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Dynamic Fusion of Electromyographic and Electroencephalographic Data towards Use in Robotic Prosthesis Control

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Abstract. We demonstrate improved performance in the classification of bioelectric data for use in systems such as robotic prosthesis control, by data fusion using low-cost electromyography (EMG) and electroencephalography (EEG) devices. Prosthetic limbs are typically controlled through EMG, and whilst there is a wealth of research into the use of EEG as part of a brain-computer interface (BCI) the cost of EEG equipment commonly prevents this approach from being adopted outside the lab. This study demonstrates as a proof-of-concept that multimodal classification can be achieved by using low-cost EMG and EEG devices in tandem, with statistical decision-level fusion, to a high degree of accuracy. We present multiple fusion methods, including those based on Jensen-Shannon divergence which had not previously been applied to this problem. We report accuracies of up to 99% when merging both signal modalities, improving on the best-case single-mode classification. We hence demonstrate the strengths of combining EMG and EEG in a multimodal classification system that could in future be leveraged as an alternative control mechanism for robotic prostheses.

1. Introduction

The type of assistive robot perhaps most closely integrated to the life of an individual is the robotic prosthetic. Prosthetic hands in particular represent an important improvement to the ability of those with limb differences to thrive in the modern world. Whilst there has been much recent development in the field of bionic upper-limb prostheses these devices are often expensive and their control mechanisms obtrusive, making rehabilitation an even more challenging process. There is a significant need in much of assistive robotics to reduce the degree of abstraction between the controller and the robot; when a device acts as a literal extension of the human body it ought to be as natural to use and as responsive as the body itself. This is one of the core justifications for the use of bioelectric data in robotic control, however the high cost [1] of many medical devices is a barrier to accessibility for many amputees.

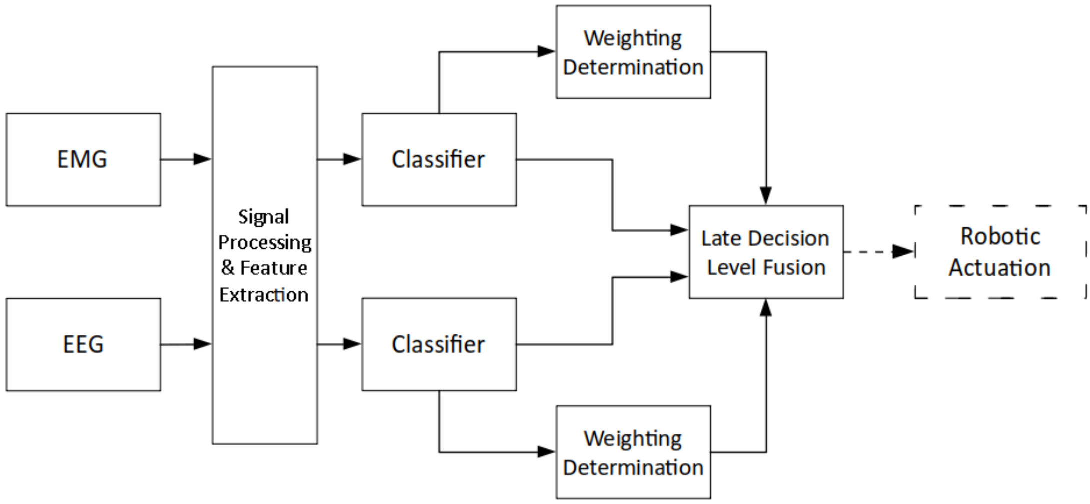

Figure 1. Structural overview of the multimodal system, including intended future extension to robotic actuation.

We present a system using low-cost commercially available devices to measure bioelectric signals, and demonstrate that a multimodal decision-level fusion approach can be effective in classifying such data. We intend for this to serve as a proof-of-concept, such that future work can leverage our approach to achieve real-time multimodal control of robotic prostheses.

The majority of prosthetic limbs are controlled through electromyography (EMG), the measurement of electrical activity induced when muscles are moved. The muscles which actuate the fingers of the human hand are situated within the forearm, and connected via tendons to the fingers [2]. In particular, actuation of the *flexor digitorum profundus* and *extensor digitorum communis* [2] are essential to controlling common finger movements such as grasping motions. EMG is performed through the use of non-invasive electrodes which measure electrical potential on the surface of the skin to assess the levels of activity in the underlying muscles. In this study we use Thalmic Labs' Myo armband, a low-cost EMG device with much precedent for use in robotic control applications [3,4].

The emerging alternative approach to prosthesis control is the use of a Brain-Computer Interface (BCI), wherein a device is controlled using data acquired from the human brain. Electroencephalography (EEG) is a non-invasive method of measuring electrical activity in the brain [5] via electrodes placed on the scalp. There are not currently any low-cost commercial EEG sensing devices for measuring activity in the motor cortex, which would be the most intuitive approach for use of EEG in prosthesis control. In this study we use an InteraXon Muse, which is designed as a meditation aid and is particularly suited to assessing levels of relaxation and attention in an individual. It was hence determined the mental states used in this study would be those of a Focused, Relaxed, and Neutral brain; previous research has evidenced the Muse's suitability for use in this kind of classification [6,7].

In this study statistical data fusion methods are used to implement a combined approach, enabling the strengths of both EMG and EEG to be leveraged simultaneously. Both EMG and EEG data were classified and the results merged with a number of late (decision-level) fusion algorithms. This study aims to establish what degree of improved performance this type of multimodal fusion can achieve over single-mode classification, and assess the quality of methods based on the Jensen-Shannon divergence when compared to other fusion models.

The structure of our approach is shown in Figure 1. In this proof-of-concept study we perform classification and fusion offline and hence do not implement robotic actuation; we however include this stage in the structural diagram to illustrate how we intend to apply this system in future work.

2. Related Work

Few previous studies have attempted to combine EMG and EEG data. In 2010 Förster et al. [8] were able to improve the accuracy of EMG-based classifiers by around 10% (reaching up to 81% in the best case) by observing error-related potentials (ErrP), patterns of electrical activity in the brain which present when an individual observes an unexpected error [8]. Such a signal could be detected from the participant's brain when the classifier responded incorrectly to the gesture they performed, and hence could be used as an indicator for the classifier to correct itself.

In 2015, Khan et al. [9] enabled a robotic hand to be actuated when a participant both moved their biological hand and concentrated on the object to be moved. Attentiveness of the participants was measured with a Neurosky Mindwave EEG device; the hand was actuated when an individual moved their forearm muscles and concentrated on an object with attentiveness above a given threshold [9]. The system was trialled on both amputees and able-bodied individuals, and the authors reported a success rate of up to 90%.

In 2019 Tryon et al. [10] presented multiple possible fusion methods and evaluated their effectiveness. These included logical AND and OR operations, which due to their binary nature are not suitable for the situations explored in our three-class study. They also tested linearly weighted distributions at 50% EEG & 50% EMG, 25% & 75%, and 75% & 25%, along with a data-level fusion method wherein both EEG and EMG features were provided to a single classifier. None of these simple methods were able to provide greater accuracy than single-mode EMG classification; this provides some of the motivation to evaluate more sophisticated multimodal fusion systems as investigated here.

3. Data Acquisition

There are no publicly available multimodal EMG/EEG datasets based on the low-cost Myo and Muse devices that would be suitable for use in this study. Consequently, we needed to collect all the data used in the development of this work.

For the purposes of fusion, the defined classes must be aligned between the sensing modes, resulting in a multi-tasking activity. It was decided that a focused mental state would correspond to a closing of the hand (finger flexion), a relaxed state to an opening of the hand (finger abduction), and a neutral state to a lack of movement. This was determined to be the most intuitive mapping for everyday use as most tasks would be likely to induce a certain level of concentration; an individual would likely focus on an object they wished to pick up. The participants' mental states and physical movements were thus coupled for the duration of the experiment: concentration was induced while the individual closed their hand, and relaxation while they opened it. This created a ternary classification problem, with three multi-tasking states defined as follows:

- Focused brain, whilst closing the hand
- Relaxed brain, whilst opening the hand
- Neutral brain, whilst not moving the hand

Synchronous data from both sensing modes were collected simultaneously, with approximately two minutes of data per class being recorded to form the training set and a subsequent minute per class forming an isolated test set. Ultimately a total of thirty recording sessions, one for training and one for the isolated testing set per class per subject, totalling fifty minutes were collected from five individuals (three male, two female).

3.1. Electromyography

EMG data was collected with a Thalmic Labs Myo [11] armband, which consists of eight connected pods that house individual EMG sensors, equally spaced around the circumference of a wearer's forearm.

Figure 2. Defined gestures for electromyographic data acquisition. The fist is either clenched [left], splayed open [right], or returned to a neutral position [centre].

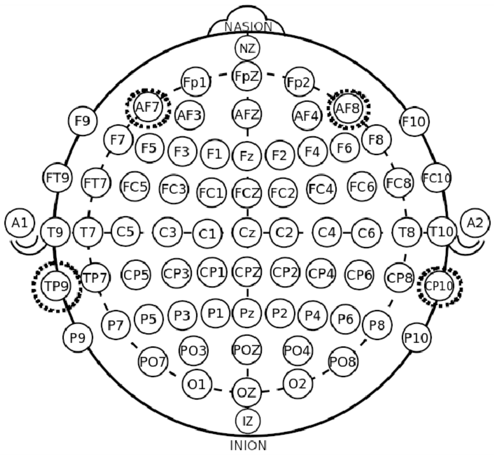

Figure 3. International 10-20 Electroencephalographic Electrode Placement Standard [12]. Locations measured by the Muse headset circled.

The Myo was placed on a participant’s right forearm, and the fit adjusted as necessary to ensure good connection between the electrodes and their skin.

The participant either closed, splayed open, or held their right hand in a neutral pose as seen in Figure 2 for the duration of the task. The forearm was held perpendicular to the body with the hand resting on a table, to reduce electrical interference from muscle activity in the elbow or wrist. Data was streamed and recorded from the Myo at 200Hz via Bluetooth using PyoConnect [13]. This produces a rectified smoothed envelope of the electromyographic signals, which is known to be informative in identifying muscle contraction and relaxation [14].

3.2. Electroencephalography

An InteraXon Muse [15] was used to collect EEG data. This commercial EEG device is worn on the forehead and houses four measurement electrodes at different points around the head, with a fifth used as a voltage reference. The sensors rest on locations TP9, AF7, AF8, and TP10 of the International 10-20 Electrode Placement Standard [11], while the reference electrode is at NZ at the front of the forehead. The measured locations can be seen in Figure 3.

To alter the participants’ mental states, stimuli were presented which have been effective in inducing distinguishable changes in brain activity in previous studies [6]. To induce a state of relaxation, the participant listened to calming music [16]. To induce concentration, the participant followed a video of the “shell game”, following a ball placed under one of three shuffled upturned cups [17]. For the neutral class, no stimulus was presented. The participants were requested to keep their eyes open and to minimise movements of the face and neck to limit the amount of electromyographic interference in the collected data. In an attempt to minimise the influence of stress, the experiments took place in a neutral office environment familiar to the participants. The EEG data was streamed via Bluetooth from the Muse to a Motorola G7 [18] via the Mind Monitor application [19,20], and the raw EEG signals extracted for processing.

4. Feature Extraction

For both the EMG and EEG domains, a training set and an isolated testing set were constructed, and the same ensemble of features extracted from each. Both the recorded EMG and EEG signals were divided into epochs of one second, with a 500ms overlap between consecutive epochs. An array of statistical features which have been indicated to be informative in previous related work [21,22] were extracted from these epochs by the algorithm described fully in [6]. These features were extracted from each epoch for every individual sensor, meaning that the total number of features produced was significantly higher in the EMG domain due to the Myo band comprising of eight sensing electrodes in comparison to the Muse's four. Every instance in a given set was formed by concatenating the features of two overlapping 1s epochs, and hence corresponded to 1.5 seconds of data. One instance of every epoch was shared with its predecessor and one with its successor; 500ms of novel data was hence introduced to the set with each additional instance.

5. Classification

5.1. Methods

This study makes use of a late fusion approach, wherein the EMG and EEG classification results are fused at the decision level. Despite the activity being synchronous the modes were therefore classified independently; EMG between a closed, open, or neutral hand and EEG between a focused, relaxed, or neutral mental state. A number of different algorithms were used to classify the resulting EMG and EEG datasets, to establish which models could provide the best performance and hence ought to be used in the multimodal fusion system. Four different classical machine learning models were used to classify the data: a K-Nearest Neighbours model, a Support Vector Machine, a Gaussian Naïve Bayesian classifier, and a Random Forest. Deep networks were not used as they perform best with an extremely large number of training instances, but their use could be explored in future work with expanded datasets.

For the Nearest Neighbours model [23], the parameter K was tuned by searching with cross-validation from values between 2 and 20, in steps of 2. Even-numbered K values only were used to aid in the breaking of ties, as the model was classifying between an odd number of classes. Support Vector Machines [24] using a Linear kernel with a fixed gamma value of 0.01 and complexity values 2.0, 4.0, 6.0, 8.0, and 10.0 were trialled, the fitting of the SVMs' hyperplanes being performed via a version of Platt's Sequential Minimal Optimisation algorithm [25]. In addition, a Gaussian Naïve Bayesian model [26] and a Random Forest [27] were used.

5.2. Results

The performance of the models was evaluated by applying them to the isolated, unseen test dataset and assessing the classification accuracy achieved. Tables 1 and 2 present the single-mode classification accuracy values for EMG and EEG data, respectively. For those models with tunable parameters, the best-case results are shown. In all tables, the values in parentheses indicate 95% Wilson confidence intervals on the reported accuracies.

Strong performance was observed in all the models in the EMG domain, with the 2- Nearest Neighbours classifier being the most accurate. Performance was generally lower in the EEG domain (though above the chance level of 33% in all cases), however the Random Forest was able to achieve an 85.56% classification accuracy. It is noted that in the majority of EEG classifiers, the True Positive rate of the Relaxed class was notably higher than the other classes. This may indicate differences in the effectiveness of the stimuli in inducing the desired mental states. Data collection was conducted in a neutral, familiar environment to reduce stress but this may have inadvertently influenced the ability of the participants to maintain concentration. It is possible that for example reward-oriented tasks may motivate participants to concentrate more intensely on the presented stimulus; future work may seek to determine more appropriate stimuli for inducing different levels of concentration and relaxation in participants.

Table 1. Classification performance of EMG dataset.

Classification Algorithm	Percentage Accuracy
KNN (K = 2)	**98.77** [98.12, 99.19]
SVM (C = 2.0)	98.59 [97.91, 99.05]
Gaussian Naïve Bayesian	83.69 [81.86, 85.36]
Random Forest	95.19 [94.07, 96.11]

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Table 2. Classification performance of EEG dataset.

Classification Algorithm	Percentage Accuracy
KNN (K = 12)	52.41 [50.03, 54.77]
SVM (C = 6.0)	61.33 [58.99, 63.61]
Gaussian Naïve Bayesian	48.42 [46.05, 50.79]
Random Forest	**85.56** [83.81, 87.15]

6. Fusion

6.1. Methods

The probability distributions produced by the EMG's Random Forest classifier and the EEG's K-nearest-neighbour classifier were extracted. To better emulate real-world tasks, instances of alike class were assembled into groups of 20 (each hence corresponding to approximately 20 seconds of data), which were then randomly shuffled. These shuffled sets were fused by various algorithms described below, implemented in MATLAB [28]. The resulting fused probability distributions were compared against a set of verification data, grouped and shuffled by the same procedure, to assess how frequently the fusion algorithm predicted the correct class. This procedure was repeated 10 times & the mean accuracies reported.

As a benchmark, the two sensing modes were fused with an equal weighting. Subsequently, a probabilistic weighting was determined. A random 10% subsample of each distribution was taken and the classification accuracy of each mode estimated based on the performance of these subsamples. Weights were determined for each mode by the normalisation process seen in (1). The weight w of each mode m is equal to that mode's accuracy, a_m, divided by the sum of accuracies from all modes:

$$w_m = \frac{a_m}{\sum_k a_k} \tag{1}$$

We also made use of a fusion strategy initially presented in [29] which assigns weights to each sensing mode based on the Jensen-Shannon (JS) Divergence [30], a symmetric form of the Kullback-Leibler Divergence [31,32]. This strategy has proven effective, achieving significantly improved results over single-mode classification, though similar improvements were achieved with simpler fusion methods. It should be noted that the system in [29] fused two-state (binary) classification from three sensing modes, whilst in this context it fuses three-state (ternary) classification from two modes.

The JS Divergence D_{JS_m} between a global entropy-based weighting calculated for each mode's entire distribution and the classified instance was computed as in [29], and distributed over the modes (2) to determine weightings for them. These weightings were then statically applied to the whole distribution and a fused distribution produced:

$$w_{JS_m} = \frac{D_{JS_m}}{\sum_k D_{JS_k}} \tag{2}$$

Subsequently, a dynamic approach was taken wherein the fused posterior probability distribution was dependent on both the prior distribution as determined by the JS weighting and the previous fused posterior instances:

$$P(\kappa|m_{1\ldots n}) = \prod_{t=1}^{T} \left[P(\kappa^{t-1}) \left(\sum_i^N P(m_i^t|\kappa^t)\, w_i^t \right) \right] \tag{3}$$

where $P(\kappa|m_{1\ldots n})$ is the fused posterior probability κ given the modal probabilities $m_{1\ldots n}$, $P(\kappa^{t-1})$ is the fused posterior immediately preceding the current (set to an equal distribution of $\frac{1}{3}$ in the initial time window), $P(m_i^t|\kappa^t)$ is the posterior probability of a given mode i at a given time t, and w_i is the mode's JS-weight.

Table 3. Performance comparison of Fusion methods.

Fusion Algorithm	Percentage Accuracy
Uniform Distribution [Benchmark]	98.41 [97.70, 98.91]
Probabilistic Weighting	98.47 (97.77, 98.95)
Static Jensen-Shannon	98.53 (97.84, 99.00)
Dynamic (Time-series) J-S	**99.29** (98.77, 99.60)

6.2. Results
Table 3 presents the accuracies achieved by each method of fusion; all methods outperformed the benchmark. Fusion outperformed single-mode EEG classification in every case and was competitive with single-mode EMG classification. The Dynamic Jensen-Shannon Divergence method reached a greater accuracy than either sensing mode did individually, at 99.29%. Whilst some of this improvement is incremental, use of the Dynamic JS-Divergence method over even the best case single-mode classification reduced the error rate from 1.23 to 0.71, a factor of over 40%. The advanced fusion methods using Jensen-Shannon divergence require more complex implementations than the simple approaches. However, it is noted that the vast majority of the Dynamic JS approach's errors only arose at the transition between one class and the next. In the context of a robotic prosthetic these predictable localised errors would manifest as a delay in actuation, which is preferable over randomly dispersed erroneous movements thus justifying the slight increase in required computation.

7. Conclusions
We demonstrate that statistical fusion of electromyographic and electroencephalographic classification can be achieved, improving classification accuracy of multi-tasking activities. We present a proof-of-concept multimodal system utilising low-cost EMG and EEG sensors along with statistical late fusion methods to successfully classify bioelectric data, with accuracy of up to 99%. We demonstrate that this decision-level fusion approach improves classification accuracy over single-mode classification, notably by almost 15% compared to EEG. We also show that sophisticated statistical fusion methods based on Jensen-Shannon Divergence offer performance improvements over simple fusion methods.

These contributions indicate that the inclusion of EEG measurement alongside the conventional EMG approach could lead to marked improvements in the performance of gesture classifiers for prosthesis control, and that this could be achieved at minimal cost through use of commercial devices. We intend for this study to lay the groundwork for future research to implement multimodal fusion systems in real-time, enabling robotic prosthesis actuation. Future work could also look to apply the algorithms used here to fuse EMG data with EEG data obtained from the motor cortex allowing for an improvement in the intuitiveness of the system for an end user.

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