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PAPER

Efficient EMG-Based Facial Expression Classification Using Minimal Time-Domain Features and the *k*-Nearest Neighbors Classifier

Marisa Lertvittayavivat[1], Surapong Chatpun[1], Bojan Petrović[2], Methawee Limaksorn[1], Pornchai Phukpattaranont[1] (✉)

[1]Prince of Songkla University, Songkhla, Thailand

[2]University of Novi Sad, Novi Sad, Serbia

pornchai.p@psu.ac.th

ABSTRACT

This study investigates the classification of six facial expressions using surface electromyography (EMG) signals recorded from the faces of ten healthy participants (aged 21–22 years). The objective is to identify effective time-domain features for distinguishing muscle activity patterns and to evaluate the performance of various classifiers. Three widely used features, i.e., integrated EMG, root mean square (RMS), and mean absolute value, were extracted and standardized using z-score normalization. Five classifiers were compared, namely *k*-nearest neighbors (KNN), support vector machine (SVM), ensemble (EN), neural network, and naive Bayes. The results indicate that the KNN classifier, in combination with the three selected features, achieved the highest classification accuracy of 98.73%. However, the study is limited by a small and homogeneous sample size, which may affect the model's generalizability. Additionally, the exclusive use of time-domain features may reduce robustness under conditions such as muscle fatigue. Future work may explore frequency-domain features, deep learning models, or the integration of EMG with other data sources, such as video, to enhance accuracy and applicability in real-world scenarios.

KEYWORDS

electromyography (EMG) signals, facial muscle, feature extraction, facial expression classification, machine learning, pattern recognition

1 INTRODUCTION

Facial expressions play a critical role in nonverbal human communication, conveying emotions, intentions, and physiological states. Recognizing these expressions has important consequences for various domains, including affective computing, human–computer interaction, rehabilitation, and clinical diagnostics.

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Surface electromyography (EMG) signals have become a useful method for studying facial muscle activities, providing a way to safely measure the electrical signals linked to facial movements. Recent advances in machine learning have enabled significant progress in decoding facial expressions from the EMG signals. Research has shown that using multi-channel EMG signals along with machine learning can help recognize complicated facial expressions more accurately and reliably. For instance, Cai et al. [1] used machine learning on multi-channel EMG data to detect muscle movements linked to certain facial expressions, while Sanipatín-Díaz et al. [2] created a portable system for recognizing facial expressions using EMG sensors and learning models for application on mobile devices. In addition, Adamov et al. [3] provided a comparative study of EMG signals across facial muscles, offering foundational insights into the physiological mechanisms underpinning facial expressions.

More sophisticated approaches have been proposed to enhance interpretability and physiological fidelity. Shu et al. [4] introduced a musculoskeletal modeling framework to estimate facial keypoint displacements based on muscle synergies derived from EMG signals, enabling more precise expression generation. Similarly, Xi et al. [5] explored facial expression distribution prediction using emotion distribution learning, reflecting a growing interest in probabilistic and distributional modeling. Deep learning has also been adopted in wearable systems such as smart glasses, enabling real-time expression and activity recognition [6]. Echoukairi et al. [7] proposed improved methods for automatic facial expression recognition, while Chi et al. [8] reviewed the role of deep convolutional neural networks in mobile face recognition. In addition, Muhi et al. [9] introduced a robust masked face recognition approach using a bag of convolutional neural networks with enhanced local feature extraction and region of interest techniques.

Beyond emotional expression, the EMG signal has been applied to evaluate muscle function in clinical contexts, such as monitoring facial nerve palsy [10] and assessing voluntary facial movements [11]. Moreover, it serves as a crucial tool in pain assessment, where specific muscle activities (e.g., zygomaticus and corrugator supercilii) correlate with pain intensity [12], [13]. Jiang et al. [13] and Yang et al. [14] have proposed multi-modal and IoT-based systems to monitor acute and chronic pain using physiological signals, including EMG signals. In addition, Wang et al. [15] investigated the recognition of primary taste sensations, introducing a novel application of EMG in sensory analysis.

Despite these advancements, several challenges persist. Issues related to signal quality, electrode placement consistency, individual variability, and model generalizability continue to hinder the widespread deployment of EMG-based systems [16], [17]. In response, some studies have explored perifacial EMG acquisition systems [18] and evaluated the use of EMG in specific speech-related tasks, such as speech rehabilitation and recognition [19], [20]. However, there remains a need for more integrated frameworks that balance physiological accuracy, computational efficiency, and real-time capabilities. This study aims to address these gaps by investigating the feasibility of high-accuracy classification using minimal features and a low-complexity configuration. By optimizing channel selection and feature extraction methods, the proposed framework aims to reduce system complexity while enhancing classification performance. The primary contribution of the proposed method lies in achieving high-accuracy classification of six facial expressions (98.73%) using only three time-domain features in conjunction with a *k*-nearest neighbors (KNN) classifier.

2 THEORY

2.1 Perioral muscles

The facial EMG signal is caused by the contraction of facial muscle. For the purpose of facial expression analysis, the EMG signals of six primary facial muscle groups were recorded in this paper, including the anterior belly of the digastric (CH1), zygomaticus major (CH2), levator anguli oris (CH3), mentalis (CH4), depressor anguli oris (CH5), and orbicularis oris (CH6) muscles [11]. These muscles were selected based on their functional relevance to dynamic facial gestures and their suitability for EMG-based signal acquisition. Table 1 shows the muscle names and their corresponding anatomical locations, functional roles, and facial expressions.

Table 1. Summary of facial muscle groups involved in facial expressions

Muscle Name	Anatomical Location	Functional Role	Facial Expression
Anterior belly of digastric (CH1)	Neck, between posterior belly and lower jaw	Pushes/pulls lower jaw; assists in opening the mouth	Mouth opening [21]
Zygomaticus major (CH2)	Corner of the upper mouth	Elevates corners of mouth	Smiling
Levator anguli oris (CH3)	Upper lip, near canine teeth	Elevates upper lip	Grinning
Mentalis (CH4)	Front of the chin	Elevates and protrudes lower lip; creates chin wrinkle	Chin wrinkling
Depressor anguli oris (CH5)	Corner of the lower mouth	Depresses lower lip and chin	Blowing [16, 17]
Orbicularis oris (CH6)	Surrounds the mouth (sphincter muscle)	Contracts and protrudes the lips	Lip pursing [22, 23]

2.2 Feature extraction

EMG signals can be converted into a concise and useful representation by feature extraction, which is crucial for further signal classification and analysis. Features are generally extracted from either the time domain or the frequency domain, depending on the application and the characteristics of the signal [24]. Popular time-domain techniques for measuring signal amplitude include integrated EMG (IEMG), root mean square (RMS) and mean absolute value (MAV) and each providing distinctive yet supporting insights into signal shape [1, 12, 15, 18, 25]. A concise summary of these feature extraction methodologies is as follows.

1. IEMG is the sum of the absolute value of the EMG amplitude over a period of time, which can be expressed as [1]

$$\mathrm{IEMG} = \sum_{i=1}^{N} |x_i| \tag{1}$$

where x_i is the EMG amplitude at sample index i and N is the length of the EMG signal.

2. RMS is the square root of the mean square for the EMG signal. We use the RMS feature to evaluate the signal amplitude and signal energy. It can be given by [25]

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{2}$$

3. MAV represents the signal energy, which is frequently used for detecting the onset of the EMG signal. The MAV feature is the average of the absolute value of the EMG signal. It can be defined as [25]

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{3}$$

2.3 Classification

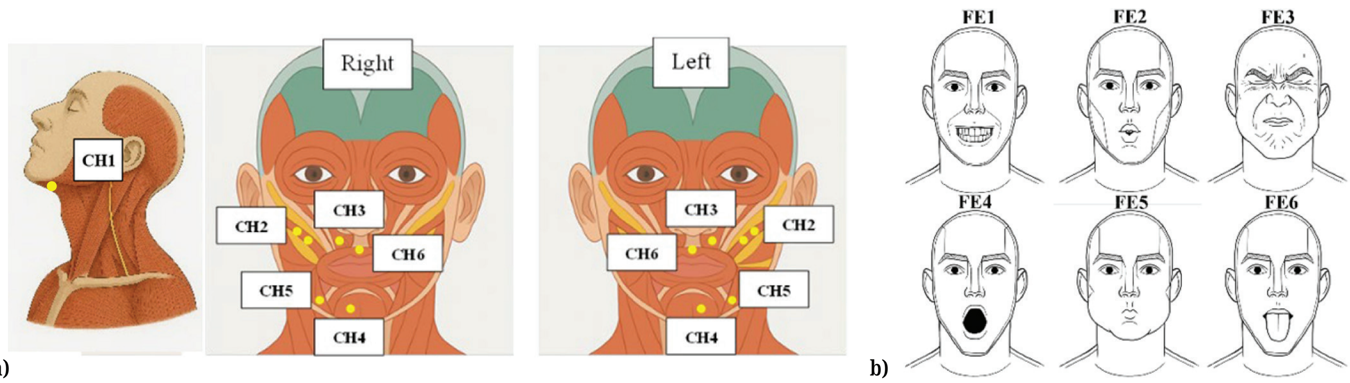
Five classifiers are tested and compared in this paper, i.e., KNN, support vector machine (SVM), ensemble (EN), neural network (NN), and naive Bayes (NB). Brief details of each classifier and its corresponding parameters used are as follows.

- The KNN is a method for classifying feature vectors based on the k training samples, which are the test sample's closest neighbors. It is then categorized into the category with the highest probability. The value of k in this paper was 1.
- The SVM divides classes using a discriminant hyperplane, seeking to identify the best hyperplane that optimizes the margin between data points from various classes. The margin is the separation between each class's closest training locations and the hyperplane. The C-Support vector SVM with a Gaussian kernel was employed in this study. In the kernel function, the cost parameter was set to one, and the gamma parameter was set to one divided by the number of features.
- The EN techniques in machine learning involve combining multiple models with decision trees to improve performance. Bagging is a popular EN approach that creates numerous datasets from the original data using bootstrap sampling and trains a model on each dataset in this study.
- The NN is a multilayer perceptron consisting of an input layer, one or more hidden layers, and output layers. Every neuron in every layer is linked to the output of the one before it. The input layer, ReLU hidden layer, and linear output layer together form the one-layered feed-forward back-propagation neural networks that we built in this paper.
- The NB classifier uses a training dataset to determine the best hypothesis. Bayes theorem provides a method for determining a hypothesis' probability based on its prior probability of the data found and the total data. In this study, the kernel type used was Gaussian, and it was unbounded.

3 MATERIALS AND METHODS

3.1 EMG data acquisition

Figure 1a shows the electrode placements on six facial muscles used for EMG signal acquisition. The targeted muscles included the anterior belly of the digastric (CH1), zygomaticus major (CH2), levator anguli oris (CH3), mentalis (CH4), depressor anguli oris (CH5), and orbicularis oris (CH6), all of which are involved in facial expressions in this paper. A bipolar configuration with an inter-electrode distance of 20 mm was employed for CH2. For the monopolar channels (CH1, CH3, CH4, CH5, and CH6), reference electrodes were positioned on the earlobes and the left wrist. A ground electrode was placed on the bony region of the right wrist. The EMG signals were recorded using disposable Ag/AgCl electrodes (H124SG, Kendell™). Data acquisition was carried out using a commercial EMG system (Mobi6-6b, TMS International B.V.) with a gain of 19.5. The signals were band-pass filtered between 20 Hz and 500 Hz and sampled at 1,024 Hz.



a) b)

Fig. 1. Electrode placements and facial expressions: (a) Electrode placements on six facial muscles (b) Six facial expressions performed by participants

Ten able-bodied participants (age, 21–22 years; height, 153–176 cm; weight, 45–65 kg) were recruited for the experiment. None of the subjects had any neuromuscular disease or facial aesthetic. Each subject performed six distinct facial expressions, as illustrated in Figure 1b. The expressions included grinning (FE1), pursing the lips (FE2), pressing the lips together (FE3), opening the mouth (FE4), puffing the cheeks (FE5), and sticking the tongue out (FE6). Each expression was maintained for a duration of 4 seconds per trial and repeated 10 times. Visual cues of each expression were presented via video to ensure consistency. Recordings were first conducted on the left side of the face, followed by a 5-minute rest period, after which the right side was recorded. The study protocol was approved by the Human Research Ethics Committee of the Faculty of Medicine, Prince of Songkla University (REC.67-516-38-2). Prior to participation, written informed consent was obtained from all participants.

3.2 Data processing

Following the recording of EMG signals from six facial muscles corresponding to six distinct facial expressions, the data were processed using a four-step analytical framework implemented in MATLAB R2023b: (1) data cleaning, (2) segmentation, (3) feature extraction, and (4) performance evaluation using classification algorithms. The detailed procedures for each analytical step are described below.

Step 1) Data cleaning: The acquired EMG signals were contaminated by noise, primarily due to power-line interference and electrocardiographic (ECG) artifacts. To attenuate the power-line interference, a 50 Hz notch filter was applied. Subsequently, a second-order bidirectional Butterworth high-pass filter with a cutoff frequency of 30 Hz was employed to suppress ECG contamination.

Step 2) Segmentation: In this step, the 4-second EMG recordings were segmented using a disjoint windowing technique with a fixed window length of 128 ms. This procedure yielded 31 non-overlapping segments per trial for each EMG channel.

Step 3) Feature extraction: In this step, three time-domain features, namely IEMG, RMS, and MAV as described in Section 2.1, were extracted from each EMG segment. The resulting feature matrix comprised 1,860 rows (31 segments × 10 trials × 6 movements) and 18 columns (3 features × 6 channels). To minimize inter-subject variability and facilitate subsequent analysis, all features were normalized using z-score normalization.

Step 4) Classification: In this step, the feature groups obtained from Step 3 were used as inputs to five classifiers, as briefly described in Section 2.2. The classification performance of each feature group was evaluated and compared based on classification accuracy. A 5-fold cross-validation strategy was employed, wherein the dataset was split into training and testing sets with an 80:20 ratio. This process was repeated five times to ensure that each of the five folds served as the testing set once. Notably, each run involved a different partitioning of the data to ensure robustness. The final performance of each feature group across the classifiers was determined by computing the mean classification accuracy across all cross-validation runs.

4 RESULTS

4.1 Signals and features

Figure 2 shows representative EMG signals recorded from six facial muscles during the FE1 expression on both the left and right sides of the face. We can see that the amplitude and waveform characteristics of each EMG channel from the left face correspond with those from the right face. Moreover, we can see these coincide in other expressions. Figure 3 presents an additional example of EMG signals linked to the FE2 expression on both sides of the face.

Subsequently, the EMG signals were segmented, and the features were extracted, as described in Section 3.2. Figure 4 shows boxplots illustrating the distribution of IEMG features for the FE1 and FE2 facial expressions. We display the data separately for the left and right facial regions to highlight potential side-specific variations. The IEMG features successfully differentiated between the two expressions, with consistent trends observed across corresponding channels on both sides of the face. Channel CH4 showed the highest IEMG values during FE1, while channel CH6 was most dominant during FE2. These findings demonstrate the discriminative capability of IEMG features in distinguishing between the two facial expressions.

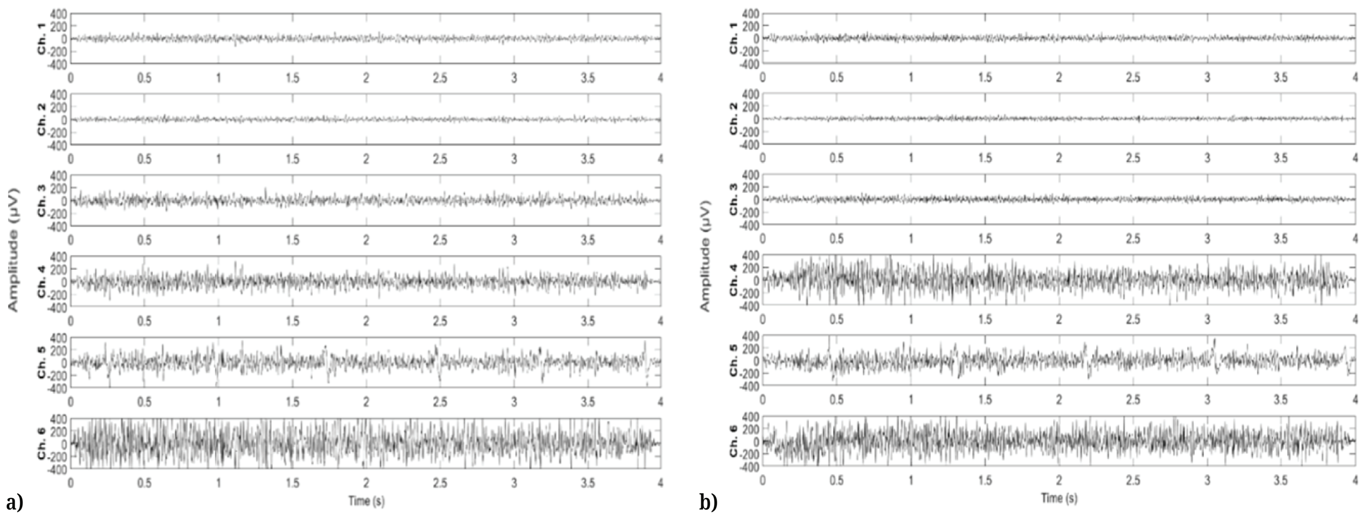


Fig. 2. Representative six-channel EMG signals recorded during the grinning facial expression (FE1): (a) Signals from the left side of the face (b) Signals from the right side

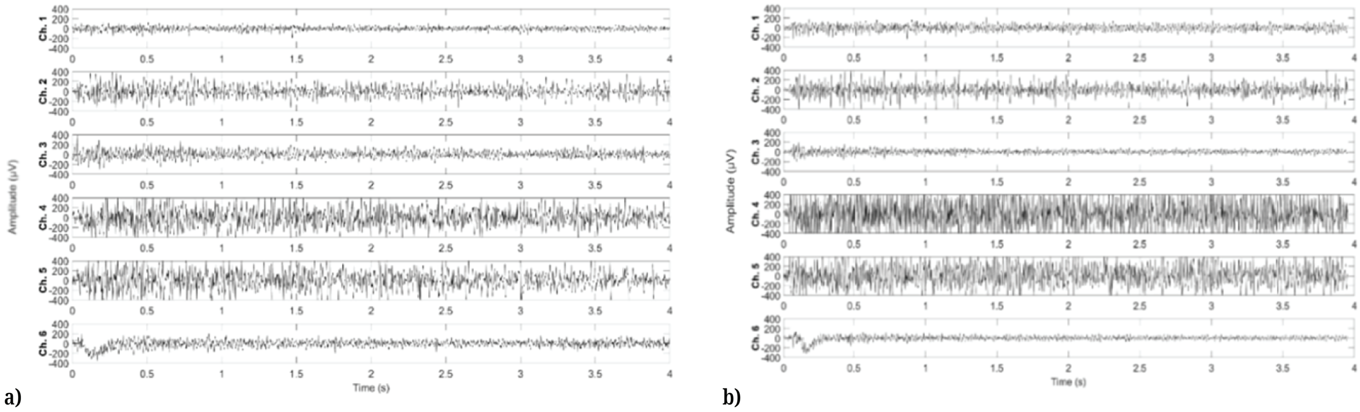


Fig. 3. Representative six-channel EMG signals recorded during the lip pursing facial expression (FE2): (a) EMG signals from the left side of the face (b) Signals from the right side

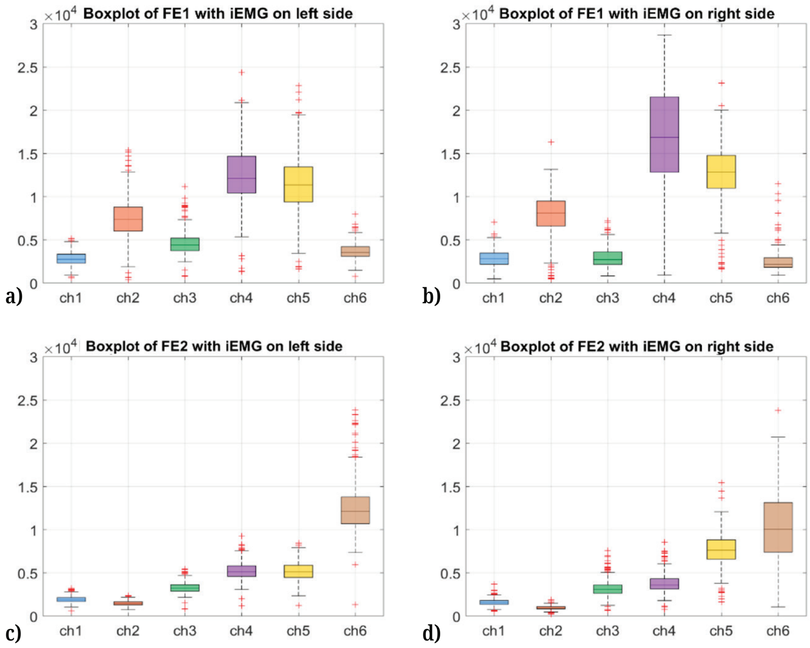


Fig. 4. Boxplots showing the distribution of IEMG features for two facial expressions: (a) grinning (FE1) – left side, (b) grinning (FE1) – right side, (c) lip pursing (FE2) – left side, (d) lip pursing (FE2) – right side

4.2 Classification accuracy

Table 2 shows the average classification accuracies for six facial expressions based on EMG signals recorded from the left side of the face. Various feature sets, namely IEMG, RMS, and MAV, were evaluated individually and in combination. The highest accuracy (98.32%) was achieved using the combined feature set (IEMG, RMS, MAV) with the KNN classifier. Multi-feature combinations generally outperformed single-feature inputs, and KNN consistently yielded superior performance.

To compare, Table 3 shows the average classification accuracies from EMG signals taken from the right side of the face, using the same feature groups and classifiers as in Table 2. We observed the best performance with the combined feature set (IEMG, RMS, MAV) using the KNN classifier, achieving a highest accuracy of 98.73%. Like the left-side results, multi-feature inputs led to improved classification outcomes, with KNN demonstrating the most robust performance across feature combinations.

Table 2. Mean classification accuracies (%) for six facial expressions using various feature–classifier combinations (Left-side EMG signals)

Features	KNN	SVM	EN	NN	NB
IEMG	88.40	87.90	88.53	87.59	64.83
RMS	87.99	89.47	88.62	87.28	63.98
MAV	88.71	89.74	88.53	88.13	**66.08**
IEMG, RMS	95.17	92.43	92.19	90.23	63.17
RMS, MAV	97.53	93.21	**97.93**	90.73	64.29
IEMG, MAV	94.96	92.67	92.07	88.09	65.24
IEMG, RMS, MAV	**98.32**	**93.97**	96.90	**91.07**	64.27

Table 3. Mean classification accuracies (%) for six facial expressions using various feature–classifier combinations (Right-side EMG signals)

Features	KNN	SVM	EN	NN	NB
IEMG	87.85	88.63	87.98	86.53	65.22
RMS	87.62	88.49	86.59	86.77	64.73
MAV	87.34	89.06	87.53	87.72	64.38
IEMG, RMS	95.86	92.43	92.41	**88.19**	64.49
RMS, MAV	97.50	93.12	**97.94**	86.24	**66.92**
IEMG, MAV	95.58	91.98	92.16	88.02	63.94
IEMG, RMS, MAV	**98.73**	**94.09**	97.01	87.98	57.89

5 DISCUSSION

5.1 Classification accuracy from bilateral EMG signals

Table 4 shows the average classification accuracies achieved using various combinations of feature selection techniques and classifiers applied to EMG data from both sides of the face. Among the classifiers evaluated, KNN, SVM, and EN achieved their highest accuracies when paired with the combination of IEMG, RMS, and MAV features. In contrast, NN and NB classifiers performed best with features derived from the IEMG and MAV combination, with NB achieving its highest performance using MAV alone. The combination of IEMG, RMS, and MAV features with the KNN classifier yielded the highest overall classification accuracy of 97.84%.

A comparison of classification accuracies achieved using the KNN algorithm with unilateral EMG signals (refer to Tables 2–3) versus bilateral EMG signals (refer to Table 4) reveals slight differences. This finding suggests that high classification accuracy in facial expression classification can be achieved using EMG signals from only one side of the face. The use of unilateral EMG not only reduces the number of required electrodes, thus lowering equipment costs, but also enhances user comfort during data acquisition.

Table 4. Mean classification accuracies (%) for six facial expressions using various feature–classifier combinations (Both-side EMG signals)

Features	KNN	SVM	EN	NN	NB
IEMG	85.95	87.61	86.40	78.56	58.72
RMS	86.65	87.94	86.65	84.07	64.61
MAV	85.95	87.43	87.07	84.06	**62.41**
IEMG, RMS	93.97	85.86	91.28	79.19	59.17
RMS, MAV	97.35	91.22	97.32	79.23	58.94
IEMG, MAV	93.85	85.46	91.10	**84.25**	59.15
IEMG, RMS, MAV	**97.84**	**91.90**	**95.93**	84.06	59.96

Furthermore, the comparable classification accuracies from the left and right facial EMG signals in healthy subjects suggest a high degree of symmetry in the extracted features across both sides of the face. This symmetry has potential implications for rehabilitation and diagnostic applications. For instance, in patients undergoing facial rehabilitation, disparities in EMG features between the impaired and unimpaired sides could serve as indicators of functional asymmetry. Over the course of treatment, convergence of EMG features from both sides may provide a quantitative measure of rehabilitation progress.

Figure 5 presents a confusion matrix that illustrates the classification performance of six facial expressions, which are based on IEMG, RMS, and MAV features derived from bilateral EMG signals and classified using the KNN algorithm. The highest classification accuracy is achieved for expression FE1 (97.8%), while the lowest is observed for expression FE4 (95.9%). The greatest classification error (3.4%) occurred between expressions FE4 (opening the mouth) and FE6 (sticking the tongue out), likely due to the similarity in their associated facial muscle activations, which may lead to overlapping EMG feature patterns.

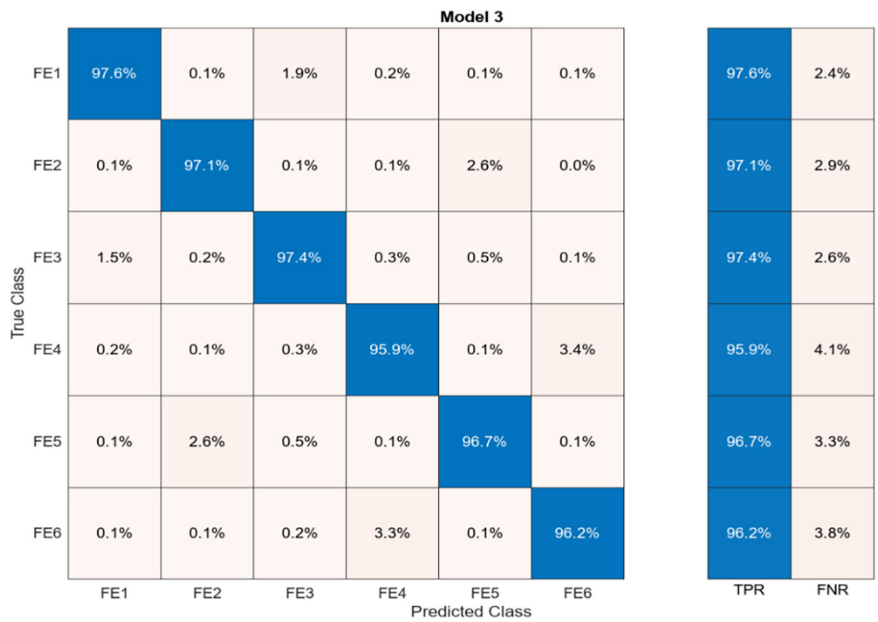


Fig. 5. Confusion matrix for six facial expressions using the combination of IEMG, RMS, and MAV features with the KNN classifier (Both-side EMG signals)

Note: TPR represents the true positive rate, and FNR represents the false negative rate.

5.2 Channel reduction

Tables 5 and 6 present the average classification accuracies for six facial expressions using the KNN classifier based on the combination of IEMG, RMS, and MAV feature sets, as the number of EMG channels is progressively reduced from the right side of the face. In other words, we initially evaluate classification performance using all possible combinations of five channels selected from the six available. Among these, the combination of CH1, CH2, CH4, CH5, and CH6 yields the highest classification accuracy and is thus selected as the optimal five-channel set. Subsequently, we test all combinations of four channels drawn from this selected set. As shown in Table 5 (rows two through seven), the combination of CH1, CH2, CH5, and CH6 achieved the highest accuracy among the four-channel configurations and is selected as the optimal subset. We apply this procedure iteratively to identify the best combinations of three, two, and single channels. As the number of channels decreases, classification accuracy declines accordingly. On the left side of the face, accuracy drops from 98.32% (six channels) to 64.80% (single channel), while on the right side, it decreases from 98.43% to 66.28%. These results highlight the trade-off between classification accuracy and the number of available EMG channels, which is critical for designing efficient and practical facial expression recognition systems with minimal sensor deployment.

Table 5. Average classification accuracies for six facial expressions using the combination of IEMG, RMS, and MAV feature sets and the KNN classifier, as the number of EMG channels is progressively reduced from the left side of the face

Channel Combination	Mean	Note
CH1-CH2-CH3-CH4-CH5-CH6	***98.32***	6 channels
CH1-CH2-CH4-CH5-CH6	***96.51***	Remove CH3
CH2-CH3-CH4-CH5-CH6	95.50	
CH1-CH3-CH4-CH5-CH6	95.64	
CH1-CH2-CH3-CH5-CH6	95.95	
CH1-CH2-CH3-CH4-CH6	95.91	
CH1-CH2-CH3-CH4-CH5	95.70	
CH1-CH2-CH5-CH6	***93.40***	Remove CH3 and CH4
CH2-CH4-CH5-CH6	92.15	
CH1-CH4-CH5-CH6	92.08	
CH1-CH2-CH4-CH6	93.07	
CH1-CH2-CH4-CH5	91.29	
CH1-CH2-CH6	***86.33***	Remove CH3, CH4, and CH5
CH2-CH5-CH6	85.02	
CH1-CH5-CH6	85.56	
CH1-CH2-CH5	83.03	
CH2-CH6	***76.30***	Remove CH3, CH4, CH5, and CH1
CH1-CH6	75.72	
CH1-CH2	72.76	
CH2	***64.80***	Remove CH3, CH4, CH5, CH1, and CH6
CH6	64.60	

Table 6. Average classification accuracies for six facial expressions using the combination of IEMG, RMS, and MAV feature sets and the KNN classifier, as the number of EMG channels is progressively reduced from the right side of the face

Channel Combination	Mean	Note
CH1-CH2-CH3-CH4-CH5-CH6	***98.43***	6 channels
CH1-CH2-CH4-CH5-CH6	***97.53***	Remove CH3
CH2-CH3-CH4-CH5-CH6	96.59	
CH1-CH3-CH4-CH5-CH6	96.21	
CH1-CH2-CH3-CH5-CH6	97.14	
CH1-CH2-CH3-CH4-CH6	97.30	
CH1-CH2-CH3-CH4-CH5	96.40	
CH1-CH2-CH5-CH6	***94.78***	Remove CH3 and CH4
CH2-CH4-CH5-CH6	93.32	
CH1-CH4-CH5-CH6	92.13	
CH1-CH2-CH4-CH6	94.66	
CH1-CH2-CH4-CH5	92.32	
CH1-CH2-CH6	***87.41***	Remove CH3, CH4, and CH5
CH2-CH5-CH6	87.00	
CH1-CH5-CH6	85.42	
CH1-CH2-CH5	83.39	
CH2-CH6	***78.10***	Remove CH3, CH4, CH5, and CH1
CH1-CH6	75.51	
CH1-CH5	69.00	
CH2	***66.28***	Remove CH3, CH4, CH5, CH1, and CH6
CH6	60.74	

5.3 Comparisons with previous work

Table 7 shows a comparative analysis of the proposed method against various previously published techniques for EMG-based facial expression recognition. The proposed method utilizes six channels from the left side of the face and employs a compact feature set, IEMG, RMS, and MAV, resulting in a total of eighteen features for each expression. Despite its simplicity, the approach achieves a high classification accuracy of 98.73%, outperforming or matching many prior studies, especially those using more complex feature sets. In other words, while the length of the feature vector for the proposed method is 18, the length of feature vector from previous studies is mostly greater than 18 (28–159). Notably, some methods achieve higher accuracy but often require more features, additional channels, or computationally intensive classifiers. This underscores the efficiency and effectiveness of the proposed method for practical EMG-based expression recognition systems.

Table 7. Performance comparison of the proposed method with previous studies

References	#Ch	#M	#F	Classifier	Accuracy (%)
Cai et al. (2018) [1]	6	8	74	SVM	99.52
Shu et al. (2025) [7]	7	6	28	RF	99.20
Adamov et al. (2025) [3]	1	5	12	LDA	80.00
Kelati et al. (2022) [12]	2	5	159	KNN	99.40
Zhang et al. (2023) [18]	16	5	128	RF	91.79
Wang et al. (2021) [15]	6	6	126	RF	74.76
Present study	6	6	18	KNN	98.73

Notes: #Ch: the number of EMG channels, #M: the number of classes, #F: the number of features for each expression.

5.4 Contribution and limitations

This study presents a facial expression classification framework using six-channel EMG signals, designed to reduce system complexity while maintaining high classification accuracy. The proposed method achieves an accuracy of 98.73% in classifying six facial expressions using only three time-domain features, i.e., IEMG, MAV, and RMS, in combination with a KNN classifier, as detailed in Section 4.2. Importantly, the resulting feature vector has a length of just 18, which is significantly shorter than those used in prior studies (see Section 5.3). This reduction in dimensionality contributes to lower computational requirements and supports real-time or embedded system deployment.

In addition to reducing system complexity, the method utilizes EMG signals from only one side of the face, which helps decrease the number of required electrodes. This not only reduces electrode costs but also enhances user comfort during data acquisition, an important consideration for practical applications in assistive technology and wearable systems.

Nonetheless, the study has certain limitations. The dataset used is relatively small and homogenous, which may affect the generalizability of the model to more diverse populations. Moreover, the exclusive use of time-domain features may limit the model's robustness, particularly under conditions such as muscle fatigue or signal variability. For broader applicability and improved performance, future work should consider the integration of frequency-domain features, which may capture signal changes due to fatigue more effectively. Additionally, exploring deep learning models and multimodal approaches, such as combining EMG with face video inputs, may further enhance classification accuracy and system adaptability in real-world scenarios.

6 CONCLUSIONS

This study presents a system for classifying six distinct facial expressions using surface EMG signals recorded from six facial muscle channels. To enhance classification performance, three feature extraction techniques were evaluated, i.e., IEMG, RMS, and MAV. These features were then used as inputs to five machine learning classifiers: KNN, SVM, EN learning, NN, and NB. Among these, the KNN classifier demonstrated the highest classification accuracy when applied to the selected features, successfully distinguishing between the six facial expressions. The combination of IEMG, RMS, and MAV features with the KNN classifier achieved an accuracy of up to 98.73%, highlighting the effectiveness of the proposed approach for robust and accurate facial expression recognition using multi-channel EMG signals. This system has the potential to support real-time, non-invasive human-computer interaction and healthcare applications, particularly in areas such as emotion monitoring, assistive technology, and rehabilitation.

Future research will likely focus on improving the robustness and accuracy of these systems, exploring more complex facial behaviors, and integrating EMG with other sensing modalities for a more holistic understanding of human states and expressions. It is also useful for rehabilitation in patients with conditions such as stroke and Bell's palsy.

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9 AUTHORS

Marisa Lertvittayavivat is currently a master's degree student in the Department of Electrical and Biomedical Engineering, Faculty of Engineering, Prince of Songkla University (PSU), Songkhla, Thailand. She graduated with a bachelor's degree in biomedical engineering from PSU. Her main topic of research is closely related to electromyogram (EMG) signal processing (E-mail: marisa.bm77@gmail.com).

Surapong Chatpun received B.Eng. in mechanical engineering from Chulalongkorn University, Thailand, in 1996, and M.Eng. from the University of Tokyo, Japan, in 2003. He earned his Ph.D. in Bioengineering from the University of California, USA, in 2010. He currently leads the Cardiovascular Engineering Research Laboratory (CERLab), Faculty of Medicine, Prince of Songkla University, Thailand. His research focuses on applying engineering approaches, such as continuum mechanics, numerical methods (e.g., FEM), fluid mechanics (e.g., CFD), image processing, and computer-aided design, combined with life sciences knowledge and available technologies to enhance understanding of the circulatory system's function and mechanisms in both normal and pathological conditions. He also designs and invents medical devices not only for cardiovascular applications but also for other clinical areas, such as rehabilitation and orthopedics. He is currently coordinating a Horizon2020 project in the field of the intelligent wearable system for enhanced personalized gait rehabilitation (E-mail: surapong.c@psu.ac.th).

Bojan Petrović received his D.D.S. (2000) and Ph.D. (2010) in Medical Sciences from the University of Belgrade, Serbia. He is currently a Full Professor at the Department of Dentistry, Faculty of Medicine, University of Novi Sad. He worked as the attending clinician at the Dental Clinic of Vojvodina, Department of Pediatric Dentistry since 2000. His interdisciplinary research focuses on biomedical engineering applications in dental science, including salivary diagnostics, flexible sensor systems, dental materials, special care dentistry, physical anthropology, and oral motor function rehabilitation. He actively contributes to Horizon Europe projects and serves on ethics committees and doctoral defense boards (E-mail: bojan.petrovic@mf.uns.ac.rs).

Methawee Limaksorn received the Doctor of Dental Surgery (D.D.S) from Chulalongkorn University, Thailand, in 1998 and a Graduate Diploma in Clinical Medical Sciences (General Dentistry) from Mahidol University, Thailand, in 2002. She currently works at the dental hospital, Faculty of Dentistry, Prince of Songkla University, Thailand (E-mail: lmethawee@yahoo.com).

Pornchai Phukpattaranont received the B.Eng. (Hons.) and M.Eng. degrees in electrical engineering from the Prince of Songkla University, Songkhla, Thailand, in 1993 and 1997, respectively, and the Ph.D. degree in electrical and computer engineering from the University of Minnesota, Minneapolis, MN, USA, in 2004. He is currently a professor of electrical and biomedical engineering at the Prince of Songkla University. Examples of his ongoing research include the pattern recognition system based on electromyographic signals, electrocardiographic signals, and microscopic images of breast cancer cells. His current research interests include signal and image analysis for medical applications and artificial intelligence for medical applications (E-mail: pornchai.p@psu.ac.th).