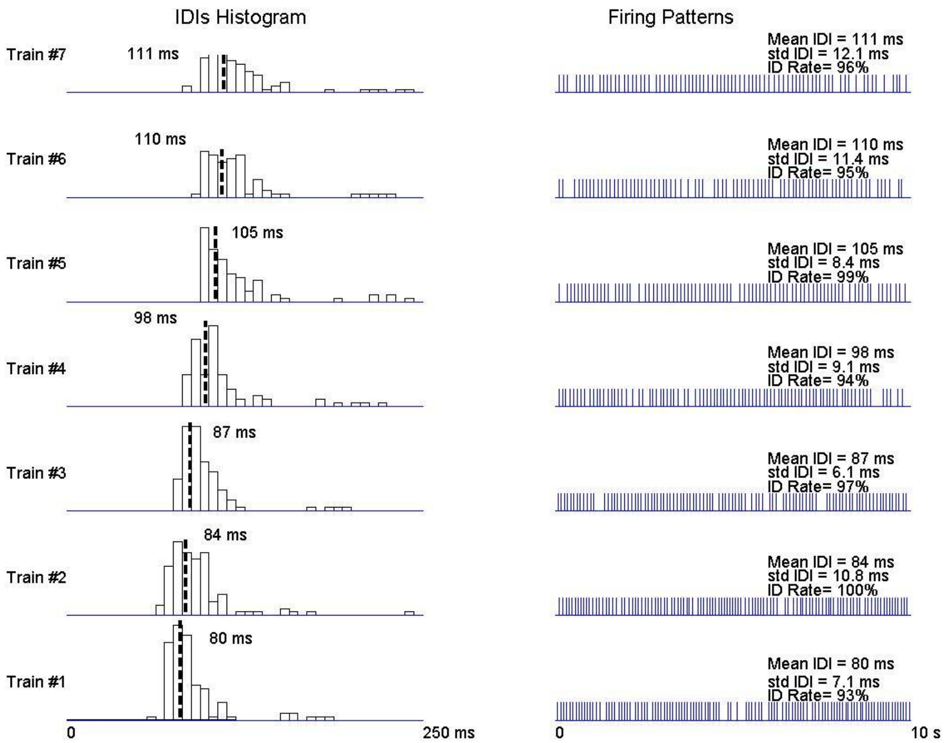

FIGURE 9. Decomposition summary for the tested EMG signal.

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Figure 10 displays a 1-s interval (from second 2 to second 3) of the decomposition results for the 7 MUPTs of the tested EMG signal and the unassigned MUPs. Portions of MUPTs are displayed with the time scale used for displaying MUPs expanded by a factor of 10 relative to the firing time scale used. This allows the actual shape of each MUP to be better visualized. An erroneous MUP classification is indicated by displaying the number of the correct train next to the MUP. The errors made by the AMTF are related to the shape variability of MUPs occurring at expected firing times for other MUPTs. In these cases, the erroneous decisions are being made based on the fact that the shape and firing pattern information are not sufficient to correct the decision.

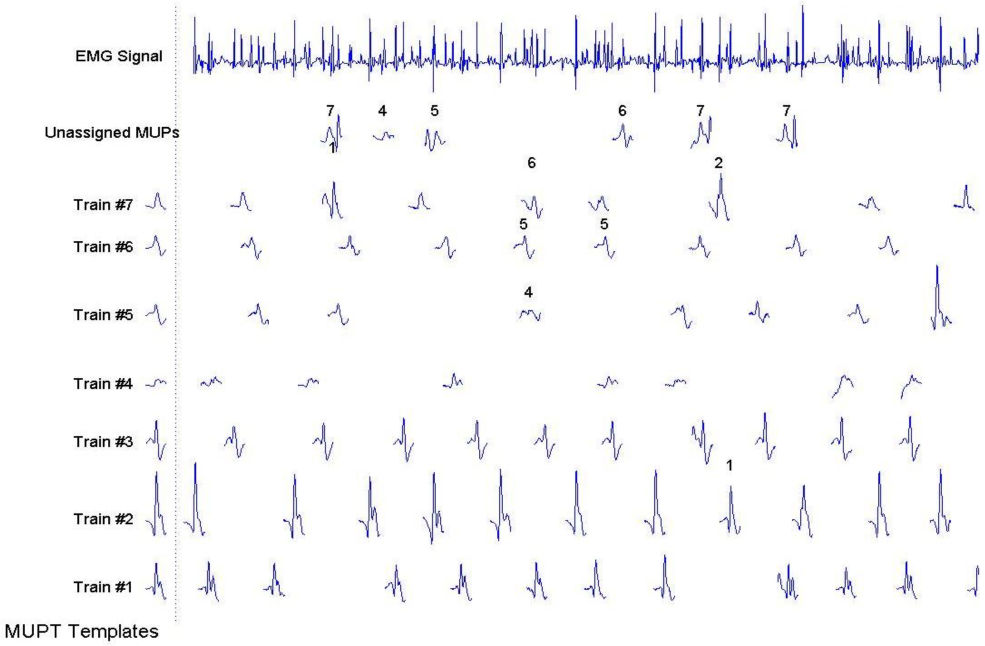

FIGURE 10. MUP trace for a 1-s interval of decomposition results.

8. CONCLUSION

In this paper, we presented and constructed a MATLAB interactive software package consisting of a set of integrated graphical user interfaces (GUIs) to efficiently help users work in an interactive environment for MUPs classification during EMG signal decomposition. The package relieves users from the boring and painful efforts associated when dealing with the extensive textual information associated with the MUP classification task; provides users with a full control of MUP classification process; allows users to experiment with different parameters that can be selected and changed using the displayed control objects; re-runs the classification task with the changed parameters and senses the effect of the change on the task results.

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