Phantom motion intent decoding for transhumeral prosthesis control with fused neuromuscular and brain wave signals

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Abstract
In recent years, the electroencephalography (EEG) brain–computer interface (BCI) has been researched in the area of upper-limb prosthesis control due to the promise of being able to record neurological signals which follow activation patterns in the cortex directly from the brain with non-invasive electrodes. This is seen as a way of bypassing the limitation posed by acquiring neuromuscular signals predominantly with electromyography (EMG) directly from the stump, which possesses residual limb anatomy post-amputation. In this study, the sequential forward selection algorithm to form a 10-optimal-channel representation, alongside an extended signal feature vector was applied, to investigate the motion intent decoding performance of EMG-only, EEG-only, and a fused EMG–EEG sensing configuration for four transhumeral amputees with varying stump lengths. The results showed a considerable improvement for the EMG-only configuration with the advanced feature vector, but only a small increase for the EEG-only, and thus a marginal improvement when information from both signals was fused together. This is likely due to the EEG requiring a greater number of channels spread across the skull to provide a reliable intent decoding. Further work will now involve optimisation studies to find a greater representation of electrode representation and parsimony, to minimise the number of channels while boosting motion intent decoding accuracy.

1 | INTRODUCTION AND BACKGROUND

The loss of a limb occurs worldwide for a variety of reasons, as per Staats et al. [1]. Factors such as leprosy, landmines, and wars are key causes for amputations in developing countries; while in more developed countries, vascular diseases such as diabetes and trauma are some of the key causes. Upper-limb amputations deprive an individual of the ability to work and also impact their level of independence. In addition to losing a body part, the loss of an upper limb distorts the motor control pathway, which includes the active limbs, brain, efferent, and afferent neurons [2].

Depending on the level of upper-limb amputation, unique names are used to characterise individuals with different degrees of limb loss. For instance, the term transhumeral is used to characterise upper-limb amputees with above-elbow amputations who still retain a portion of their upper arm below the shoulder joint [1,2]. Functional prosthetic limbs, also known as myoelectric prostheses, are electrically powered and work with electromyogram (EMG) bio-sensing. EMG acquires the bio-electrical signals associated with gesture intent, and concurrently produces a respective actuation in the prosthesis limb [3,4]. The favoured control scheme for the myoelectric prosthesis is the pattern recognition-based strategy as per Nsugbe et al. [4] and Fougnier et al. [5], which drives/actuates the motors to perform hand motion in the prosthesis limb based on a decoded bio-potential signal. Thus, the effectiveness of the prosthesis controller is reliant on the gesture intent decoding capability of the device, which can be broken into three key phases, namely: (1) the sensing phase, which is concerned with the acquisition of the bio-potential signal, representing an encoded gesture intent; (2) the signal processing phase, which involves the preparation of the signal and
 extraction of relevant features afterward; and (3) the classification phase, which represents the stage where the gesture intent is identified, typically by a trained artificial intelligence (AI) classifier. The decision output from the AI classifier serves as an actuation input to what is then used to initiate the driving of the motors embedded in the prosthesis, in a manner that allows the desired movement to be performed [3,4].

The myoelectric prosthesis represents the closest alternative to a replacement of an upper limb after limb loss. However, there is a challenge in the design of this technology, particularly for the transhumeral amputees due to the stochastic and complex resulting EMG signals from their stump [3,6]. Prior work to solve the intent decoding problem for transhumeral prosthesis was done by Gaudet et al. [6], who used wearable EMG alongside kinematic sensors to classify phantom motions in five transhumeral amputees, obtaining a recognition accuracy in the range of 60%–93%. Despite these results, the EMG signal appeared to be reliant on the quality of the residual muscle around the stump, and recognition accuracy was seen to degrade over time since amputation [6].

Nsugbe et al. [4] investigated the fusion of EMG and near infrared (NIR), employing an electrophysiological-based and haemodynamic-based fusion method for transhumeral prosthesis control. Results across 12 non-amputated participants produced an average of 79%–81% (classifier-dependent). However, as the NIR sensor works with photon emissions in the infrared waveband, the transmission of light is inhibited by tissue characteristics and thickness, thereby limiting its applications [3].

There is a consensus in the literature that suggests brain–computer/bio-sensing methods-based acquisition of motion intent signals bypass the limitations of muscle-based/ bio-sensing methods (i.e. tissue thickness, residual muscle quality), but have also been critiqued for invasiveness, high variability, and low spatial resolution [3,7]. Notable work by Li et al. [7] in the area of transhumeral prosthesis control, involving brain–computer bio-sensing, investigated a fusion of both EMG and electroencephalography (EEG) across four transhumeral amputees. It can be seen from Li et al. [7] work that a small amount of signal features were extracted, and thus a relatively large number of electrode channels were necessary in order to achieve a high level of classification accuracy across all participants. This method, although effective in a research environment, is likely to be unfeasible in a real-time operating environment due to ergonomic challenges and computational complexity. From this, it would appear that there is a need to investigate the recognition capability and performance of EMG and EEG fusion with a set of expanded features and relatively few electrode channels. This exercise may potentially spur commercial and practical appeal as it represents a possible configuration which the prosthesis control architecture could integrate into a myoelectric limb.

Therefore, in this article, using the data acquired by Li et al. [7], the specific investigations and contributions are as follows:

- Investigation of a low input channel of 10 optimal electrodes and an enhanced feature vector, we observe the gesture intent decoding accuracy of EMG only, EEG only, and the fusion of EMG–EEG sensing.
- Investigation of an optimal class boundary separator for the various sensor input configurations, using the linear and non-linear variants of the discriminant analysis.
- Investigation and correlation of key physical attributes of the transhumeral amputees to the recorded intent decoding accuracy, to observe key characteristics which influence intent decoding accuracy, and thereby their potential ability to use a myoelectric prosthesis.

2 | MATERIALS AND METHOD

The work presented in this article was initiated using the dataset acquired by Li et al. [7]. This section describes the mathematical model, the sensing apparatus, and the data collection process carried out by Li et al. [7], followed by the signal processing and the classification architecture devised and applied to the obtained dataset of this study.

2.1 | Mathematical models and data collection instrumentation

Mathematical models are useful representations that show how a selected number of variables contribute towards obtaining a final behavioural response under the given conditions. In this case, the mathematical models help to account for the main anatomical and physiological variables involved in the interaction that produces a quantifiable extracellular action potential, which is acquired with the electronic sensors [8]. This section provides an overview and model-based description governing the emanation of both the EMG and EEG signals, alongside the acquisition instrumentation used for dataset collection.

2.1.1 | Electromyography

EMG is based on the concept of electrophysiological signals that cause a distinct flow of transmembrane current within the proximity of the muscle fibres. This current flow allows for EMG signals to be measured within some distance of the source [8,9].

The flow of electrical current through the muscle tissue can be framed as the principle of volume conduction, and represented by a three-dimensional (3D) formulation of Ohm’s law for a specific case of active biological tissue. Impedance can be viewed as the inverse of conductivity $\sigma$, thus the acquired 3D potential recorded at a specific point $R_0 (x_0, y_0, z_0)$ with a uniform conductivity $\sigma_0$, generated by a source current $I_s$ at point $P (x, y, z)$, can be formulated as seen in Equation (1) [8]:

$$V_{R_0} = \frac{1}{4\pi\sigma_0} \frac{I_s}{r_i}$$

(1)
where, $V_{p0}$ is the voltage potential and $r_i$ represents the shortest distance between points $P_0$ and $P$.

Equation (1) shows that the voltage potential recorded in a specific location has direct proportionality to the intensity of the current source, and that the greater the values of $\sigma_i$ and $r_i$, the lower the value of the potential voltage [8,10]. However, it should be noted that bioelectricity can seldom be described as a solitary injected current at a specific point, but rather a compound summation stemming from multiple sources [8,10].

**Dipole basis representation of extracellular potentials**

The dipole represents a double layered source generator whose framework was extended to bioelectricity by Wilson et al. [11] and Plonsey et al. [12]. It is based on the notion of a membrane electric potential being varied across a fixed portion of the yields of an electric field in the extracellular medium, and can be likened to what produced by a lumped dipole [11,12]. With this framework, it can be assumed that the electrical potential produced by both a double layered disk and a dipole, with an equivalent moment and disc area, can be approximated as being identical [8].

Consider a fibre element of length $dx$, within the range of an action potential, as a current flows from the fibre into an extracellular region, and assuming the current flow to be focussed along the axis of the fibre. This could be mathematically expressed as $p^-dx$, with $p^-$ representing the dipole current/unit length [8]. As the current emanates from a fixed source into an unconstrained space, its behaviour can be likened to a dipole source generator which is immersed in a conducting medium. As a result, the generated extracellular potential can be mathematically structured as seen in Equation (2) [8,10]:

$$d\phi_e = \frac{1}{4\pi\sigma_e} \frac{d(x)}{dx} p^-(x,t)dx$$

where, $\sigma_e$ represents the conductivity of the extracellular medium, and $r$ is the distance from the source of the excitation to the instrument recording point $P_v$. Assuming the element $p^-dx$ is situated along the coordinates $(x, y, z)$ and $P_v$ at $(x_o, y_o, z_o)$, then the distance ($r$) can be defined as seen in Equation (3):

$$r = [(x - x_o)^2 + (y - y_o)^2 + (z - z_o)^2]^{1/2}$$

From Equation (3), the total field can be computed by calculating the sum of the various potentials from the resulting dipole current element as seen in Equation (4):

$$\phi_e(x_o, y_o, z_o, t) = \int_{x=-\infty}^{x=\infty} \frac{p^-(x,t)}{4\pi\sigma_e[(x-x_o)^2 + (y-y_o)^2 + (z-z_o)^2]^{3/2}} dx$$

where, $t$ is time.

In reality, it can be said that the excitation source is likely to emanate from a distributed number of sources rather than a single dipole source, as denoted in Equation (4). Thus, the excitation dipole source can be expressed in the form of Equation (5):

$$p^- = -\pi a^2 \sigma_i \frac{\partial IAP}{\partial x} - d_x^-$$

where, $a$ represents the radius of the fibre, $\sigma_i$ is the intracellular conductivity, $\partial IAP/\partial x$ is the dipole strength along the fibre axis and $d_x^-$ is the fibre length.

### 2.1.2 | EMG sensors

The EMG data were acquired using the high-density surface EMG system Refa 128 model, TMS International BV, Netherlands, with the placement of 32 electrode channels distributed around the stump of each amputee. The distribution of the electrodes was adapted to the stump length of each participant, resulting in a unique placement pattern among the participants. This is detailed in more depth in Section 2.2. In terms of the data acquisition, the EMG signal was filtered with a bandpass filter in the region of 10–500 Hz, with a sample rate of 1024 Hz and a 24 bit resolution [7].

### 2.1.3 | Electroencephalography

EEG is a passive measurement technique used in the acquisition of the electrical signals from the surface of the skull. Acquired EEG measurements reflect the neurological potential signals from various cortical sections in the brain [13,14]. The acquired electrical signal is said to emanate from pyramidal neurons on the scale of billions, synchronously firing within the human skull [13,14].

EEG is a useful tool in the localisation of the region from which neural activities that generate the acquired EEG signals emanate [13,14]. Mathematical models have been formulated to theoretically address both: (i) the forward EEG problem, which consists of estimating the associated electric potential for a given set of electrodes, a model for the head, and a conductivity overlay of the tissues in the head; and (ii) the inverse problem, which is based on source localisation given a set of resulting measured potentials [13,14].

### Quasi static Maxwell equation

Electromagnetic interactions can be modelled with Maxwell’s equations, which hold the basic laws of electromagnetism, and can be represented using four key fields, namely: the electric field $E$, the electric displacement $D$, the magnetic field $H$, and the magnetic induction $B$. The tissues in the head can be approximated as linear, and as a result, we can establish the following linear relationship as seen in Equation (6) [13,14]:

$$D = \varepsilon E \text{ and } B = \mu H$$
where, \( \varepsilon \) and \( \mu \) represent the electric and magnetic permeability. Assuming permeability in the head to be the same as the free space, Equation (6) can be reformulated as shown in Equations (7a–d):

\[
\begin{align*}
\nabla \cdot (\varepsilon \mathbf{E}) &= \rho \\
\nabla \cdot \mathbf{B} &= 0 \\
curl \mathbf{E} &= -\partial_t \mathbf{B} \\
curl \mathbf{B} &= \mu_0 \mathbf{J} + \mu_\varepsilon \partial_t (\varepsilon \mathbf{E})
\end{align*}
\]

(7a–d)

where, \( \rho \) is the charge density, \( \mathbf{J} \) is the current density, and \( \mathbf{E} \) is linked to Ohm's law through \( \mathbf{J} = J + \sigma \mathbf{E} \). \( \sigma \) is the density of the neural current, and \( \varepsilon \) is the conductivity of the head tissue.

In the frequency spectrum, the desired content for EEG signals has been shown to be in the 1–100 Hz region. Within this frequency band, and at these frequencies, the time derivatives of Equations (7c and d) can be ignored as per Hämäläinen et al. [15].

The forward EEG problem helps to provide a theoretical formulation of the means of estimating the electric potential using measurement apparatus with a mathematical model-based representation, and is the focus of this section [13,14].

Dipoles have been seen to be useful approximations in neuroelectromagnetism for simulating the result of microscopic-based current interactions in localized regions of the brain [16]. Applying the dipole theory, a closed form analytical solution can be deduced by means of series expansion. Berg et al. [17] and Zhang et al. [18] applied the framework of three dipoles in a homogeneous sphere to approximate the solution for a four-layer spherical head model.

This method was based around a multilayer head of \( L \) concentric spheres with a radius span of \( 0 < r_1 < r_2 \ldots < r_L \) and anisotropic conductivities \( \sigma_1, \ldots, \sigma_L \) [17,18].

Assuming a singular dipole source is located at a particular point \( S \) at the closest sphere with radius \( r_i < r_1 \) of moment \( q_i \), the electric potential \( u(q_i, r_i, x) \) measured at point \( x \), and located at the furthest sphere \( \left\| x \right\| = r_L \) can be expressed as Equation (8) [17,18].

\[
u(q_i, r_i, x) = \frac{\left\| q_i \right\|}{4\pi \sigma L r_L^2} \sum_{n=1}^{\infty} 2n + 1 \frac{\left( r_i \right)^{n-1}}{r_L^n} f_n \left[ n \cos \alpha P_n \left( \cos \gamma \right) + \cos \beta \sin \alpha P_n^\prime \left( \cos \gamma \right) \right]
\]

(8)

where, \( \alpha \) represents the angle between point \( S \) and its moment \( q \), \( \beta \) is the angle between \( \mathbf{S} \) and the measurement point \( x \), \( \gamma \) is the angle between the two planar vectors marked by \( S \) and \( q \) on one side and \( S \) and \( x \) on the other, and \( P_n \) and \( P_n^\prime \) are the Legendre polynomial coefficient associated with the series. For the case of isotropism, \( f_n \), the EEG measurement for the \( n \)th element can be computed as seen in Equation (9) [13,14,17,18]:

\[
f_n = \frac{n}{nm_{22} + \left( 1 + n \right)m_{21}}
\]

(9)

The coefficients \( m_{22} \) and \( m_{21} \) of the matrix \( m_{ij} 1 \leq i, j \leq 2 \) can be obtained with Equation (10).

2.1.4 | EEG sensors

The EEG sensors used were the 64 Channel EasyCap, Herrsching, Germany, with the Neuroscan system version 4.3 and Al–AgCl electrodes distributed using the 10–20 system standard as can be seen in Figure 1 [19].

Li et al. [7] carried out a small preparation exercise on the subjects, which in certain cases involved hair cleaning, in order to facilitate impedance matching stayed below a threshold of 10 k\( \Omega \). The EEG signal bands were filtered in the region of 0.05–100 Hz, and sampled at a rate of 1024 Hz.

\[
\begin{bmatrix}
\begin{array}{cc}
m_{21} & m_{12} \\
m_{22} & m_{22}
\end{array}
\end{bmatrix} = \frac{1}{\left( 2n + 1 \right)^{L-1}} \prod_{i=1}^{L-1} \left[ \left( n + \frac{(n + 1)\sigma_i}{\sigma_i+1} \right) \left( n + 1 \right) \left( \frac{\sigma_{i+1}}{\sigma_i+1} \right) \right]^{2n+1}
\]

(10)

2.2 | Participant information and data collection

Li et al. [7] acquired the dataset from four transhumeral amputees whose demographic information can be seen in Table 1. Ethical approval was granted for the study by the Institutional Review Board of Shenzhen Institutes of Advanced Technology, with a unique reference number of SIAT-IRB-150515-H0077. All participants provided written consent for their data to be used for research purposes and the inclusion of their photographs in subsequent publications [7].

The participants performed a total of five motion classes during the data collection process, namely: Hand Open (HO), Hand Close (HC), Wrist Pronation (WP), Wrist Supination (WS), and No Movement (NM). Apart from NM, all candidate gesture movements represent gesture motions which were seen to produce contraction in the anatomy along the humerus, as seen in the work done by Nsugbe et al. [4]. They represent a mixture of essential functional and rotation-based movements required by a myoelectric prosthesis user [20].

After signing the consent forms, the protocol of the experiment was explained to the participants, and a computer screen showing the relevant hand gestures was used to prompt the participants to perform the gesture motion [7]. The gesture motion on the screen lasted for 5 s, followed by a 5-s lag time before the next gesture motion appeared on the screen [7]. This corresponded to the participant holding the movement for 5 s followed by inactivity for another 5 s [7]. A
A total of 10 repetitions were performed for each gesture set with the same muscular contraction level, with occasional breaks taken between acquisitions as required in order to avoid muscular and mental fatigue [7]. The average data collection time for each amputee was said to be in the region of 2–3 h, and Figure 2 shows a picture of the acquisition setup.

Due to the varying nature of the stump of the transhumeral amputees (see Table 1), the electrode placement had to be adapted to the stump of the amputee. A sum total of 32 electrode channels were placed on the stump around the deltoids, bicep and triceps, depending on the stump, as seen in Figure 3. It is worth mentioning that, due to the shorter stump lengths of TH1 and TH2, 12 electrode channels had to be placed on the deltid muscles [7].

**TABLE 1** Information on amputee subjects

| Subject | Age (years) | Amputation Side | Stump length (cm)* | Time since amputation (years) | Cause of amputation |
|---------|-------------|-----------------|--------------------|-------------------------------|---------------------|
| TH1     | 49          | Left            | 20                 | 3                             | Trauma              |
| TH2     | 46          | Left            | 25                 | 9                             | Trauma              |
| TH3     | 35          | Right           | 27                 | 5                             | Trauma              |
| TH4     | 36          | Right           | 30                 | 7                             | Trauma              |

*Stump length was measured from shoulder blade downward.

**FIGURE 1** Electroencephalography (EEG) electrode location and configuration. Reprinted from [7] with permission.

**FIGURE 2** Subject TH3 and experimental apparatus shortly before commencement of data collection. Reprinted from [7] with permission. EMG, electromyography.
2.3 Electrode channel selection procedure and pre-processing

The sequential forward selection (SFS) greedy search algorithm was applied towards the identification of optimal electrodes for the intent decoding exercise. Here optimality is defined in terms of parsimony, which seeks to identify the lowest amount of electrode channels required to form a satisfactory representation of the phenomena of interest. More details of this can be seen in the work by Li et al. [7]. A systemic flow of the SFS procedure for the electrode selection can be seen as follows [7,21]:

**Step 1**—Initialise with empty set. $S_0 = \{ \emptyset \}$

**Step 2**—Select the next electrode with maximum classification accuracy; $Acc(S_k + x^*_j) = \arg \max \limits_{k \in \{1,2,\ldots,n\}} Acc(S_k + x^*_j)$

**Step 3**—$S_{k+1} = S_k + x^*_j$

**Step 4**—Repeat until all elements in set $k$ have been exhausted where, $S_k$ represents electrodes that have already been selected, $Acc$ is classification accuracy, $x^*_j$ is electrode channel, $k$ is the set of electrodes, and $j$ represents the $j$th element in set $k$.

Using the SFS algorithm, an optimal set of 10 electrodes were identified which formed an optimal low channel representation of the data collected for both the electromyography (EMG) and electroencephalography (EEG), and represented

![Diagram of Electrode Location and Configuration](image)

**FIGURE 3** Electrode location and configuration for subjects TH1–TH4 (n/a, not available)

**TABLE 2** Optimal EMG and EEG electrodes for all transhumeral participants

| TH1-EMG | TH1-EEG | TH2-EMG | TH2-EEG | TH3-EMG | TH3-EEG | TH4-EMG | TH4-EEG |
|---------|---------|---------|---------|---------|---------|---------|---------|
| 1       | 1       | 8       | 8       | 8       | 2       | 4       | 3       | 2       |
| 2       | 2       | 20      | 10      | 16      | 6       | 7       | 5       | 27      |
| 3       | 6       | 30      | 13      | 23      | 12      | 25      | 8       | 28      |
| 4       | 12      | 31      | 15      | 25      | 18      | 26      | 14      | 29      |
| 5       | 15      | 37      | 16      | 23      | 21      | 30      | 15      | 30      |
| 6       | 16      | 38      | 19      | 27      | 24      | 31      | 24      | 37      |
| 7       | 17      | 39      | 20      | 39      | 25      | 36      | 25      | 46      |
| 8       | 20      | 55      | 22      | 55      | 26      | 42      | 27      | 47      |
| 9       | 22      | 56      | 26      | 56      | 30      | 46      | 28      | 53      |
| 10      | 27      | 60      | 27      | 58      | 31      | 47      | 31      | 55      |

Abbreviations: EEG, electroencephalography; EMG, electromyogram.
the signal sources used in the signal processing stage in this work. Table 2 shows the optimal electrodes for the various transhumeral participants.

The varied electrode results from the SFS algorithm for both the EMG and EEG highlights the need for an electrode placement optimisation routine as part of the calibration process for myoelectric prosthesis users. This is due to the varied anatomical structure of human beings and uniqueness of individual stumps, since myoelectric prosthesis does not allow an overly high amount of electrode channels. From this, it can be advised that an optimisation exercise should be carried out in order for the maximisation of the signal quality to be achieved with key electrode placement [7].

It was noted from the EEG SFS results that TH1 and TH2 had a commonality of the electrode placed along the visual cortex (EEG 55 and 56), contributing a fair amount in terms of electrode location. A possible reason for this could be due to these two participants possessing a relatively shorter stump length. Also, there is a high emphasis on the activation of the visual cortex to aid in the projection of the movement in the mind of the amputees while they imagined themselves performing the required motion [22].

For the analysis process of the data, each experimental run was divided into 10 segments corresponding to the 10 repetitions made by the subject during the acquisition run, with each segment comprising 5120 samples.

2.4 | Signal processing and classification method

2.4.1 | Feature extraction

In the previous work by Li et al. [7], four time-domain features were extracted from both the signals, namely: the mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and slope sign change (SSC) [23,24]. This set of features has been seen to be insufficient for the effective recognition of transhumeral signals, as reported by Nsugbe et al. [4] and Gaudet et al. [6]. Thus, we have constructed an enhanced feature vector comprising a total of 11 features extracted from both the EMG and EEG, and can be grouped as follows.

Contraction intensity and power features

The MAV gives an indication of the mean of the bio-potential signal produced by a gesture motion. The root mean square (RMS) provides a quantification of the overall power present in the signal. The WL gives a combined sum of the frequency information in a signal across a given duration. The ZC is a robust feature which characterises the dynamic behaviour of a signal by quantifying the amount of times it crosses a predefined threshold. The SSC also works with a predefined threshold and quantifies the amount of times the slope value changes sign across consecutive sample points. A mathematical formulation of these features can be seen in Nsugbe et al. [4] and Phinyomark et al. [25].

The threshold value used for the ZC and SSC features was 1 µV.

Frequency feature

The cepstrum coefficient (MCEP) is a spectral method which deconvolves time-domain signals into the sum of their spectrums, whose sequence involved in computing includes taking the signal fast Fourier transform (FFT), and calculating the log of the FFT followed by the inverse of the FFT. The maximum of the MCEP was extracted from the cepstrum and used as a feature. A mathematical structure of the cepstrum can be seen in Nsugbe et al. [4] and at MathWorks.com [26].

Predictive and non-linear complexity features

The autoregressive (AR) feature provides a stochastic difference equation of time varying processes, and the AR model is formulated by regressing and combining previous sample points. It has been seen that coefficients of AR models vary with the biological state of the entity in question when the signal was acquired [4,27]. The fourth order AR model was used in this case, as was seen previously with the Akaike Information Criterion, and the coefficients were used as input features [27]. A mathematical structure of the AR model can be seen in Nsugbe et al. [4].

The sample entropy (SampEN) is a modified approximate entropy feature which is used to quantify the degree of regularity and complexity in a time-series. For the work done in this article, the subseries length $m$ and tolerance $r$ values were 2 and 0.2, respectively, as they were found to be the optimal values in previous studies [4,28]. Within the non-linear complexity heading, three fractal features were considered, as follows:

- Maximum fractal length (MFL) is a feature capable of quantifying the intensity associated with relatively low muscular contractions, and can be mathematically expressed as seen in Nsugbe et al. [4] and Too et al. [29]. The remaining two fractal features calculated involved a multi-step sequential flow in order to arrive at a final parameter which was used as the input feature. These features, alongside the computation steps, can be seen as follows.
- Higuchi fractal dimension (HFD) is a computationally efficient method for calculating fractal dimension, which can be used to describe and quantify self-similarity within a signal. The steps taken to calculate this can be seen as follows, whereas the mathematical structure can be seen in Gómez et al. [30]:

1. Assuming a given time series $X = x_1, x_2, ..., x_N$, devise a new time series $X_m^k$, where $m = 1, 2, ..., K$ for the initial time values and $k$ is the total time interval
2. The length of a set of new time-series can now be defined $L(m,k)$
3. For a discrete time interval $k$, the curve length can be deduced as the mean of the $k$ values in $L(m,k)$ for the range of values of $m$
4. Perform plot of $L(k)$ versus $1/k$ on a double log plot for $k = 1, 2, \ldots, k_{max}$ and fit with a linear curve, where $k_{max}$ was chosen to be 11 as per suggestions made by Gomez et al. [30]. The final HFD, which was the final parameter extracted, can be finally calculated as the slope of the line of best fit in terms of $\log(L(k))$, as shown in (13):

$$\alpha = \frac{\log F_I(n)}{\log(n)}$$

where, $\log \cdot \log$ is the L₂ Norm, $a_i$ is the prediction error in an $L_2$ sense, and $N$ is the set containing prediction errors for each point on the curve.

- Detrended Fluctuation analysis (DFA) is a feature used to characterise the level of repeatability in a highly varying time-series by taking into account long-scale power law correlations. It holds advantages over spectral methods due to its ability to reject noise caused by artefacts and measurement errors [31–33]. The feature is useful in uncovering hidden patterns within time-series data which encode physiological patterns and characteristics [31–33]. The steps required for the calculation of the DFA are as follows, as shown in [31–33]:

1. Given a time series $X = x_1, x_2, \ldots, x_N$, calculate the random walk of $X$ as seen in Equation (11):

$$y(i) = \sum_{i=1}^{X} |s(i) - s|$$

where, $s$ is the mean of the time series $X$.

1. Partition series $y(i)$ into segments whose length is determined by $N/n$, where $N$ represents the length of $X$, $n$ is a user defined value and $\lfloor \cdot \rfloor$ is a floor function

2. For each of the data segments obtained in Step 2, a polynomial fit in a least square sense of order 1 is fit to each segment to obtain $y_k$, and is termed the DFA of order 1 (although the polynomial order 1 has been frequently used in prior studies on this step, it is not a constrained parameter, thus higher order fits can also be investigated as per the users’ need).

3. At this step, the signal $y(i)$ is now centred and de-trended for each data segment, which produces the detrended fluctuation signal:

$$Y_i = y(i) - y_I(i)$$

1. For a time segment $n$, calculate the RMS of the detrended signal denoted as $F(n)$

2. Steps 1–5 are repeated for the amount of times that $n$ is defined. In this work $n$ was selected as 10 for a window range of 50 ≤ 10 ≤ 500, as per the format recommended by Phinyomark et al. [25].

3. Perform a double log plot of $(\log F(n)$ vs. $\log(n))$. The linear relationship between the two quantities on both axes is indicative of self-fluctuations, and the slope of the line determines the scaling $\alpha$ as can be seen in Equation (13), and also constituted the final value used in the feature vector.

For the EMG/EEG only sensing, a total of five gesture sets, with 10 repetitions each, for four amputees across 10 electrodes and 11 signal features yield a total of 22,000 sample points, which were used for the respective analysis. While in the case of the sensor fusion EMG–EEG, the merged feature vector provided a total of 88,000 sample points (i.e. 5 gestures × 10 repetitions × 4 amputees × 20 electrodes × 22 features).

2.4.2 | Gesture classification methods

Discriminant analysis has been recognised as a computationally effective classification method capable of providing satisfactory classification accuracy for EMG and EEG data [4,34]. In this study, the linear (LDA) and non-linear of a quadratic variant (QDA) are used for the classification exercise in order to be able to contrast the classification accuracy when a linear classifier is used in comparison with a non-linear classifier. The discriminant analysis framework is structured around the projection of high dimensional data into a lower dimensional representation which can preserve the data structure, and aims to achieve maximum separation between data classes [4,34]. The discriminant function for the LDA and QDA can be seen in Equations (14) and (15) respectively:

$$\delta_l(x) = \mu_c^T \Sigma_c^{-1} x - \frac{1}{2} \mu_c^T \Sigma_c^{-1} \mu_c$$

where, $\delta_l$ is the discriminant function, $\mu_c^T$ is the mean vector of the training for a class $c$, and $x$ is the feature vector. $\Sigma_l$ is the pooled covariance matrix.

$$\delta_k(x) = -\frac{1}{2} \log|\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) \log \pi_k$$

where, $\delta_k$ is the QDA discriminant function for a specified feature vector, $x$ is the mean vector of the training samples for a specific motion class $k$, $\pi_k$ represents a prior probability for each class $k$, and $\Sigma_k$ is the pooled covariance matrix [4,35].

A $k$-fold cross validation method was employed to assess the classification performance of the classifier, with $k$ chosen as 10. This meant a 10 × 10 cross validation with a mean of all $k$-fold repetitions in order to achieve a representative figure, which served as the classification accuracy. The $k$-fold method was chosen as it allows for training and testing of the classifier performance using a $k$-defined number or training and test set, to help provide an idea of the model performance given unique variants of data, and has been seen to be favoured in the prosthesis control literature [4,7].
3 | RESULTS

For each sensor input configuration, two classification exercises were done. The first involved the classification of each of the five gesture sets mentioned in Section 2.2, followed by two gesture classification exercises comprising of HO and HC gesture sets, which have been seen to be the most essential gesture sets for amputees. These were included for the purpose of amputees whose residual anatomy on the stump does not allow for good classification accuracy. These two exercises were done for both the LDA and QDA classifiers, making four separate exercises per sensing module across the three variants considered, and 12 altogether; that is, EMG-Only, EEG-Only, and EMG–EEG combined.

Figure 4 shows the results of the classification exercises; the blue bars represent the features used by Li et al. [7], while the red bars represent the enhanced feature sets. For the EMG-only, the QDA classifier performed the best on average across all four amputees with 63% classification accuracy, and with an increment of 15% compared with the original feature set used by Li et al. [7]. In the case of the HO/HC, both the LDA and QDA could be said to have provided equivalent performance capabilities in the region of 90%, while the increment in classification accuracy between the two feature sets is not overly substantial. Thus, in the interest of computational parsimony, a combination of the LDA and a reduced feature set would suffice for the case of solely HO/HC gestures.

For the case of the EEG-only across all four amputees, both classifiers appear to perform equivalently at about 30% classification accuracy for the case of all the gestures. This low classification accuracy suggests that, with EEG being a high channel sensing tool, 10 electrodes may be insufficient to distinguish between phantom motions in a multi-class classification scenario. The HO/HC produced a classification accuracy of 68% and 63% respectively, while also showing that the enhanced feature set provided a 5% increment in the best case. This set of results show that a low channel (10 electrodes) representation of the EEG is mainly suited to a small number of gesture sets, while the inclusion of advanced features does not appear to be beneficial in return for the time it would take to compute them.

For the signal fusion of EMG–EEG, due to the low classification accuracy of the EEG, only a small increase of 2%–3% was observed for the various exercises with the QDA, marginally providing the best performance. Thus, showing that for a case of a low channel representation, the EMG alongside the enhanced feature set and the QDA appears to offer the best all round performance. Its classification accuracy supersedes that of EEG, and the improvement afforded by the fusion of the various sets of signals appears to be marginal relative to the EMG only, thereby not warranting the trade-off for additional cost and hardware.

The best classification accuracy was obtained from TH1, as can be seen in Figure 4. Individual results across all five gestures can be seen for the EMG–EEG for the Li et al. [7]
features, and the enhanced features from the QDA can be seen in Figures 5 and 6.

It can be seen from Figures 5 and 6 that the HO, HC, and NM motions provide the best classification accuracy, with the wrist rotational movements (WP and WS) producing a lower classification accuracy. The inclusion of additional features not only appears to boost the overall classification accuracy, but also aids the classifier with greater success in classification of the rotational based movements, which require a different muscular recruitment pattern when compared with the HO and HC. Although only the confusion plots from TH1 are presented in this article, it is worth mentioning that there was a consistent trend amongst all four amputees with the HO, HC and NM motions providing the higher classification accuracies.

From the physical information provided on the amputee participants in Table 1, it would appear that the time since amputation appears to be the key physical driver behind the degree of a classification accuracy produced by the classifier. This notion is also echoed in the work done by Gaudet et al. [6]. It has been said previously in the literature that due to the phenomenon of neuroplasticity, cortical based re-organisation occurs within the motor cortex as the brain adapts over time to the loss of a limb. Accurate timescales and estimates are uncertain for this, but as a rule of thumb, the longer an amputated subject has been post-amputation, the more of an automated neurological-based re-organisation would have taken place, thus steadily reducing the degree of assertion and control over phantom motions which cause the residual anatomies around the stump to contract [36,37].

This trend has not been seen to be consistent in the results obtained in this study, albeit with a constrained sample size of four. The two subjects which provided the best classification accuracies, TH1 and TH2, had EMG electrodes placed on their deltoids due to the nature of their stumps, whereas the remaining two subjects had EMG electrodes placed primarily around their stumps and not on their deltoids. However, it is still worth mentioning that the best classification accuracy was achieved for a subject who had been amputated for 3 years, while the lowest came from a subject who was amputated for 7 years. Hence it is apparent that time since amputation plays an important role in the degree of classification accuracy achievable, but it has not been possible to probe deeper into this question due to a constrained sample size of four amputee subjects.

For transhumeral amputations specifically, from this study it can be said that the length of the residual stump has not been seen to contribute significantly to the classification accuracy but instead bring ergonomic challenges as to possible locations of sensing electrodes as described in Section 2.2. In terms of age of participants, it has not been possible to draw any links between this and the level of classification accuracy [6,38].

There are sources in the literature that suggest that the neurological formation and homunculi-based representation in the motor cortex of individuals amputated due to trauma, and congenital amputees, differ. For transhumeral amputees, this remains an area that requires further investigation, as it has not been possible to investigate this question further due to the recruited amputees, whose data was used for the analysis, being trauma-based amputees [37,39].

It should be noted that the results obtained for the set of features used by Li et al. [7] appear to vary from those that were obtained in their study. This is likely due to signal division and windowing techniques alongside different classifier validation methods.

4 | CONCLUSIONS AND FUTURE WORK

In this study, we have systematically demonstrated that the inclusion of additionally meaningful descriptors to the training feature vector leads to an enhancement in the classification
accuracy of the classifier using 10 SFS optimal electrodes. The best improvement was noted for the EMG where an average across all four subjects produced a 15% classification increase across all five gestures, with the QDA classifier providing the best result. This is most likely due to its ability to fit non-linear decision boundaries around data clusters. The EEG did not show a strong improvement with the inclusion of additional features, leading to the impression that the number of electrodes selected was unsatisfactory in providing sufficient information to recognise the neurological activation pattern during gesture motion. Further work is needed to identify an appropriate amount of EEG channels which, when combined with the proposed features, will lead to enhanced and satisfactory classification accuracy. With the EEG classification accuracy being relatively low, this meant that the fusion of the EMG–EEG only provided a marginal enhancement in the classification accuracy. Nonetheless, it is thought that if the prior point regarding EEG is addressed then there could be a possibility that the signal fusion would undergo a greater degree of enhancement—this is subject to further investigation [7,40].

In terms of the physical attributes of the amputee subjects, the stump length provided ergonomic challenges and dictated where the electrodes were placed. This meant that various amputees had unique electrode locations which limited the degree to which like-for-like result comparison could be carried out across the various subjects, due to unique electrode placement in the case of the EMG. This is the time since amputation is known to be a key factor which has been seen to influence the classification accuracy. It has not been possible to investigate this notion closely due to varying electrode placements, as mentioned, but it was noted that the best classification accuracy was produced from a subject who had been amputated for 3 years while the lowest came from a subject who was 7 years post-amputation.

The results from the HO/HC exercise showed that the classifiers perform better with a reduced number of gestures, so further work will need to be done in the form of an optimisation routine to help identify an optimal number of gesture sets for each amputee, given their time since amputation and anatomical structure. We believe that this, alongside the SFS optimal electrode location, will help tailor and customise a prosthesis control interface towards the amputee subject in question.

In addition to investigating further signal features that can help enhance the classification of the EEG signal, further work could also be done on contrasting between a supervised learning classifier framework (such as the one used in this study) with unsupervised learning classifiers, to observe their respective intent decoding capabilities. Although this study has been based on motion intent decoding and classification, the signal features extracted from the EEG signal could also be applied in early diagnosis of neurodegenerative diseases such as Alzheimer's and dementia to name a few.

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REFERENCES

1. Staats, T.B.: The rehabilitation of the amputee in the developing world. A review of the literature. Prosthet. Orthot. Int. 20(1), 45–50 (1996)
2. Limbless Statistics. http://www.limbless-statistics.org/. Accessed January 2020
3. Fang, Y., et al.: Multi-modal sensing techniques for interfacing hand prostheses. A review. IEEE Sens. J. 15(11), 6065–6076 (2015)
4. Nsugbe, E., et al.: Gesture recognition for transhumeral prosthetics using EMG and NIR. IET Cyber-Systems and Robotics 2, 122–131 (2020a). https://doi.org/10.1049/iet-csr.2020.0008
5. Fougner, A., et al.: Control of upper limb prostheses: terminology and proportional myoelectric control—a review. IEEE Trans. Neural Syst. Rehabil. Eng. 20(5), 663–677 (2012)
6. Gaudet, G., Raison, M., Achiche, S.; Classification of upper limb phantom movements in transhumeral amputees using electromyographic and kinematic features. Eng. Appl. Artif. Intell., vol. 68, pp. 153–164 (2018)
7. Li, X., et al.: A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. J. NeuroEng Rehabil. 14(1), 2 (2017)
8. Rodriguez-Falces, J., Navallas, J., Mal, A.: EMG modeling. In: Naik, G.R. (ed.) Computational intelligence in electromyography analysis - a perspective on current applications and future challenges. InTech, Rijeka, Croatia (2012)
9. Gram, J.R., Kasman, G.S., Holza, J: Introduction to surface electromyography. Aspen Publishers, Gaithersburg (1998)
10. Petersen, E., Rostalski, P.: A comprehensive mathematical model of motor unit pool organization, surface electromyography, and force generation. Front. Physiol. 10, 176 (2019)
11. Wilson, E.N., Macleod, A.G., Barker, P.S.: The distribution of the action currents produced by heart muscle and other excitable tissues immersed in extensive conducting media. J. Gen. Physiol. 16(3), 423–456 (1933)
12. Plonsey, R., Barr, R.C.: Bioelectricity: a quantitative approach, pp. 3. Springer, New York (2007)
13. Darbas, M., Lohrengel, S: Review on mathematical modelling of electroencephalography (EEG). Jahresber. Dtsch. Math. Ver. 121(1), 3–39 (2019)
14. Doschoris, M., Kariotou, F.: Mathematical foundation of electroencephalography. In: Sittiprapaporn, W. (ed.) Electroencephalography. InTech, Rijeka, Croatia (2017)
15. Hämäläinen, M., et al.: Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. Rev. Mod. Phys. 65(2), 413–497 (1993)
16. Nunez, P.L., Srinivasan, R.: Electric fields of the brain: the neurophysics of EEG, 2nd ed. Oxford University Press, New York; Oxford (2006)
17. Berg, P., Scherg, M: A fast method for forward computation of multiple-sphere spherical head models. Electroencephalogr. Clin. Neurophysiol. 90(1), 58–64 (1994)
18. Zhang, Z.: A fast method to compute surface potentials generated by dipoles within multilayer anisotropic spheres. Phys. Med. Biol. 40(3), 335–349 (1995)
19. EASYCAP GmbH: EEG Recording Caps & Related Products. http://brainvision.co.uk/products/products-by-manufacturer/easycap-gmbh. Accessed August 2019
20. Triwiyanto, T., et al.: A low cost and open-source anthropomorphic prosthetics hand for transradial amputee. In: International Conference on Science and Applied Science (ICAS) 2019 (2019)

21. Gutierrez-Osuna, R.: L9: Linear discriminants analysis. http://research.es.tamu.edu/prism/lectures/pr/pr_l11.pdf. Accessed August 2019

22. Hegarty, S.: What phantom limbs and mirrors teach us about the brain. https://www.bbc.co.uk/news/magazine-15938103. Accessed August 2019

23. Hudgins, B., Parker, P., Scott, R.N.: A new strategy for multifunction myoelectric control. IEEE Trans. Biomed. Eng. 40(1), 82–94 (1993)

24. Englehart, K., Hudgins, B.: A robust, real-time control scheme for multifunction myoelectric control. IEEE Trans. Biomed. Eng. 50(7), 848–854 (2003)

25. Phinyomark, A., et al.: EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Syst. Appl., 40, pp. 4832–4840 (2013)

26. Cepstrum analysis. https://uk.mathworks.com/help/signal/ug/cepstrum-analysis.html. Accessed August 2019

27. Graupe, D., Salah, J., Zhang, D.: Stochastic analysis of myoelectric temporal signatures for multifunctional single-site activation of prostheses and orthoses. J. Biomed. Eng. 7(1), 18–29 (1985)

28. Montesinos, L., Castaldo, R., Pecchia, L.: On the use of approximate entropy and sample entropy with centre of pressure time-series. J. NeuroEng. Rehabil. 15(1), 116 (2018)

29. Too, J., Rahim, A., Mohd, N.: Classification of hand movements based on discrete wavelet transform and enhanced feature extraction. IJACSA. 10(6)83 (2019)

30. Gómez, C., et al.: Use of the Higuchi’s fractal dimension for the analysis of MEG recordings from Alzheimer’s disease patients. Med. Eng. Phys. 31(3), 306–313 (2009)

31. Asmi, P.S., Subramaniam, K., Iqbal, V.N.: Classification of fractal features of uterine EMG signal for the prediction of preterm birth. Biomed. Pharmacol. J. 11(1), 360–374 (2018)

32. González-Salas, J.S., et al.: Analyzing chaos systems and fine spectrum sensing using detrended fluctuation analysis algorithm. Math. Probl. Eng., 2016, pp. 1–18 (2016)

33. Golinski, A.K.: Detrended fluctuation analysis (DFA) in biomedical signal processing: selected examples. SLGR. 29, 42 (2013)

34. Linear, quadratic, and regularized discriminant analysis. https://www.statisticQUAREABLES.com/post/machine-learning/linear-discriminant-analysis/. Accessed December 2019

35. Penn State University: Quadratic discriminant analysis. https://online.stat.psu.edu/stat508/book/export/html/696. Accessed December 2019

36. Crawford, C.: Phantom limb: amputation, embodiment, and prosthetic technology. New York University Press, New York (2014)

37. Ramachandran, V.S., Rogers-Ramachandran, D.: Phantom limbs and neural plasticity. Arch. Neurol. 57(3), 317 (2000)

38. Guo, W., et al.: Towards an enhanced human-machine interface for upper-limb prosthesis control with combined EMG and NIRS signals IEEE Trans. Human-Mach. Syst. 47, 564–575 (2017)

39. Schott, G.D.: Penfield’s homunculus: a note on cerebral cartography. J. Neurol. Neurosurg. Psychiatr. 56(4), 329–333 (1993)

40. Lalitharatne, T.D., et al.: Towards hybrid EEG-EMG-based control approaches to be used in bio-robotics applications: current status, challenges and future directions. Paladyn. J. Behav. Robot. 4(2): 147-154 (2013)

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