A Self-learning and Adaptive Control Scheme for Phantom Prosthesis Control Using Combined Neuromuscular and Brain-Wave Bio-Signals

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Overview and Problem Statement

- **Estimated** to be around **6,000 amputations** (National Amputee Statistical Database (NASDAB))

- Although Upper Limb amputees make up **small segment** of amputees - they have **high functional needs**

- With **Trauma** reported as main **cause** of amputation

- **Loss** of upper limb is said to influence overall **independence & ability to work**
Overview and Problem Statement

Functional Prosthesis/Myoelectric Prosthesis Control Scheme

Pattern Recognition/Motion Intent Decoding Sequence
Overview and Problem Statement

Current Limitations of Pattern Recognition Control:

- Intent decoders/Classifiers are trained via the ‘Supervised Learning’ framework - thus, expert in loop required & lag time induced from training process
- Classifier degradation due to uncertainties i.e. electrode shift, physiological changes in stump etc

 Proposed Solution

- Design of Self Learning and Adaptive Controllers with ‘Unsupervised Learning’ framework which can help further enhance intuitiveness of prosthesis control and increase overall autonomy

https://medium.com/the-21st-century/machine-learning-a-strategy-to-learn-and-understand-chapter-3-9daaad44fc55
Biosensors and Data Collection

Electromyography (EMG)

Represent superimposed electrical manifestations of action potentials from motor neurons, and can be mathematically modelled using dipole theory as a continuous extracellular action potential from a multiple source as seen in equation 1:

\[
\phi_e(t) = -\frac{a^2.\sigma_i}{4.\sigma_e} \cdot \int_{-\infty}^{+\infty} \frac{\partial IAP(x,t)}{\partial x} \cdot a_x \cdot \frac{\partial}{\partial x} \left( \frac{1}{r(x)} \right) dx
\]

Where \( \phi_e \) is the time varying extracellular potential, \( \sigma_e \) is the conductivity of the extracellular medium, \( \sigma_i \) is the intracellular conductivity, \( a \) is the radius of the fiber, \( t \) is time, \( r \) is the distance of the source excitation to the recording sensor, \( x \) is a point in space within the fiber element, \( a_x^- \) is the length of the anatomical fiber and \( \frac{\partial IAP}{\partial x} \) is the dipole strength at a point along the fiber axis.

EMG Sensors

The EMG instrumentation used for data acquisition by Li et al [1] was the Refa 128 high-density electrodes by TMS International BV, Netherlands, with 32 electrodes [2]. The acquisition electronics comprised of a bandpass filter in the 10-500Hz frequency range, 24bit resolution and a sample rate of 1024Hz.

1. Li, X.; Samuel, O.W.; Zhang, X.; Wang, H.; Fang, P.; Li, G. A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. J. NeuroEng. Rehabil. 2017, 14(2), doi: 10.1186/s12984-016-0212-z
2. Nsugbe E.; Phillips C.; Fraser M.; McIntosh, J. Gesture Recognition for Trans-humeral Prosthesis Control Using EMG and NIR. IET Cyber-Systems and Robotics 2020, doi: 10.1049/iet-csr.2020.0006
Biosensors and Data Collection

Electroencephalography (EEG)

EEG signals occur from the synchronous neuronal firing of billions of pyramid-like cells within the skull of a human being. Using a combination of dipole theory, and assuming the forward EEG problem, a measured potential of an EEG signal can be formulated as follows:

$$u(r_s, q, x) = \frac{\|q\|}{4\pi \sigma_L r_L^2} \sum_{n=1}^{\infty} \frac{2n+1}{n} \left( \frac{r_s}{r_L} \right)^{n-1} f_n [ncos \alpha P_n(cos \gamma) + cos\beta sin \alpha P_n^1(cos \gamma)]$$

(2)

Where $s$ is the dipole source located within proximity of sphere of radius $r$, of moment $q$, boundary sphere $r_L$, anisotropic conductivity within boundary sub-domain of $L$, $f_n$ is the EEG measurement for nth element in the infinite set, $\alpha$ is the angle between the point $S$ and measurement point $x$, $\gamma$ is the angle between two planar vectors pairs of $S$ & $q$ and $S$ & $x$, $P_n$ and $P_n^1$ represent the Legendre polynomial coefficient of the series.

EEG Sensors

The 64 sensors EEG channel EasyCap, Herrsching, Germany, with the Al-AgCl electrodes and Neuroscan system version 4.3 was used. The EEG signals were band passed filters in the region of 0.05-100Hz with a sample rate of 1024Hz.
Data Collection

- Simultaneous acquisition of EMG and EEG signals

- The Hand Open and Hand Close Gestures were used for the work done as part of this paper and represent key hand gestures in prosthesis control.
Proposed Self-Learning Architecture

- Assuming the acquisition of a bio-signal, the Self-Learning architecture comprising of an electrode selection process followed by a 3-phase self learning process as seen below:

0.1 Optimal Electrode Channel Selection
1. Feature Extraction and Fusion
2. Dimensionality Reduction
3. Iterative Clustering
Proposed Self-Learning Architecture

0.1 Optimal Electrode Channel Selection

- A first stage dimensionality reduction process which was done using a greedy search algorithm termed **Sequential Forward Selection (SFS)**

Create an empty set: $Y_k = \{\emptyset\}$, $k = 0$.
Select best remaining feature:
$x^+ = \arg \max_{x+ \in Y_k} [J(Y_k + x^+)]$
If $J((Y_k + x^+) > J(Y_k)$
   a. Update $Y_{k+1} = Y_k + x^+$
   b. $k = k + 1$
   c. Go back to step 2.

- From which 10 optimal Electrodes were selected for both EMG(from 32) and EEG(from 64)
Proposed Self-Learning Architecture

1. Automated Feature Extraction and Vector Fusion

- **EMG Bio-signal**
  - Mean Absolute Value: $\frac{1}{N} \sum_{n=1}^{N} |x_n|$
  - Waveform Length: $\sum_{n=2}^{N} |x_n - x_{n-1}|$
  - Zero Crossing: $\sum_{n=1}^{N} \text{sgn}(-x_{i}x_{i+1}) \text{sgn}(x) = \begin{cases} 1, & x > 0 \\ 0, & \text{otherwise} \end{cases}$
  - No. of Slope Sign Changes: $\sum_{n=1}^{N} \text{sgn}(-x_{i}x_{i+1}) \text{sgn}(x) = \begin{cases} 1, & x > 0 \\ 0, & \text{otherwise} \end{cases}$

- **EEG Features**

- **EMG Features**

- **EEG Features**
2. Dimensionality Reduction

Dimensionality Reduction with Principal Component Analysis (PCA)
Associated Steps:
- Mean Centring and Covariance Calculation
- Eigenvalues & Eigenvectors calculation, sorting and truncation
First 2 PC’s were selected which accounted for 95% of the info in the data

https://www.researchgate.net/publication/332536913_Unsupervised_machine_learning_in_atomistic_simulations_between_predictions_and_understanding
Proposed Self-Learning Architecture

3. Iterative Clustering

- Comparison Case Study involved two Unsupervised learning methods; K-Means clustering and Gaussian Mixture Model (GMM)

No. of clusters = No. of hand gestures
Cluster assignment was run 5 times each with the model that produced lowest performance index $J$ selected

$$J = |(Number \ of \ motion \ repetitions \ performed \ * \ Number \ of \ electrode \ channels) - \sum_{i=1}^{n} x_i^k|$$

Where $x_k^i$ is a data point assigned to a specific class $k$
Proposed Self-Learning Architecture

- Flow diagram of Self-Learning process
## Results

For different sensor configurations i.e. EMG only, EEG only and EMG-EEG

|                      | GMM-EMG Only | K-Means-EMG Only | GMM-EEG Only | K-Means-EEG Only | GMM-EMG-EEG | K-Means-EMG-EEG |
|----------------------|--------------|------------------|--------------|------------------|-------------|-----------------|
| **Cluster Model 1**  | 83%          | 81%              | 64%          | 63%              | 68%         | 83%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
| **Cluster Model 2**  | 99%          | 81%              | 64%          | 58%              | 98%         | 83%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
| **Cluster Model 3**  | 99%          | 81%              | 64%          | 58%              | 98%         | 83%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
| **Cluster Model 4**  | 99%          | 81%              | 64%          | 58%              | 98%         | 83%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
| **Clustering Model 5** | 99%      | 81%              | 64%          | 58%              | 70%         | 83%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
| **Hold-Out Test**    | 100%         | 80%              | 90%          | 60%              | 100%        | 80%             |
| **Accuracy**         |              |                  |              |                  |             |                 |
Possible Extension towards Adaptive Control

- **Extension of Self Learning Control towards Adaptive Control**

  - Classifier Re-calibration to adapt to dynamic changes in the signal acquisition chain, which ultimately causes classifier degradation i.e. electrode shifts and physiological changes in stump.

- The Self-learning process for classifier recalibration - thus a form of Adaptive Control, can be initiated in either of two ways:
  * As an interrupt following a series of misclassified motion intents
  * As an interval based re-calibration prompt

https://www.embs.org/tbme/articles/limb-position-tolerant-pattern-recognition-myoelectric-prosthesis-control-adaptive-sparse-representations-extreme-learning/
Conclusion and Further Work

Conclusion

- A 3-phase Self Learning Controller framework has been proposed to help reduce lag-time in the prosthesis controller customization
- The Self Learning Control scheme consists of Feature Extraction Stage, Dimensionality Reduction and Unsupervised Iterative Clustering
- The control architecture can also be extended towards an adaptive framework to minimize classifier degradation due to drifts and uncertainties

Further Work

- Validation of designed control architecture on a wider cohort of Transhumeral amputees
- Further formalisation of the prospect of the adaptive control framework
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