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Classification of sEMG signals of hand gestures based on energy features ☆

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ABSTRACT

The performance of a robotic exoskeleton depends upon the accuracy of control commands from the controller fed with Surface ElectroMyoGraphy (sEMG) input signals. The classification of hand gestures based on sEMG signals extracted from a human hand depends upon the type of EMG features extracted. In this paper, an ensemble of energy features is proposed for the sEMG classification. The idea is motivated by the energy features' relation to the movement force, dependence on related mechanical factors, robustness with respect to the repetition of trials and the presence of noise. The suitability of the proposed energy features is tested by using the standard machine learning classifiers, including the K-Nearest Neighbour (KNN), Probabilistic Neural Networks, Ensemble KNN, Quadratic Discriminant Analysis and the Cubic Support Vector Machines. In order to show the superiority of the proposed energy features, the experiments are conducted over benchmark NinaPro DB1 sEMG hand gesture dataset. The fine KNN classifier has achieved the highest validation accuracy of 88.8%, an improvement of 13% over the state of the art accuracy. The performance of the classifiers is analyzed with various evaluation metrics using the proposed feature ensemble. The contribution of individual features for the performance is also analyzed and observed that spectral band energy features have provided an highest accuracy of 85.2%. Additionally, the proposed method is found to be computationally least expensive.

1. Introduction

1.1. Motivation

According to the 2011 census survey of India, 1.1 million people require an artificial support due to impairment in locomotion [1]. Some of these patients may need an intelligent assistive device to support the wrist and hand movements for their regular activities. Recall that in a human, the muscular movements of the hand are controlled by the central nervous system via motor neurons. A partially disabled person loses full control of the hand movements due to lapses in signal flow along these neural pathways to the muscles. To recover this control, an exoskeleton hand [2] (exo–hand) can be designed. It can assist in the proper movements of the hand by analyzing the surface Electromyography (sEMG) signals obtained from the hand muscles. Specifically, the signal processing software in an exoskeleton's computer should be able to analyze the sEMG signals and decide what type of movement is intended for a task. In this paper, the focus is on Pattern recognition (PR) algorithms that play a critical role in identifying these categories of the movements.

1.2. Literature review

A vital stage of any pattern recognition (PR) framework is the feature extraction from the raw data. For the sEMG signals, several frameworks have been proposed for this purpose. Along with relevant features a suitable learning algorithm is also important for classification of hand movements. Here, we present a short and concise review of PR methods for hand gesture classification.

1.2.1. Hand gestures

Hand-Designed Features: The features used for EMG classification

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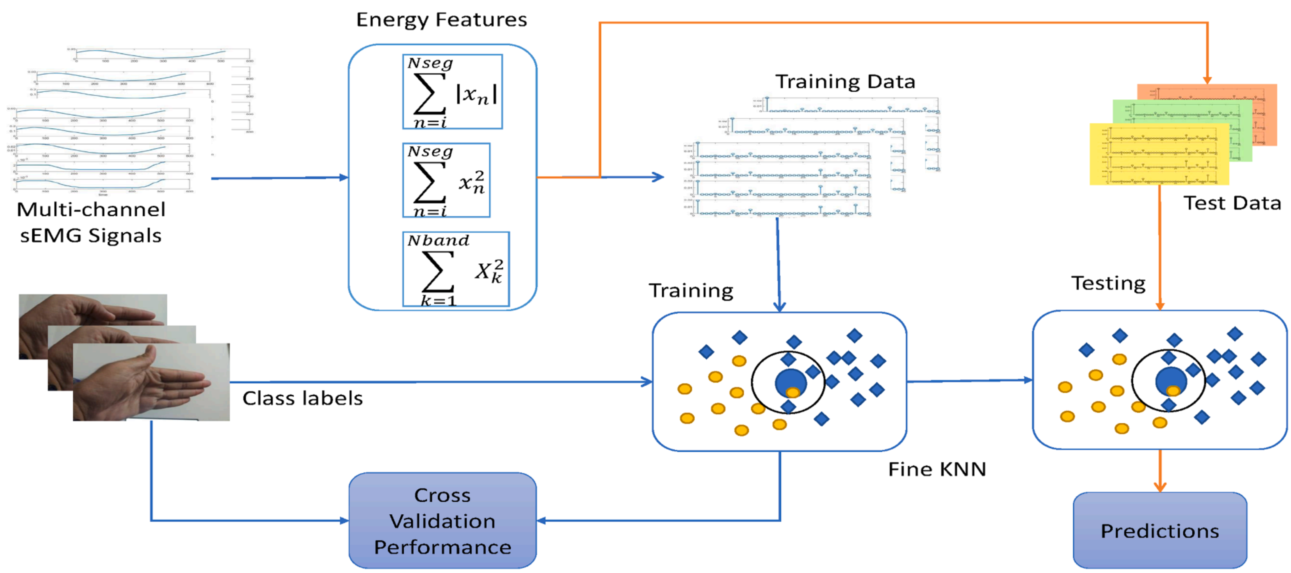

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Fig. 1. Block diagram of the proposed classification scheme using energy features.

can be categorized as follows. (1) Time domain (TD) based features such as Mean Absolute Value (MAV) and wavelength [3], myopulse rate, willison amplitude, and cardinality [4] and mean prominence of local peaks [5]; (2) Frequency domain (FD) based features such as Auto regression model coefficients [6], logarithms of moments of Fourier transforms [7]; (3) Combinations of TD and FD features [8]; (4) Wavelets based features such as wavelet packet transform [9] and ternary pattern and discrete wavelet transform [10]; (5) Variational mode decomposition and composite permutation entropy index based features [11]; and (6) Various combinations of these different classes [12,13]. Apart from discovering features the other aspects of feature analysis include feature reduction [14,15], role of measurement conditions such as movement speed [16] and temporal variations on a daily scale [4].

Learning Based Features: In 2016, Atzori et al. [17] have proposed a Convolutional Neural Network (CNN) architecture for classification of the NinaPro sEMG dataset. They have achieved a performance comparable to that of the state-of-the-art in classical machine learning (ML) approaches. Du et al. [18] have applied a CNN for high density EMG data obtained from a 2D array of sensors from 23 subjects and achieved better accuracy for within sessions, but lower accuracy across sessions. Tsinganos et al. [19] have used the temporal CNN for the classification of 52 classes NinaPro sEMG dataset. Cote et al. [20] have utilized the transfer learning technique over the CNNs over a 17 subjects dataset.

Though several feature extraction techniques have been explored in the literature, these approaches are limited to the specific scenarios such as (1) real-time control of exoskeletons where shorter training time is critical [21,22], (2) simultaneous hand movement classification with multiple DoFs [23], (3) classification of both upper limb and lower limb movements [12] and (4) conditions, such as sensitivity to noise. Hence, the existing models are unable to cope up with the inherent noise in the sEMG signals and are not robust to varying conditions of sEMG signal measurements. Most of the features are tested for lower number of hand motion classes and lower number of sEMG channels.

In this work we restrict to the hand designed features and propose the energy based features for sEMG based hand movement classification. We show that the proposed approach outperforms the existing state-of-the-art methods. The proposed approach is expected to serve a couple of purposes, including (a) it can be used as a ML benchmark for other ML classification or any deep learning frameworks to be developed and (b) it can also serve as an alternative sEMG classification method specifically in hardware implementation where the device cost and the time taken for a decision is more important with a reasonable accuracy of the decision.

1.3. Proposed contributions

As pointed out by the related works, different methods utilize different features and classifiers for sEMG signal classification. In this paper, we explore the utility of energy features based on moments of absolute values of the sEMG segments in time and frequency domain. Following are the main contributions of this paper:

- In this work, we build a feature ensemble of important energy features for sEMG signal based hand pose classification.
- In order to validate the performance improvement due to energy feature ensemble, we use widely adapted machine learning classifiers in sEMG literature, namely fine KNN, Probabilistic neural networks, Ensemble KNN, Cubic SVM and Quadratic Discriminant Analysis (QDA) to train and test the data.
- We perform the hand movement classification experiments on the sEMG signals from the benchmark NinaPro DB1 database [24] which contains the samples from 27 subjects.
- Finally, we compare the proposed classification framework of the recent feature ensemble and classifier combinations to show the improvement due to the proposed framework. We also analyzed the impact of different features within the propose ensemble.

The paper is organized as follows: In Section 2, the proposed methodology and implementation scheme is discussed. The results are discussed with various analyses in Section 3. The Section 4 concludes the work with key findings and possible future directions.

2. Proposed methodology and implementation

2.1. Methodology

The proposed implementation scheme is illustrated in the Fig. 1. The sEMG signals extracted from M electrodes corresponding to M channels consist of N distinct sEMG signals/patterns. The number $N = S \times C \times T$, where S is the total number of subjects, C is the number of different hand gestures and T is the number of repetitions of each gesture per subject. The full sEMG dataset can be represented as,

$$\mathbf{x} = \{\mathbf{x}_n\}_{n=1}^{N} \tag{1}$$

where each observation vector $\mathbf{x}_n$ consists of M channels and is given as

$$\mathbf{x}_n = \{\mathbf{x}_{n,m}\}_{m=1}^{M}, \quad n = 1, \dots, N \tag{2}$$

and each of the m-th channel consists of a vector

$$\mathbf{x}_{n,m} = \{x_{n,m}(i)\}_{i=1}^{N_T} \tag{3}$$

where $N_T = N_s \times T$ is the number of values in one trial of duration T and N_s is the sampling rate (samples/s).

2.1.1. Feature extraction

In this work, we propose a feature ensemble consisting of only three types of features: the Mean Absolute Value (MAV), the Temporal Segment Energies (TSE) and the Spectral Band Energies (SBE). These features are commonly used as a part of the feature ensembles in EMG signal classification. Both the temporal energy and the mean absolute value are based on the amplitude of the EMG signal. The relationship between the EMG signal amplitude and the force magnitude of limb movements varies from a linear to non-linear model [25–27]. Basically, this relationship depends on various mechanical and physiological factors such as movement speed [25], muscle activation levels [28], muscle resting and contraction lengths [29] and muscle composition [27]. Importantly, based on these factors, the EMG amplitudes vary across different hand gestures and EMG electrodes and provide the theoretical foundation for discriminative power of the proposed features. A formal presentation of feature extraction is given below. From the sEMG signals, statistical features are extracted for each trial $\mathbf{x}_{n,m}$ as described below.

Time domain (TD) features: For a given trial, the signal is divided into multiple segments. The features MAV [30] and TSE are computed for each of them. Let

$$\mathbf{s}_g = \{x_{n,m}(i)\} quad i = 1, \dots, N_g \tag{4}$$

where N_g is the number of values in one segment and is related to N_T as $N_T = N_g \times N_{seg}$ where N_{seg} is the number of segments per trial.

The MAV features are defined for each of the segments $\mathbf{s}_g$ as follows:

$$f_{MAV}(g) = \frac{1}{N_g} \sum_{i=1}^{N_g} |x_{n,m}(i)| \tag{5}$$

and the TSE features for each segment are defined as

$$f_{TSE}(g) = \sum_{i=1}^{N_g} |x_{n,m}(i)|^2. \tag{6}$$

The resulting MAV feature vector for the m-th channel is given as

$$\mathbf{f}_{MAV}^{(m)} = \{f_{MAV}(g)\}_{g=1}^{N_a} \tag{7}$$

where N_a is the No. of segments per trial for computation of MAV features. The vector of MAV features representing the M channels is

$$\mathbf{f}_{MAV} = \{\mathbf{f}_{MAV}^{(m)}\}_{m=1}^{M} \tag{8}$$

Similarly, the feature vector $\mathbf{f}_{TSE}$ is also constructed.Spectral Band Energies (SBE): In this case, the periodogram of the signal is computed and the resulting spectral densities are divided into multiple bands and the spectral energies are computed for each of them. Consider the Discrete Fourier Transform (DFT) of a m-th channel's trial $\mathbf{x}_{n,m}$, given as

$$\mathbf{X}_{n,m}(k) = \sum_i x_{n,m}(i) e^{-j2\pi\frac{ik}{N_T}}. \tag{9}$$

Table 1
Summary of features extracted.

Feature name	Feature length
Mean Absolute Value (MAV)	$2 \times M$
Temporal Segment Energies (TSE)	$4 \times M$
Spectral Band Energies (SBE)	$4 \times M$

Table 2
Setup Information for the Classifiers.

Classifier	Model Setup
Fine KNN	No.of neighbours = 1, Distance metric = Correlation, Distance weight = Equal
PNN	Spread = 1
Ensemble KNN	No.of Learning cycles = 30, learners = KNN, Subspace dimension = 70
QDA	Score transform = 'none' Fill coeffs = 'off'
Cubic SVM	Polynomial kernel, Order = 3, Box Constraint = 1, Multi-class Method = one-vs-one

Next the spectrum is divided into N_B bands

$$\mathbf{X}_{n,m} = \{\mathbf{X}_b\}_{b=1}^{N_B} \tag{10}$$

where $\mathbf{X}_b$ is the b-th band in $\mathbf{X}_{n,m}$ with elements

$$\mathbf{X}_b = \{X_b(k)\}_{k=1}^{N_b} \tag{11}$$

where $X_b(k)$ is same as $\mathbf{X}_{n,m}(k)$ within the b-th band and N_b is the number of DFT samples in $\mathbf{X}_b$. The corresponding SBE is given by

$$f_{SBE}(b) = \frac{1}{N_b} \sum_{k=1}^{N_b} |X_b(k)|^2. \tag{12}$$

Again the features from M channels are concatenated to form the spectral feature vector $\mathbf{f}_{SBE}$. In this method, we use the following feature ensemble $[\mathbf{f}_{MAV}, \mathbf{f}_{TSE}, \mathbf{f}_{SBE}]$ for classification of the hand gestures/poses. The effective length of the full feature ensemble is

$$N_f = (N_a + N_e + N_b) \times M \tag{13}$$

and the feature sub-set sizes are summarized in the Table 1.

2.1.2. Machine learning algorithms

Here, we address the classification of C categories of hand poses. The following classical and yet effective machine learning algorithms: K-Nearest Neighbour (KNN), Probabilistic Neural Networks (PNN), Quadratic Discriminant Analysis (QDA), Ensemble KNN (sKNN) and Cubic Support Vector Machine (SVM3) have been applied to the feature dataset. The hyper-parameter settings for different machine learning algorithms used in this work are summarized in Table 2. The pseudo code for sEMG classification is given in *Algorithm* 1. The algorithm discusses steps involved from the process of feature extraction to calculating classification accuracy. The performance of classifiers is evaluated using the classification accuracy (α) in the cross validation stage, accuracy (β) during the testing phase, Kappa coefficient (κ) for performance against chance assignment [31], precision γ for average fraction of correct classifications against predictions, recall ρ for average fraction of correct classifications against true labels and F_1 score [32]. These classifiers are selected as they provided best performance compared to other machine learning classifiers in the literature. At last the Sequential Forward Selection (SFS) is applied to the feature vector to identify the relevant feature subsets.

Algorithm 1:Surface EMG Signal Classification

Input: surface EMG signals $x_{n,m}$, class labels
For each n: 1 to N
  For each m
    For each Segment
      Compute features:
        MAV, TSE, SBE features from (8), (6), (12), respectively
  Concatenation of features: $F_0(n) \longleftarrow [f_{MAV}, f_{TSE}, f_{SBE}]$
  $L_c(n) \longleftarrow$ class label of n^{th} pattern
For m: 1 to M (average over M trials)
  $F_s \longleftarrow F_0(i), L_s = L_c(i)$ (i = shuffle(N))
  Data partition for cross validation and testing:
  $F_s \longrightarrow [F_s^{cv}; F_s^{te}], L_s \longrightarrow [L_s^{cv}, L_s^{te}]$
  Cross validation:
  $F_s^{tr} \longleftarrow$ One partition of F_s^{cv}
  $L_s^{tr} \longleftarrow$ One partition of L_s^{cv}
  $model, pred\_labels$ = FKNN(F_s^{tr}, L_s^{tr})
  $\alpha, cv\_labels = cross\_validation(model, F_s^{cv}, L_s^{cv})$
  $\beta, test\_labels = cross\_validation(model, F_s^{te}, L_s^{te})$
  Compute: Cross validation and test performance metrics averaged over M runs
Output:
  Cross Validation Metrics: $\alpha, \beta, \gamma, F_1$ and κ
  Testing Metrics: $\alpha, \beta, \gamma, F_1$ and κ

2.2. Implementation

2.2.1. NinaPro dataset description

In this study, we experiment on the sEMG data from the benchmark dataset NinaPro DB1 [24]. The dataset consists of $C = 52$ classes of hand gestures collected from $S = 27$ subjects. Each hand movement is performed for 5 s and repeated for $T = 10$ times with a rest period of 3 s between each trial. Each sEMG signal consists of 10 channels, extracted from Otto Bock sEMG sensor [33] placed at different locations on a human hand. The data acquisition rate is 100 samples/s. The total number of predictors is $P = 27 \times 52 \times 10 = 14040$.

2.2.2. Experimentation

From the 10 channel sEMG signal, we obtain features as described below. As listed in Table 1, from each of the patterns of size 512×10 a feature ensemble of size 1×100 is constructed. To avoid bias in learning during the training, the patterns are shuffled across subjects, trials and classes. The 14040×100 dataset is divided into 80% cross validation set and 20% test set. The feature matrix, thus extracted is trained and tested with the five classifiers, namely KNN, PNN, Ensemble KNN, QDA and Cubic SVM. A 10-fold cross validation is performed and the optimized classifier is used for making label prediction on the test data. For evaluation purpose, a confusion matrix is obtained, at both cross validation and testing stages. A comparative analysis is performed under various setups and conditions as described below.

3. Results and performance analysis

To evaluate the proposed classification framework, the following experiments are performed: (i) performance comparison of the proposed feature ensemble with the various state-of-the-art feature ensembles using the fine KNN classifier, (ii) evaluations of the proposed feature ensemble with multiple existing classifiers to find the suitable classifier, and (iii) comparisons with the results from the benchmark methods. The metrics $\alpha, \beta, \kappa, \gamma, \rho$ and F_1 score, as mentioned in Section 2.1.2, are computed. For better visualization, the metrics are presented as follows: first two in percentage values and the rest on a fractional scale.

3.1. Comparison with feature ensembles

The following feature ensembles are considered in the analysis of the proposed classification framework.

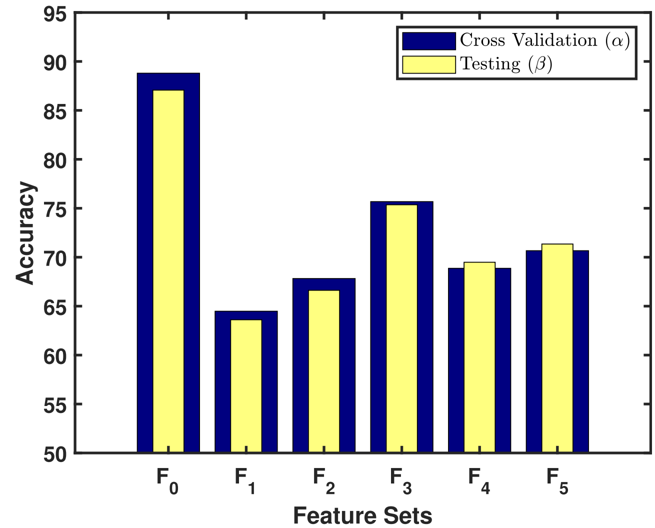

Fig. 2. Performance comparison with different Feature Ensembles with Fine KNN.

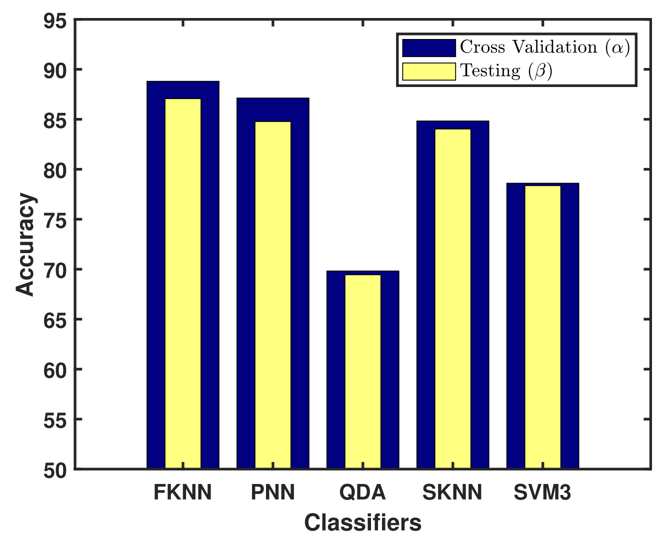

Fig. 3. Performance comparison with different Classifiers with proposed feature ensemble.

1. $\mathbf{F}_0$: MAV, TSE and SBE
2. $\mathbf{F}_1$: MAV, zero crossings, slope changes and wavelength [23]
3. $\mathbf{F}_2$: $\mathbf{F}_1$ and auto regression Coefficients [13]
4. $\mathbf{F}_3$: $\mathbf{F}_1$, myopulse rate, willison amplitude, and cardinality [4]
5. $\mathbf{F}_4$: Log moments in frequency domain [7]
6. $\mathbf{F}_5$: $\mathbf{F}_4$, modified LMF based features, time domain statistics, spectral band powers, max channel cross correlations, and local binary patterns [12]

Here the $\mathbf{F}_0$ is the proposed feature ensemble and the $\mathbf{F}_i$ for $i = 1, \ldots, 5$ are the state-of-the-art feature ensembles from the literature.

In this comparison study, for each set, the corresponding feature ensembles are computed and used as inputs to the fine K Nearest Neighbor (KNN) and their performance metrics α and β are also evaluated. As shown in the Fig. 2, the feature ensemble F_1 from [23], has produced the least classification performance ($\alpha = 64.4$ and $\beta = 63.5$). The best performance is produced by the proposed energy ensemble F_0 ($\alpha = 88.8$ and $\beta = 87.6$). The next best feature ensemble lags behind by at least 13% at $\alpha = 75.6$ and $\beta = 75.3$. The proposed feature ensemble outperforms the other feature ensembles because the energy features

Table 3
Description of Benchmark Frameworks. *Reproduced frameworks with the given feature ensemble.

Framework	Classifier	Feature Ensemble
B_0	Fine KNN	$\mathbf{F}_0$
B_1 [23] *	QDA	$\mathbf{F}_1$
B_2 [13]*	KNN	$\mathbf{F}_2$
B_3 [4]*	SVM	$\mathbf{F}_3$
B_4 [6]*	SVM	$\mathbf{F}_4$
B_5 [12]*	PNN	$\mathbf{F}_5$

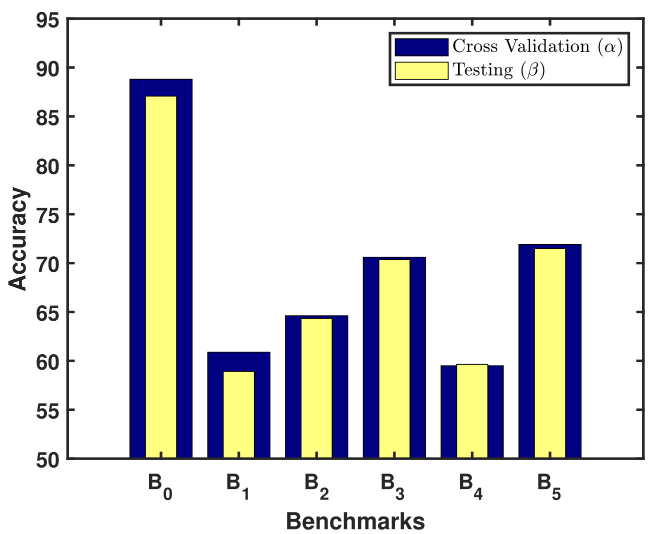

Fig. 4. Performance comparison against benchmark frameworks.

have greater relevance for hand gestures categorization as mentioned in Section 2.1.1.

3.2. Classifier comparisons

In this experiment, the proposed feature ensemble F_0 is computed and used as input to commonly used machine learning algorithms (i.e., Fine K-Nearest Neighbour (FKNN), Probabilistic Neural Networks (PNN), Quadratic Discriminant Analysis (QDA), Ensemble KNN (sKNN) and Cubic Support Vector Machine (SVM3)) for sEMG signal classification. As shown in Fig. 3, the best performance is produced by the fine KNN ($\alpha = 88.8$ and $\beta = 87.6$) and closely followed by the Probabilistic ANN (PNN) ($\alpha = 87.1$ and $\beta = 84.2$) and then by ensemble KNN ($\alpha = 84.8$ and $\beta = 84$). The quadratic discriminant algorithm shows the least performance. Thus, it is observed from this experiment that the feature representation produced by the proposed feature ensemble is more relevant with respect to the problem in hand and exhibits more class separability.

3.3. Comparison against benchmark algorithms

The performance of the proposed classification framework is compared against the existing sEMG benchmark classification methods consisting of different combinations of feature ensembles and classification frameworks as listed in Table 3. Here B_0 indicates the proposed framework and the B_i for $i = 1, \ldots, 5$ are the benchmark frameworks. The parameter setups of the different classifiers used in the numerical analyses are also shown in Table 2. The performance of these classifiers is analyzed based on the cross validation accuracy (α) and Test accuracy (β) with benchmark results and is shown in Fig. 4. The other performance metrics of the proposed framework B_0 are analyzed against those

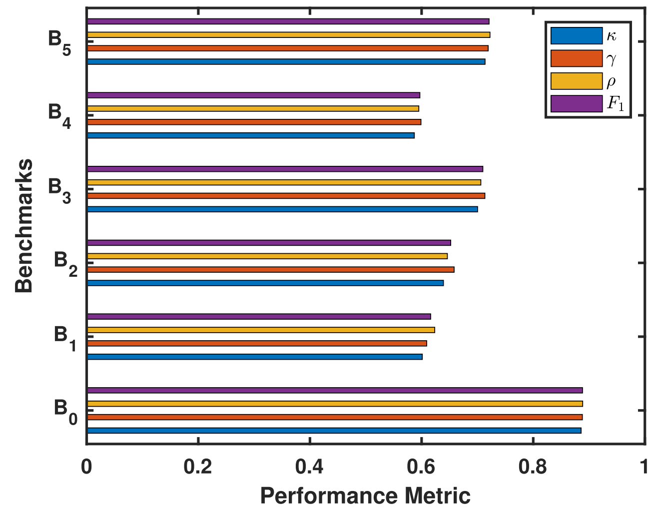

Fig. 5. Performance comparison against benchmark frameworks in terms of various metrics.

Table 4
Feature Set Contributions toward classification accuracy for the proposed framework B_0.

Feature Set	SBE	{SBE, MAV}	$\mathbf{F}_0$
α	85.2	88.2	88.8
β	83.9	86.7	87.6

of the benchmarks and are shown in Fig. 5. The major findings from this experiment are summarized as follows:

- *Cross validation accuracy (α) and Test accuracy (β)*: The proposed classification framework B_0 has achieved the highest performance of $\alpha = 88.8$ and $\beta = 87.6$, which is an improvement of 15% over the state of the art performance $\alpha = 71.9$ and $\beta = 71$ from the benchmark B_5 based on PNN. The lowest performance among the compared benchmarks is B_4 [6].
- *Other metrics: $\kappa, \gamma, \rho, F_1$*: The proposed framework B_0 leads to the highest values for each of the performance metrics, i.e.,

$$\kappa = 0.89;\ \gamma = 0.888;\ \rho = 0.889;\ F_1 = 0.888$$

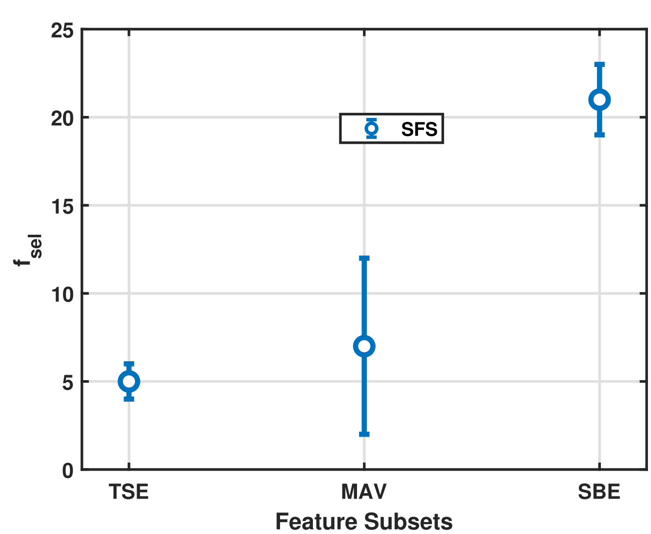

Fig. 6. Average number of features selected in each feature category.

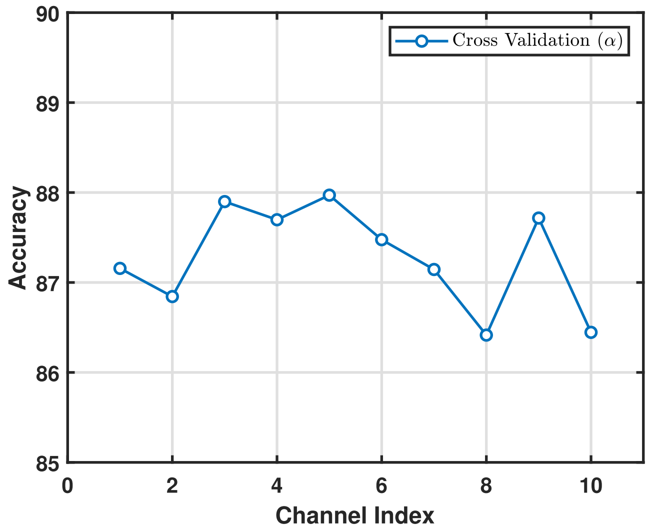

Fig. 7. The CV accuracy of B_0 as a function of omitted channel index.

The runner-up is the framework B_5 with metric values as,

$$\kappa = 0.713; \gamma = 0.719; \rho = 0.722; F_1 = 0.721$$

The lowest performance is achieved by the benchmark B_4. From this experiment, it is noticed that the proposed energy driven feature ensemble outperforms the existing state-of-the-art benchmarks. In order to understand, the better representative ability of the proposed ensemble, the feature analysis is given in the next experiment.

3.4. Feature analysis

The performance improvement of B_0 over B_5 is mainly due to the inclusion of energy features as observed from the Table 4. Clearly, the spectral features SBE provide the best performance by any single type of feature subset and the overall performance is incremented by inclusion of the subsets MAV and TSE in the same order. Next, to understand the role of individual features within the subsets SBE, MAV and TSE; we implemented the sequential forward selection algorithm. The Fig. 6. shows the average number of features selected f_{sel} per subset over 100 runs of the SFS algorithm. It demonstrates that the features from the SBE subset play the most significant role in the classification process followed by the MAV and TSE. Further, based on Table 4, for $M = 10$ the total number of features in the three subsets are $\{20, 40, 40\}$ respectively. Hence, from Fig. 6. it is determined that, on an average, the number of selected features exceeds 50% from SBE, 17% from MAV and 25% from TSE. In terms of variability among selected features, the MAV has a higher standard deviation of 5 while SBE and TSE have relatively lower standard deviations of 2 and 1 respectively.

Table 6
Time and space complexity analysis for classifiers (N – No. of patterns, M – No. of features, and C – No. of classes).

Frame work	Classifier	Theoretical best time	Theoretical worst time	Execution time (s)	Space complexity
B_0	FKNN [34]	$\mathcal{O}(NM)$	$\mathcal{O}(MN\log N)$	8.55	$\mathcal{O}(NM)$
B_1 [23]	QDA [37]	$\mathcal{O}(2MN + M^2)$	$\mathcal{O}(NM^2 + M^3)$	8.59	$\mathcal{O}(2MN + M^2)$
B_2 [13]	KNN [34]	$\mathcal{O}(NM)$	$\mathcal{O}(MN\log N)$	12.31	$\mathcal{O}(NM)$
B_3 [4]	SVM [35]	$\mathcal{O}(NM^2)$	$\mathcal{O}(N^3)$	332.88	$\mathcal{O}(N^2)$
B_4 [6]	SVM [35]	$\mathcal{O}(NM^2)$	$\mathcal{O}(N^3)$	233.66	$\mathcal{O}(N^2)$
B_5 [12]	PNN [38]	$\mathcal{O}(N^2)$	$\mathcal{O}(NMC)$	183.47	$\mathcal{O}(N^2)$

3.5. Channel sensitivity

Finally, to understand the role of individual EMG channels and corresponding electrodes, we evaluated the classification accuracy of the proposed framework by omitting one channel at a time. From Fig. 7, it is clear that the cross validation accuracy is not highly sensitive to any single channel. However, omission of the channels 3, 4 and 5 does not affect the performance much. Further, the omission of channels 2, 8 and 10 has led to loss of 1 to 2% in the accuracy.

3.6. Time and space complexity

The time complexity of each feature is analysed with respect to number of the basic operations such as additions, multiplications and comparisons. The time and space complexities of the features are listed in the Table 5. The algorithm is implemented using MATLAB 2020 on a desktop PC with intel $i5$ processor having 24 GB RAM. The space complexity is lesser for MAV, TSE and SBE features compared to complex features such as the AR and LMF. For a single run, the time complexities and corresponding execution times for the classification frameworks are given in Table 6. The theoretical time and space complexity of the classifiers are determined by considering the analysis provided in [34–38]. Notably, the proposed framework B_0 takes shortest execution time of 8.55s, while the benchmark framework B_3 requires the longest execution time of 332.88s as expected from the corresponding

Table 5
Time and space complexity analysis for features (N – No. of patterns, M – No. of features, N_T – No. of samples in a trial, P – No. of coefficients and – zero operations)

Feature	No. of additions	No. of multiplications	No. of comparisons	space complexity ($Rows \times Columns$)
MAV	$[(N_g - 1)N_{seg}]MN$	–	–	$N \times N_{seg}M$
TSE	$[(N_g - 1)N_{seg}]MN$	$[N_g N_{seg}]MN$	–	$N \times N_{seg}M$
SBE	$[N_T \log N_T/2 + (N_b - 1)N_{seg}]MN$	$[(N_T/2)\log N_T/2 + N_b N_{seg}]MN$	–	$N \times N_{seg}M$
ZC [23]	–	–	$(N_T - 1)MN$	$N \times M$
SC [23]	$3(N_T - 3)MN$	–	$(N_T - 3)MN$	$N \times M$
WL [12]	$(2N_T - 3)MN$	–	–	$N \times M$
AR [13]	$(N_T - 1)MN$	–	–	$N \times PM$
MPR [12]	$(N_T - 1)MN$	–	$N_T MN$	$N \times M$
WA [12]	$(2N_T - 3)MN$	–	$(N_T - 1)MN$	$N \times M$
Cardinality [4]	$(N_T - 1)MN$	–	$N_T MN$	$N \times M$
LMF [7]	$[N_T \log N_T/2 + (N_T - 1)P]MN$	$[(N_T/2)\log N_T/2 + (N_T - 1)P]MN$	–	$N \times PM$
TDS [12]	$9(N_T - 1)MN$	$6N_T MN$	–	$N \times 4M$

theoretical complexity. This analysis depicts that the proposed framework B_0 is computationally efficient compared to the benchmark frameworks. The storage space requirement of B_0 is lower compared to other frameworks. Moreover, the feature set F_0 is very simple and compact in exploiting the abstract features from the sEMG signals.

4. Conclusion

In this study, we have implemented a multi-class classification framework to categorize the 52 human hand gestures. We have proposed an energy based feature ensemble to extract relevant and discriminative features pertaining to the sEMG classification. The Fine KNN, PNN, Ensemble KNN, Cubic SVM and QDA classifiers are trained and tested to classify the sEMG signals with the proposed feature ensemble. The Fine KNN classifier performance is the best among the classifiers with a maximum test accuracy of 87.6%. The proposed energy based feature ensemble, using the Fine KNN classifier, outperforms the state-of-the-art feature ensembles. Moreover, the proposed benchmark outperforms the other benchmarks with a significant margin. The feature analysis depicts the importance of different energy based features in the proposed ensemble. The computational complexity analysis confirms the efficiency of the proposed method. The future plan is to integrate the proposed feature ensemble with deep learning to further improve the classification accuracy.

CRediT authorship contribution statement

Naveen Kumar Karnam: Investigation, Software, Validation, Writing - original draft, Writing - review & editing. **Anish Chand Turlapaty:** Funding acquisition, Project administration, Supervision, Conceptualization, Resources, Methodology, Writing - original draft, Visualization. **Shiv Ram Dubey:** Funding acquisition, Project administration, Resources, Conceptualization, Methodology, Writing - original draft, Supervision, Writing - review & editing. **Balakrishna Gokaraju:** Conceptualization, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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