A Hybrid Classifier Fusion Approach for Motor Unit Potential Classification During EMG Signal Decomposition

Sarbast Rasheed*, Daniel W. Stashuk, and Mohamed S. Kamel

***Abstract*—In this paper, we propose a hybrid classifier fusion scheme for motor unit potential classification during electromyographic (EMG) signal decomposition. The scheme uses an aggregator module consisting of two stages of classifier fusion: the first at the abstract level using class labels and the second at the measurement level using confidence values. Performance of the developed system was evaluated using one set of real signals and two sets of simulated signals and was compared with the performance of the constituent base classifiers and the performance of a one-stage classifier fusion approach. Across the EMG signal data sets used and relative to the performance of base classifiers, the hybrid approach had better average classification performance overall. For the set of simulated signals of varying intensity, the hybrid classifier fusion system had on average an improved correct classification rate (CC_r) (6.1%) and reduced error rate (E_r) (0.4%). For the set of simulated signals of varying amounts of shape and/or firing pattern variability, the hybrid classifier fusion system had on average an improved CC_r (6.2%) and reduced E_r (0.9%). For real signals, the hybrid classifier fusion system had on average an improved CC_r (7.5%) and reduced E_r (1.7%).**

***Index Terms*—Base classifiers, hybrid classifier fusion, motor unit potential classification, multiple classifiers.**

I. Introduction

Electromyographic (EMG) signal decomposition is the process of resolving a composite EMG signal into its constituent motor unit potential trains (MUPTs). It is mainly used to assist in the diagnosis of muscle or nerve disorders and for analysis of the neuromuscular system, and it can be considered as a classification problem that abounds in uncertainty. Figs. 1 and 2 show the decomposition summary of an EMG and Figs. 3 and 4 show the results of decomposing a 1-s interval of an EMG signal, where the classifier assigns the motor unit potentials (MUPs) into their MUPTs based on a similarity criterion. Those MUPs that do not satisfy the classifier similarity criterion are left unassigned. Our goal in this paper is to describe a novel technique to reduce the uncertainty in classifying MUPs through the combination of the decisions of multiple classifiers using a hybrid classifier fusion approach.

In hybrid classifier fusion, heterogeneous sets of base classifiers of different kinds are applied concurrently and independently and an aggregator combines their results to achieve a group consensus. In this paper, we introduce a new aggregator module which consists of two stages of classifier fusion such that each stage is used in a complementary manner: the first, at the abstract level of classifier fusion using class labels provided by the base classifiers and, the other, at the measurement level of classifier fusion using confidence values for each class provided by base classifiers.

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We formulated a set of firing pattern consistency statistics for detecting erroneous MUP classifications [11], [12] such that once the set of MUPTs are generated by the hybrid classifier fusion system, 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 assertion required for assignment of a MUP classification individually for each MUPT based on an expectation of erroneous assignments.

II. Combination of Multiple Classifiers

The combination of the outputs of multiple classifiers is based on the idea that classifiers with different methodologies or different features can complement each other. Hence, if different classifiers cooperate with each other as a team, the combined decision may reduce errors and achieve a higher performance.

Consider a decision space, P, with M mutually exclusive sets, $\omega_i \in \Omega = \{\omega_1, \omega_2, \ldots, \omega_M\}$. Each set, ω_i, represents a MUPT into which MUPs will be grouped or classified. The decision space may be written as: $P = \omega_1 \bigcup \omega_2 \bigcup \cdots \bigcup \omega_M$. The decision space, P, is the set of all possible MUPs from all MUPTs. The set of corresponding integer labels Ω is defined such that $\Omega = \{\omega_1 = 1, \omega_2 = 2, \ldots, \omega_M = M\}$ and it 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 decision space set P can then be extended to include $\Omega \bigcup \{\omega_{M+1}\}$, where ω_{M+1} designates the unassigned category for when by some established criteria the classifier decides to not assign the input MUP.

For an ensemble of K-base classifiers $e_1, e_2, \ldots, e_K$, each recognition engine in the system may simply be regarded as a functional box that receives an input MUP x and outputs a MUPT label ω_j denoted by $e_k(x) = \omega_j$ and associated decision function values that can be used as measures of confidence in the decision of classifying the input MUP to a particular MUPT. This is regardless of what internal structure a classifier has or on what theory and methodology it is based.

When combining classifier outputs based on the measurement level of classifier fusion, we use the output decision function values for each MUPT provided by the respective classifiers. Assuming, when classifying a MUP x, each classifier produces output values, in the interval [0, 1], interpreted as a confidence $\mathrm{Cf}_i(x)$ in the decision of classifying MUP x with respect to a particular MUPT ω_i $(i = 1, 2, \ldots, M)$. One can think of these outputs as *a posteriori* probabilities but they might also be certainty measures with respect to specific MUPTs as is the case with the certainty classifier [14] or as assertion measures with respect to specific MUPTs as is the case with the adaptive fuzzy k-NN classifier [12]. In terms of *a posteriori* probabilities, the confidence $\mathrm{Cf}_i(x)$ is defined as

$$\mathrm{Cf}_i(x) = P(\omega_i | x) \tag{1}$$

and in relation with a specific classifier e_k, the confidence depends on the outcome $e_{ik}(x)$ of this classifier for MUPT ω_i

$$\mathrm{Cf}_{ik}(x) = P(\omega_i | e_{ik}(x)). \tag{2}$$

The confidences in (1) and (2) are defined over all the detected MUPs in an EMG signal.

Once a set of decision confidences $\{\mathrm{Cf}_{ik}(x), i = 1, 2, \ldots, M; k = 1, 2, \ldots, K\}$ for M MUPTs and K classifiers is computed for a MUP x, they can be combined with a classifier fusion module into a new set of decision confidences that can be used, by maximum selection, for the final classification.

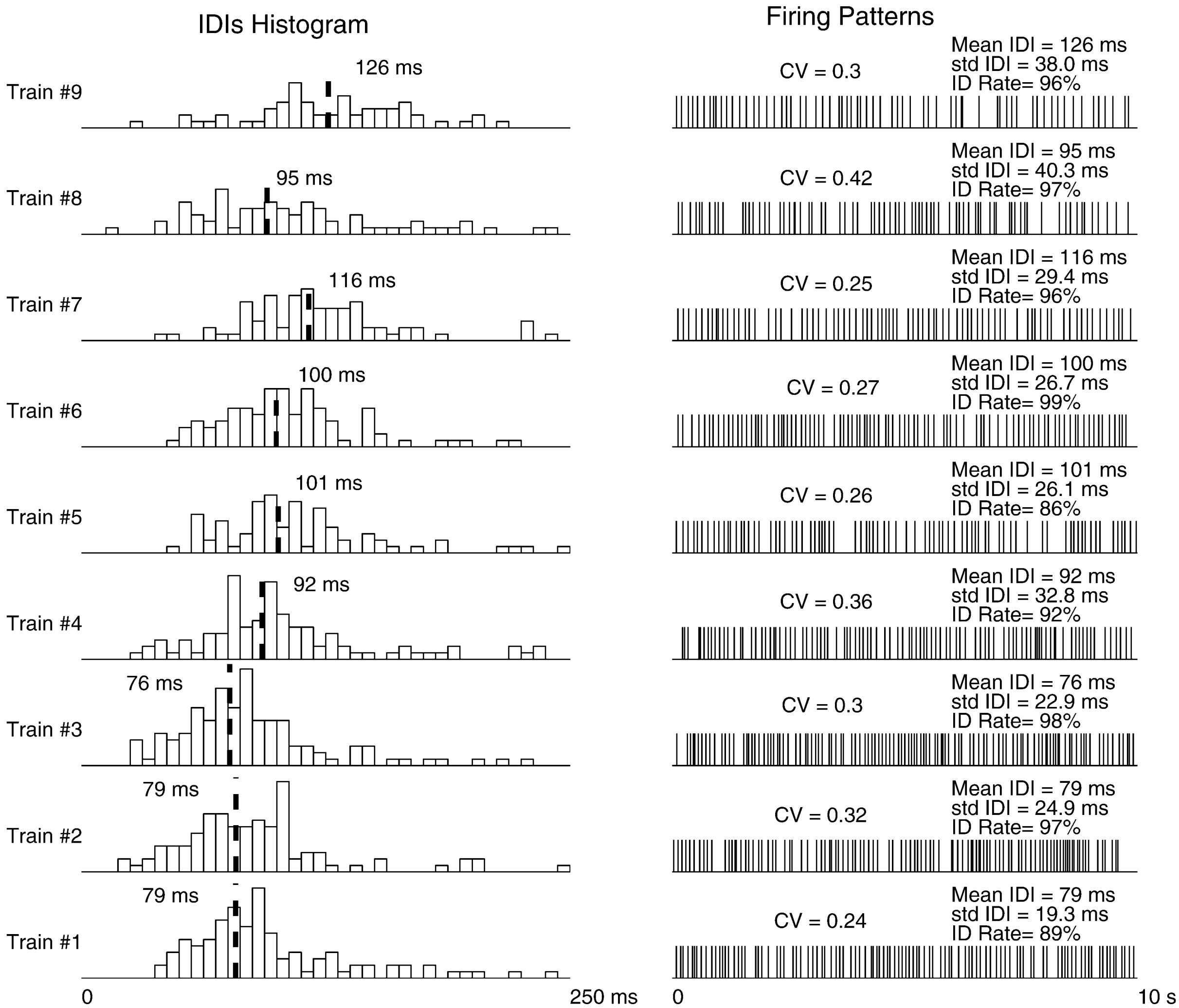

Fig. 1. Decomposition summary for the tested EMG signal in terms of IDI histogram, MUP firing times, and statistics using hybrid classifier fusion scheme consisting of the majority voting and average fixed combination rule. Estimates of MUPT IDI mean and standard deviation have been obtained using the EFE algorithm [8], [13]. ID rate stands for identification rate and CV stands for coefficient of variation.

III. Base Classifiers

Base classifiers are used in order to construct a combined classifier fusion system that may perform better than any of the base classifiers. Base classifiers should be different as it makes no sense to combine identical classifiers, but they should also be comparable, i.e., their outputs should be represented such that a combining method can use them as inputs.

The developed system uses an ensemble of a fixed number of base classifiers and it employs two different kinds of classifiers: certainty-based and fuzzy k-NN classifiers. The certainty-based classifier used is the adaptive certainty classifier (ACC) [11]. The fuzzy k-NN classifier used is the adaptive fuzzy k-NN classifier (AFNNC) [12]. The base classifiers, besides being of different kinds, utilize different types of features. The features extracted include raw time-domain data, first-order discrete derivative data, and wavelet-domain data.

IV. Design of the Hybrid Aggregation Modules

An aggregator in a classifier fusion system combines base classifier outputs to achieve a group consensus. Aggregators may be data independent [5], where they do not show any dependence on data and they solely rely on the output of classifiers to produce a final classification decision irrespective of the MUP being classified or they may be data dependent [5] with implicit or explicit dependency on data.

The proposed hybrid aggregation module is a combination of two stages of aggregation: the first aggregator is based on the abstract level and the second is based on the measurement level. Both aggregators may be data independent or the first aggregator may be data independent and the second data dependent. We used as the first aggregator, the majority voting scheme behaving as a data independent aggregator, while, as second aggregator, we used either the average combination rule behaving as a data independent aggregator or the fuzzy integral with the λ-fuzzy measure as an implicit data dependent aggregator.

A. Majority Voting Classifier Fusion Scheme

When classifying a MUP x at the abstract level, only the best choice MUPT label from each classifier $e_k(x)$ is used. The overall decision for the combined classifier system is sought given that the decision functions for the base classifiers may not agree. Therefore, to combine these abstract level classifiers, a voting method is used as a data independent aggregator.

A common form of voting that has less stringent conditions is *majority voting* [7]. A MUP x is classified to belong to MUPT ω_j if over half of the classifiers say $x \in \omega_j$.

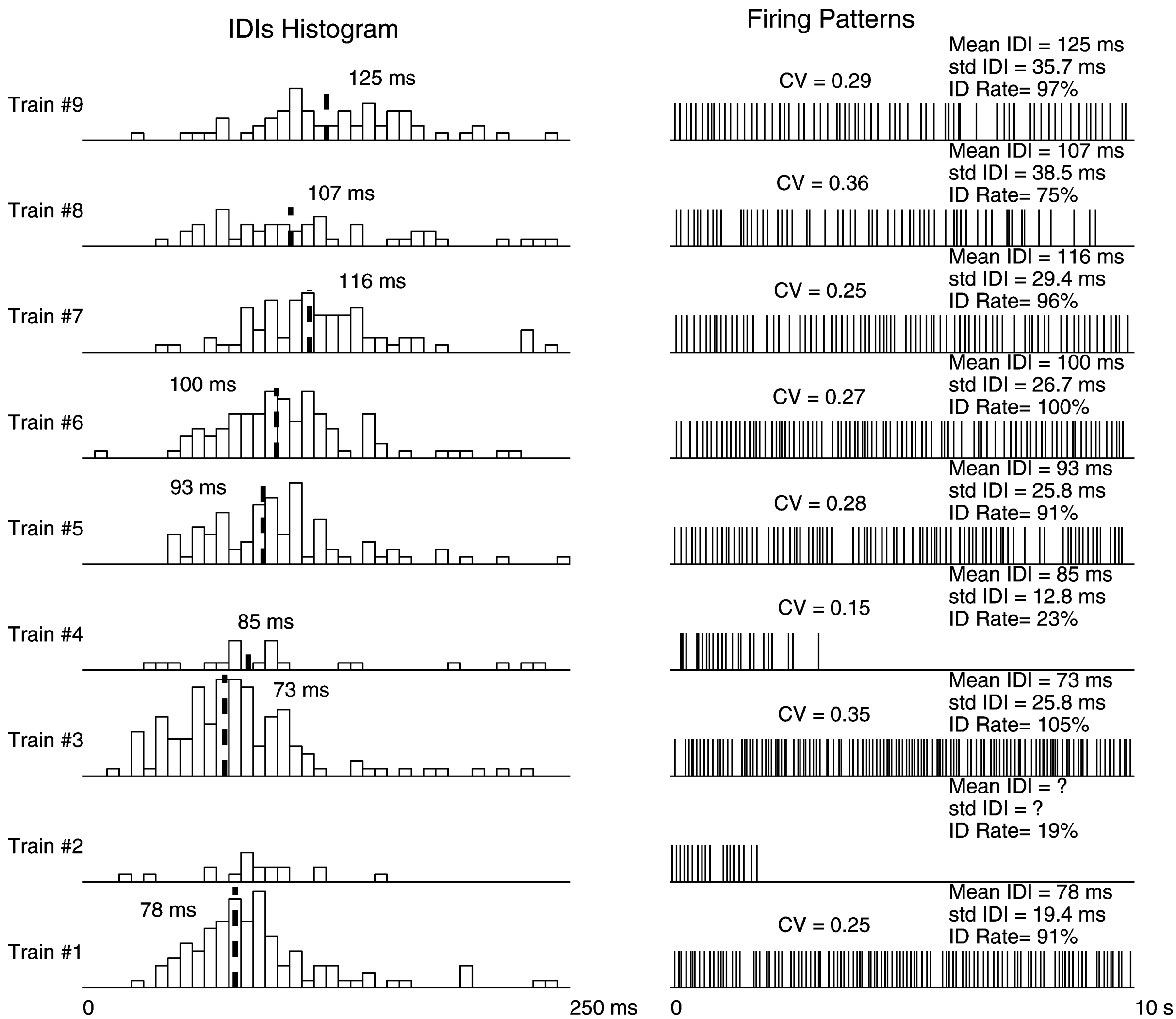

Fig. 2. Decomposition summary for the tested EMG signal in terms of IDI histogram, MUP firing times, statistics using the best base classifier $\boldsymbol{e}_5$.

B. Fixed Combination Rules

The fixed combination rules [1], [2], [6] are data independent aggregators and do not require prior training. They are used for combining the set of decision confidences $\{\mathrm{Cf}_{ik}(x), i = 1, 2, \ldots, M; k = 1, 2, \ldots, K\}$, interpreted by (2), for M MUPTs and K base classifiers $\{e_k(x), k = 1, 2, \ldots, K\}$ into combined classifier decision confidences $\{Q_i(x), i = 1, 2, \ldots, M\}$. The fixed combination rules are the *product*, *sum*, $\max$, $\min$, *median*, and *average* rules. The combined decision confidence $Q_i(x)$ for MUPT ω_i is computed by

$$Q_i(x) = \mathrm{rule}\{\mathrm{Cf}_{ik}(x)\} \quad (3)$$

where rule in (3) represents one of the fixed combination rules. The final classification is made by

$$\omega(x) = \arg\ \max_{i=1}^{M}(Q_i(x)). \quad (4)$$

In this paper, we used the average fixed combination rule as it shows better classification performance than the other rules.

C. Fuzzy Integral Classifier Fusion Scheme

Based on the measurement level of classifier fusion, one can train an arbitrary classifier using the $M \times K$ decision confidences $\mathrm{Cf}_{ik}(x)$ (for all i and all k) as features in the intermediate space [2], [3]. The *Sugeno fuzzy integral* approach trained by a search for a set of densities as described in [9] and [10] was used for combining classifiers.

The Sugeno fuzzy integral behaves as an implicit data dependent aggregator requiring the estimation of the fuzzy densities $g^{i/k}$ representing the degree of confidence in how accurate base classifier e_k is in the recognition of MUPT ω_i, implicitly from the data. In this study, as the evaluation was done using simulated EMG signals of known properties and real EMG signals decomposed manually and used as a reference, the fuzzy densities were estimated from training data by making them proportional to the correct classification rates for each MUPT using each base classifier.

D. Hybrid Classifier Fusion Scheme

We propose here a hybrid type of classifier fusion. It was investigated for MUP classification and across the EMG signal data sets used it had better average classification performance than applying any of the abstract or measurement level classifier fusion schemes individually, especially in terms of reducing classification errors.

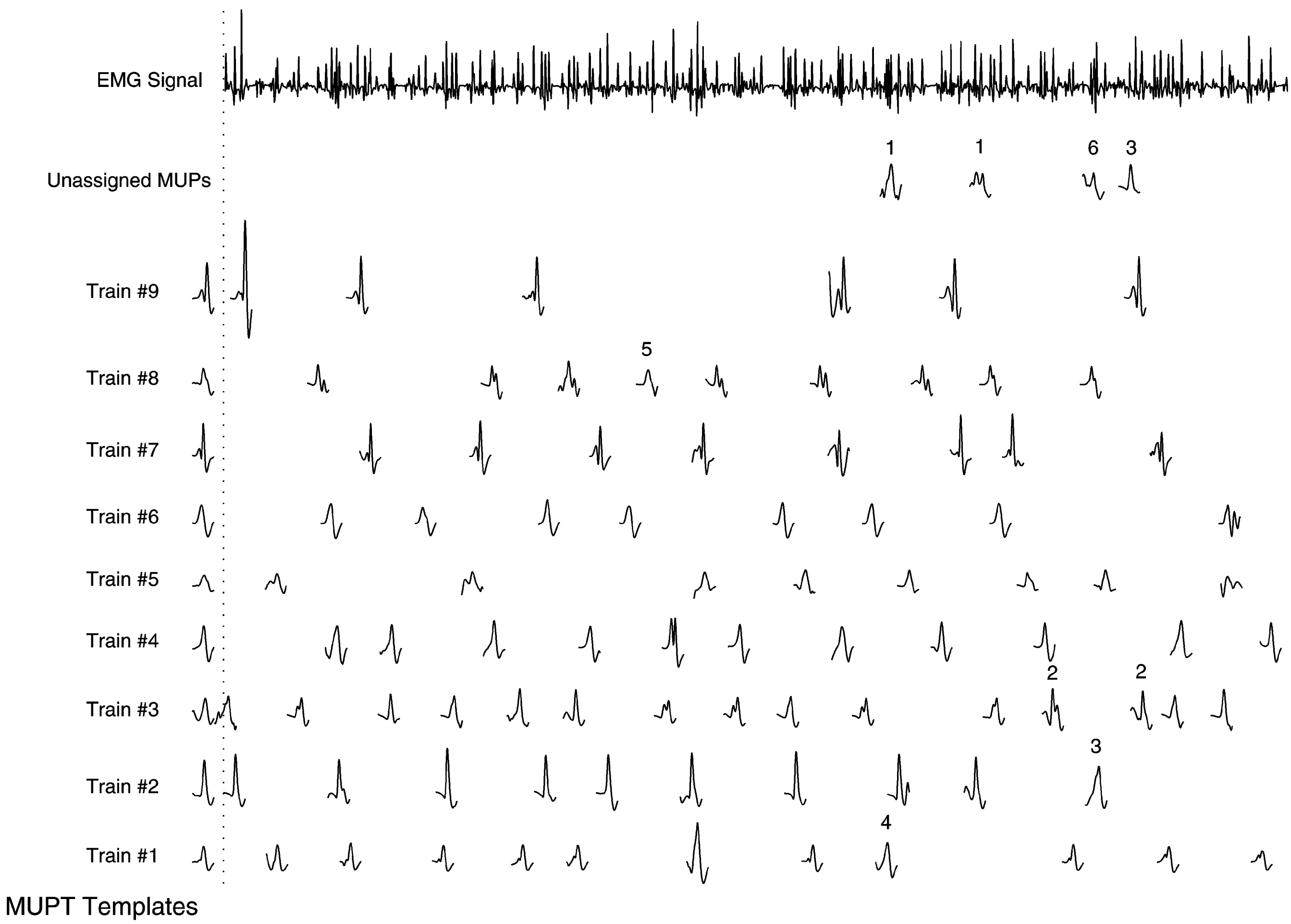

Fig. 3. MUP trace for a 1-s interval (from second 5 to second 6) of decomposition results for the tested EMG signal using the hybrid classifier fusion scheme consisting of majority voting and the average fixed combination rule. The MUP trace shows MUP waveforms displayed according to their firing times within the 1-s signal segment. From top, row 1 shows the 1-s long EMG signal segment; row 2 shows the MUPs that were left unassigned; and the remaining rows show the MUPs assigned to the MUPTs as recognized by the classifier. The left column shows the template waveforms for each MUPT for visualization comparisons. Unassigned MUPs and erroneous MUP classification are indicated by displaying the number of the correct MUPT next to the MUP. For improved visualization, MUP waveforms have been displayed using a time scale expanded by a factor of ten relative to the time scale used to depict their firing times.

The hybrid classifier fusion scheme is a two-stage process. The first stage performs classifier fusion at the abstract level using the majority voting data independent aggregator. The second stage performs classifier fusion at the measurement level using either the average fixed combination rule or the Sugeno fuzzy integral. Both stages of aggregation are used in a complementary manner.

The hybrid fusion scheme works as follows.

1) First stage: The outputs of the ensemble of classifiers are presented to the majority voting combiner. If all classifiers state a decision that a MUP is left unassigned, then there is no chance to reassign that MUP to a valid MUPT and it stays unassigned. If over half of the classifiers assign a MUP to the same MUPT, then that MUP is allocated to that MUPT and no further assignment is processed. For these MUPs, an overall confidence value is calculated for each MUPT by averaging the confidence values given by the ensemble of base classifiers who contributed to the decision of assigning the MUP. In all other situations, i.e., when half or less than half of the classifiers specify a decision for a MUP to be assigned to the same MUPT, the measurement level combination scheme is used in the second stage to specify to which MUPT the MUP should be assigned based on which MUPT has the largest combined confidence value. From the first stage, a set of incomplete MUPTs are generated missing those MUPs that need to be assigned to a valid MUPT in the second stage.
2) Second stage: This stage is activated for those MUPs for which only half or less than half of the ensemble of classifiers in the first stage specify a decision for a MUP to be assigned to the same MUPT. The outputs of the ensemble of classifiers are presented to the average fixed rule combiner, or the trainable aggregator represented by the Sugeno fuzzy integral. For each MUP, the overall combined confidence values representing the degree of membership in each MUPT are determined and accordingly, the MUP is assigned to the MUPT for which its determined overall combined confidence is the largest and if it is above the specified combined confidence threshold set for that MUPT, otherwise, the MUP is left unassigned. The MUPs satisfying the assignment condition are placed in their assigned MUPT thus forming a more complete set of MUPTs.

E. Adaptive Hybrid Classifier Fusion Approach

MUP classification using the hybrid classifier fusion approach is based on the outputs of the base classifiers and it does not take into consideration the motor unit (MU) firing patterns. Therefore, following the generation of MUPTs by the hybrid classifier fusion system, MUPTs

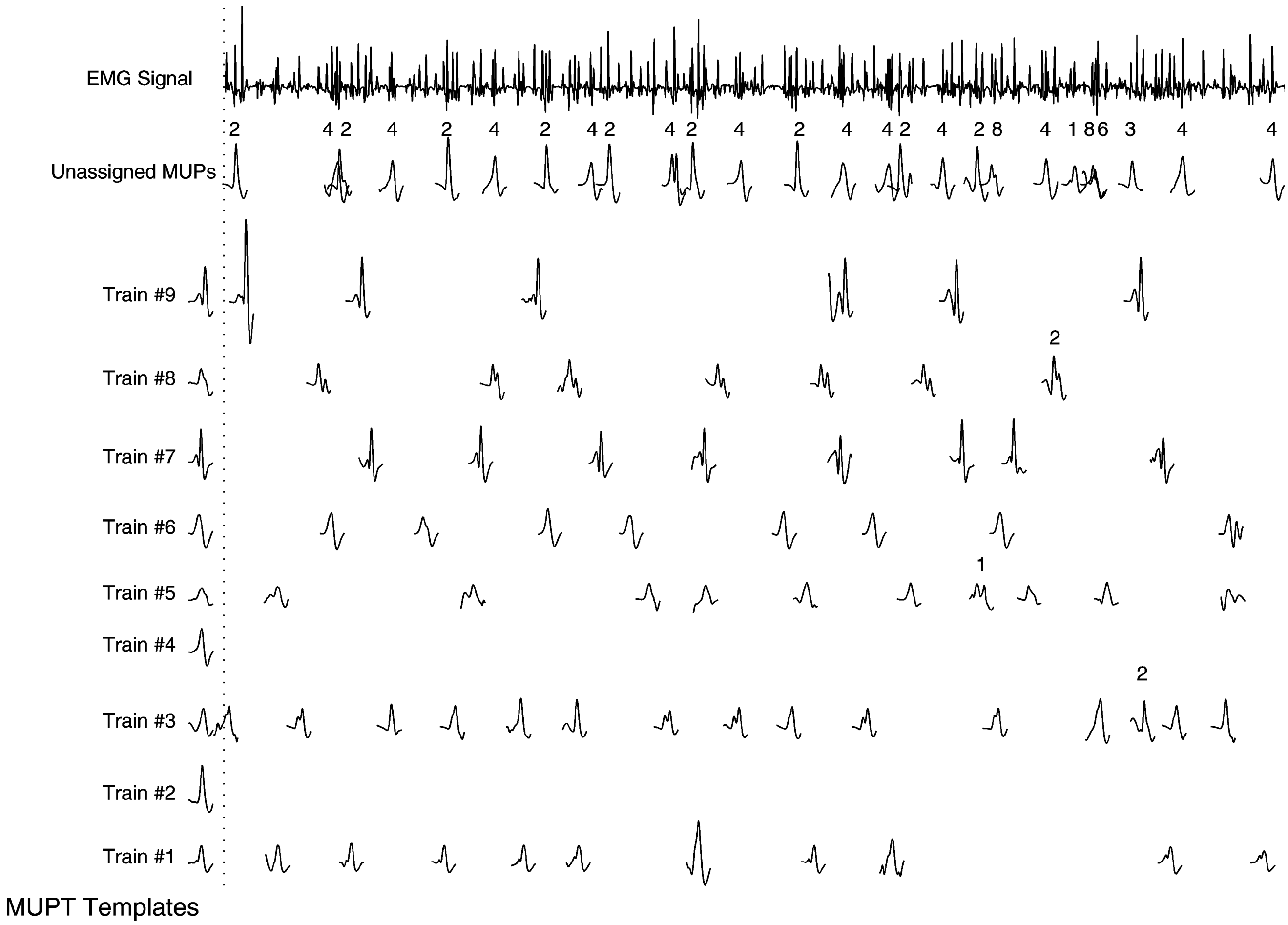

Fig. 4. MUP trace for a 1-s interval (from second 5 to second 6) decomposition results of the tested EMG signal using the best base classifier $\boldsymbol{e}_5$.

are tested for any firing pattern inconsistencies and if, based on the firing pattern statistics given in [11] and [12], it is expected that a train has too many erroneous assignments, its minimal assignment threshold is increased or otherwise it is kept constant. This firing pattern analysis allows the system to modify the assignment of a MUP for each MUPT individually based on an expectation of the number of erroneous assignments. MUPTs to which MUPs can be confidently assigned will have lower minimal assignment thresholds and have higher MUP identification (ID) rates. Alternatively, MUPTs to which MUPs cannot be confidently assigned, possibly because of shape similarity with the MUPs of another train or MUPT shape and firing pattern variability, will have higher minimal assignment thresholds and have lower MUP identification rates.

Unlike the adaptive supervised classification task [11], [12] employed by the base classifiers, during hybrid classifier fusion the adaptive MUP classification consists of only one stage and it is based on the passive use of firing pattern information to remove possible erroneous classifications.

Once the set of MUPTs are created by the hybrid classifier fusion system, the firing pattern consistency statistics for each MUPT are calculated. If a MUPT meets all the imposed constraints, it keeps its MUPs and its minimum assignment threshold is unchanged. Otherwise, the minimum assignment threshold for the train is increased and its MUPs confidence values are checked against the new value. We used a minimum assignment threshold of zero at the beginning of the process and then increased it in steps of 0.001. Those MUPs causing inconsistencies in the firing pattern of a train and MUPs with confidence values less than the minimum assignment threshold are designated unassigned and removed from the train. This process is repeated until all the imposed firing pattern constraints for all generated MUPTs are satisfied.

V. Methods

The effectiveness of using the hybrid classifier fusion system for EMG signal decomposition was demonstrated through the analysis of simulated and real EMG signals. For comparison with the performance of the constituent base classifiers, we used the same data sets used for evaluating them presented in [11] and [12]. The EMG signal data used consisted of two sets of simulated EMG signals: an independent set and a related set, each of 10-s length, and a set of real EMG signals.

The simulated data were generated from an EMG signal simulator based on a physiologically and morphologically accurate muscle model [4]. The simulator allowed 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 motor unit created each MUP. Furthermore, it allowed adjusting the amount of MUP shape variability represented by jitter and/or firing pattern variability.

The EMG signals within the set of independent simulated signals have different levels of intensity and each have unique MUPTs and MUP distributions. The EMG signals within the set of related simulated signals have the same level of intensity and the same MUPTs and MUP distributions but have different amounts of MUP shape and firing pattern variability.

TABLE I
MEAN AND MAD OF ASSIGNMENT RATE $\boldsymbol{A}_r$, ERROR RATE $\boldsymbol{E}_r$, AND CORRECT CLASSIFICATION RATE $\mathbf{CC}_r$ FOR THE DIFFERENT CLASSIFICATION APPROACHES ACROSS THE THREE EMG SIGNAL DATA SETS

Classifier	**Independent simulated signals**			**Related simulated signals**			**Real signals**		
	$A_r\%$	$E_r\%$	$CC_r\%$	$A_r\%$	$E_r\%$	$CC_r\%$	$A_r\%$	$E_r\%$	$CC_r\%$
Base Classifier e_1	85.2 (5.2)	1.8 (0.9)	83.7 (5.8)	84.0 (3.6)	4.9 (2.2)	79.9 (4.7)	83.9 (2.8)	2.9 (2.7)	81.4 (3.6)
Base Classifier e_2	86.9 (5.2)	1.6 (0.9)	85.5 (5.8)	86.0 (3.7)	5.1 (2.3)	81.6 (4.1)	80.5 (4.4)	4.7 (5.8)	76.7 (6.1)
Base Classifier e_3	86.9 (4.6)	2.5 (1.3)	84.8 (5.4)	86.2 (3.8)	5.7 (2.6)	81.3 (4.2)	82.6 (2.2)	5.9 (5.2)	77.8 (5.8)
Base Classifier e_4	88.6 (4.5)	2.1 (1.3)	86.8 (5.3)	88.3 (3.2)	6.3 (2.7)	82.7 (4.2)	80.6 (5.5)	7.5 (7.1)	74.6 (8.5)
Best Base Classifier e_5	96.6 (1.9)	3.2 (1.8)	93.6 (3.5)	91.4 (4.0)	5.6 (1.9)	86.3 (4.2)	91.2 (5.9)	7.1 (5.4)	84.6 (8.0)
Base Classifier e_6	95.8 (1.9)	3.6 (2.0)	92.5 (3.7)	90.8 (3.3)	6.2 (1.8)	85.2 (3.6)	90.2 (5.1)	8.8 (6.8)	82.2 (9.2)
Average of Base Classifiers	90.0 (3.9)	2.5 (1.4)	87.8 (4.9)	87.8 (3.6)	5.6 (2.3)	82.9 (4.2)	84.8 (4.3)	6.2 (5.5)	79.6 (6.9)
Majority Voting	88.8 (4.5)	1.1 (0.6)	87.8 (4.9)	85.2 (3.5)	2.6 (1.0)	83.1 (3.9)	81.2 (5.1)	2.4 (2.9)	79.4 (6.8)
Average Fixed Rule	95.4 (2.2)	2.5 (1.4)	93.1 (3.5)	93.4 (2.1)	4.9 (1.8)	88.8 (2.3)	93.1 (2.6)	5.5 (3.6)	88.1 (5.2)
Sugeno Fuzzy Integral	94.4 (2.9)	3.5 (1.8)	91.1 (4.4)	92.5 (2.4)	5.6 (1.3)	87.3 (2.5)	91.9 (3.3)	6.2 (3.5)	86.4 (5.4)
Majority Voting with Average Fixed Rule	95.9 (2.0)	2.1 (1.2)	93.9 (3.0)	93.2 (2.2)	4.4 (1.6)	89.0 (2.9)	90.7 (3.5)	4.3 (2.9)	87.0 (5.4)
Majority Voting with Sugeno Fuzzy Integral	95.9 (2.0)	2.1 (1.2)	93.9 (3.0)	93.5 (2.0)	4.6 (1.5)	89.2 (2.8)	91.4 (3.0)	4.7 (3.5)	87.2 (5.2)

The set of real EMG signals are of different complexities and were detected during slight to moderate levels of contraction. They have been decomposed manually by an experienced operator using a computer-based graphical display algorithm. The manual decomposition results were assumed to be the reference and were compared with those obtained automatically by the classifiers.

We followed the same MUP representation and classifier seeding used for evaluating the ACC and AFNNC base classifiers presented in [11] and [12]. For each EMG signal investigated, we extracted from the MUP raw data feature space the first-order discrete derivative features by applying a low-pass differentiation filter. Also, wavelet-domain features were extracted by taking the discrete-time wavelet transform (DTWT) with orthogonal wavelet bases.

The wavelet-domain features were extracted through multiresolution analysis implemented using a filter bank structure consisting of only the analysis bank with Daubechies 4 wavelet filters and six scale levels and then forming the feature vectors using only the detail coefficients at levels 4–6.

Classification performance was evaluated and compared in terms of percentage assignment rate A_r, error rate E_r, and correct classification rate CC_r performance indices.

The assignment rate $A_r\%$ 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

$$A_r\% = \frac{\text{number of MUPs assigned}}{\text{total number of MUPs detected}} \times 100. \tag{5}$$

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

$$E_r\% = \frac{\text{number of MUPs erroneously classified}}{\text{number of MUPs assigned}} \times 100. \tag{6}$$

The correct classification rate $\mathrm{CC}_r\%$ 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

$$\mathrm{CC}_r\% = \frac{\text{number of MUPs correctly classified}}{\text{total number of MUPs detected}} \times 100. \tag{7}$$

A MUP classification approach is considered the best or to have better performance if it provides the highest correct classification rate $\mathrm{CC}_r\%$ and lowest error rate $E_r\%$. In situations where the highest correct classification rate $\mathrm{CC}_r\%$ and lowest error rate $E_r\%$ do not judge the differentiation between two classifiers, we take the difference between the correct classification rate $\mathrm{CC}_r\%$ and error rate $E_r\%$ for each classifier and consider the classifier with the higher difference as the one with the better performance.

A fixed ensemble of six base classifiers $e_1, e_2, e_3, e_4, e_5, e_6$ was used. Four base e_1, e_2, e_3, e_4 classifiers were adaptive certainty-based classifiers (ACC) [11] and two classifiers e_5, e_6 were adaptive fuzzy k-NN classifiers (AFNNC) [12]. Two of the ACC classifiers e_1, e_2 were fed with time-domain first-order discrete derivative features, while the other two e_3, e_4 were fed with wavelet-domain first-order discrete derivative features. One of the AFNNC classifiers e_5 was fed with time-domain first-order discrete derivative features, while the other e_6 was fed with wavelet-domain first-order discrete derivative features. The ACCs e_1 and e_3 were seeded with MUPs having the highest shape certainty [11]. ACCs e_2 and e_4 and AFNNCs e_5 and e_6 were seeded with 20 isolated MUPs selected for each MUPT. The seeded data were taken from the reference data supplied by the simulator and the manually decomposed data. The selected reference set was used to calculate initial MUPT templates for the ACCs and to establish core membership values for the AFNNCs.

VI. Experimental Results

Results, in terms of mean and mean absolute deviation (MAD) of assignment rate A_r, error rate E_r, and correct classification rate CC_r are reported in Table I. These results were obtained using the ACC and AFNNC base classifiers, the one-stage classifier fusion schemes, namely majority voting, the average fixed combination rule, and the Sugeno fuzzy integral, and the hybrid classifier fusion schemes, i.e., the hybrid aggregator consisting of majority voting and the average fixed combination rule and the hybrid aggregator consisting of majority voting and the Sugeno fuzzy integral. Individual base classifier $e_1, e_2, e_3, e_4, e_5, e_6$ results for each EMG signal and also for different ensembles are reported in [9].

As shown in Table I, the hybrid classifier fusion modules had significantly better A_r, E_r, and CC_r performance across the used data sets than that of the one-stage classifier fusion schemes and the base classifiers. The improvement in classification performance obtained by the hybrid classifier fusion system can also be demonstrated by comparing a schematic EMG signal decomposition summary and MUP trace for a test EMG signal produced using results of the hybrid classifier scheme to corresponding ones produced using the results of the best base classifier in the ensemble.

The test signal used has nine MUPTs and was simulated to have a jitter value of 150 μs and an inter-discharge interval (IDI) coefficient of variation (CV) of 0.3. The hybrid classifier fusion system used consisted of majority voting and average fixed rule aggregators and the best base classifier in the ensemble across the data set was the AFNNC e_5, as indicated in Table I.

Fig. 1 presents decomposition results for the test signal in terms of IDI histograms, MUP firing times, and IDI mean and standard deviation statistics using the results from the hybrid classifier fusion system. Estimates of the IDI mean and standard deviation statistics have been obtained using the *error-filtered estimation* (EFE) algorithm [8], [13]. The EFE algorithm is based on the IDI histogram. From the estimated IDI statistics, the coefficient of variation CV for each MUPT was calculated. Note how close they are to the coefficient of variation specified within the EMG signal simulator during signal generation. The effect of motor unit firing pattern variability can be seen in the IDI histograms and MUP firing time plots. When compared with a similar summary calculated using decomposition results of the best base classifier e_5 shown in Fig. 2, we see that the hybrid classifier fusion system decomposition had better identification (ID) rates which in turn led to better estimates of the coefficient of variation for each MUPT. Specially, if we look at the firing patterns of MUPT #2 and MUPT #4, shown in Fig. 1, and compare them, respectively, with those shown in Fig. 2, we see that the hybrid classifier fusion system recognized relatively full trains, with an ID rate of 97% for MUPT #2 and 92% for MUPT #4, respectively. In addition, estimation of the coefficient of variation is close to the actual value, $\mathrm{CV} = 0.3$, where estimated $\mathrm{CV} = 0.32$ for MUPT #2 and estimated $\mathrm{CV} = 0.36$ for MUPT #4. With respect to MUPT #2 and MUPT #4, the best base classifier e_5 performance is very weak, where it recognizes only about one fifth of the MUPs, ID rate = 19 %, in MUPT #2 and about one-fourth of the MUPs, ID rate = 23%, in MUPT #4. Also, the EFE algorithm fails to estimate the IDI mean and standard deviation statistics for MUPT #2 due to the small number of recognized MUPs and for MUPT #4 the estimated $\mathrm{CV} = 0.15$. Fig. 1 demonstrates that the hybrid classifier fusion scheme can take advantage of the complementary action of the base classifiers of the ensemble and is therefore able to assign a large number of MUPs and correct some assignment errors.

The ability of the hybrid classifier fusion scheme to take advantage of the complementary action of the base classifiers of the ensemble is also demonstrated in Fig. 3, which displays relatively full MUP traces for a 1-s interval (from second 5 to second 6) of the decomposition results for the nine MUPTs of the test signal and the unassigned MUPs produced by the hybrid classifier fusion system. When compared with the best base classifier e_5 MUP traces shown in Fig. 4, we see that the hybrid classifier fusion system shows MUP traces with fewer MUPs left unassigned. The hybrid classifier fusion system was able to detect some erroneously assigned MUPs and make correct reassignments. Most of the remaining errors are related to the shape variability of MUPs occurring at expected firing times for other trains. In these cases, the information provided by the MUP shape and the firing pattern information is not sufficient to make a correct decision.

VII. Conclusion

An ensemble of a fixed number of heterogeneous base classifiers, configured for MUP classification during EMG signal decomposition, was constructed and their outputs were combined using a two-stage hybrid classifier fusion approach. The proposed approach has been described, tested, and evaluated using simulated and real EMG signals and its performance was compared to that of the constituent base classifiers and also to that of a one-stage classifier fusion approach consisting of either the majority voting scheme, or the average fixed combination rule, or the fuzzy integral fusion scheme. For these situations across the EMG signal data sets studied, the hybrid classifier fusion approach outperformed the best base classifier and the one-stage fusion schemes.

The one-stage classifier fusion schemes have classification performance better than the average performance of the constituent base classifiers and also better than the performance of the best base classifier except across the independent simulated signals. The hybrid classifier fusion approaches on the other hand have performances that not only exceed the performance of any of the base classifiers forming the ensemble but also reduced classification errors for all data sets studied.

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