University of Brasilia – FGA/UnB
Biomedical Engineering Graduate Program

Electromyographic Signal Processing Using Machine Learning and Entropy

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Programa de Pós-Graduação em ENGENHARIA BIOMÉDICA

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LUIZ JOSÉ LUCAS BARBOSA

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Suppose that we were asked to arrange the following in two categories — distance, mass, electric force, entropy, beauty, melody. I think there are the strongest grounds for placing entropy alongside beauty and melody, and not with the first three.

Eddington A, The Nature of the Physical World, 1928

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Resumo Estendido

O sinal eletromiográfico é utilizado em diversas áreas da Medicina e da Biologia, e tem sido uma opção cada vez mais explorada para o controle de próteses robóticas. Atualmente, diversas próteses comerciais de mão utilizam uma malha de controle sequencial, o que torna o movimento da prótese pouco fluido e dependente de sensores externos para execução de movimentos. No presente trabalho, foram desenvolvidos estudos de métodos para o uso sinal da eletromiografia de superfície (sEMG) no controle em tempo real de uma prótese de mão. O objetivo foi utilizar métodos de extração de características e classificação de padrões em sEMG, e o treinamento adaptativo para o reconhecimento de movimentos da mão com vários graus de liberdade, aumentando, assim, o conforto do usuário e dando naturalidade ao movimento. Os métodos propostos permitiram o reconhecimento efetivo de movimentos da mão, por meio de várias estratégias que permitiram a simplificação do processo de reconhecimento e a diminuição da janela móvel que é usualmente aplicada ao sEMG. Os classificadores foram desenvolvidos e testados com o uso das bases de dados disponíveis na plataforma *Open Source* BioPatRec [25]. A linguagem utilizada para os algoritmo foi o python, com o auxilio das bibliotecas Scikit-learn [28], ScyPy [40] e Tensorflow [1]. Diversos indicadores estatísticos, foram aplicados para avaliar o reconhecimento de padrões, de modo *off-line* e *on-line*, e os resultados demonstraram melhoria significativa no processo de reconhecimento em tempo real dos padrões, sugerindo que os métodos têm bom potencial para o uso futuro em próteses robóticas.

Palavras-chave: sinal eletromiográfico de superfície, prótese de mão, reconhecimento de padrões, redes neurais, entropia.

1 Introdução

Segundo o IBGE [17], no Brasil, 13,2 milhões de pessoas se declararam portadoras de algum tipo de deficiência motora, sendo que 470 mil foram vítimas de amputações. Uma amputação de mão é uma das lesões mais prejudiciais e pode afetar dramaticamente as capacidades de uma pessoa. Estima-se ainda, segundo o IBGE, que a incidência média anual de amputações seja de 13,9 por 100 mil habitantes. Além disso, segundo dados do Ministério da Saúde [24], o total de nascidos vivos no Brasil no ano de 2015 foi de 3.017.668 e, sabe-se que, de 1 a 2% deles sofrem de alguma anomalia congênita e destes, aproximadamente 10% possuem deformidades dos membros superiores [24, 24, 23].

Houve grandes avanços nas interfaces homem-máquina, na qual os sinais biomédicos, como os sinais mioelétricos, desempenham um papel fundamental. O controle utilizando o sinal mioelétricos é uma técnica avançada, subdividida em detecção, processamento, classificação e aplicação de sinais EMG para controlar robôs ou dispositivos de reabilitação humana. Os sinais mioelétricos são muito ricos em informações, a partir das quais a intenção de movimento do usuário em forma de contração muscular pode ser detectada, usando eletrodos de superfície. O sinal da eletromiografia de superfície é detectado de forma não invasiva a partir da superfície da pele e pode ser adaptado para força proporcional ou controle de velocidade em um esquema de controle.

Os sinais de eletromiografia possuem característica não estacionária, que dificulta a aplicação de reconhecimento de padrões mioelétricos para o controle de próteses. Na literatura, o reconhecimento de padrões eletromiográficos, quando se utiliza aprendizagem de máquina, é separado em duas etapas - uma de treinamento e outra de teste. Porém, nessa análise não são consideradas as mudanças entre o treinamento e os dados de teste induzidos por mudança de eletrodo, fadiga muscular, mudanças de impedância ou fatores psicológicos, que muitas vezes resulta em queda do desempenho [33] em virtude dos algoritmos não conseguirem generalizar os resultados. Para solucionar esse problema, vários estudos sobre treinamento adaptativo vem sendo feitos [2, 10, 18, 33, 39, 43] a fim de aprimorar o desempenho da análise do sinal sEMG.

Como os dados do sinal EMG são adquiridos em um curto período de duração, os parâmetros coletados contêm informações limitadas, que não representam todo o período de utilização da prótese. Ampliar o tempo de coleta de dados se torna impraticável, pois adicionaria uma carga muito grande ao usuário. Os sistemas de próteses que utilizam controle de reconhecimento de padrões mioelétricos não são comercializados por possuírem desempenho insatisfatório [29], justamente por causa das variações dos dados de teste em relação aos do treinamento. Portanto, torna-se necessário desenvolver um sistema de aprendizado que consiga se adaptar e contabilize as mudanças do sinal do EMG. Mais especificamente, para que a prótese se torne o mais natural possível, é necessário que se faça uma reconfiguração gradual do classificador de forma online, levando em consideração as mudanças em tempo real do sinal EMG.

A utilização de informações a priori pode facilitar a classificação, pois limita as classes que podem ser executadas ou confere maior probabilidade a alguns movimentos e diminuem a de outros movimentos. Neste estudo a obtenção de informação sobre o sinal foi dividido em três partes, A primeira é o pré-processamento e a extração de características, que são explicados no capítulo III. A segunda parte corresponde a um detector de movimento, onde um autoencoder é utilizado para determinar o exato instante em que o paciente começa a se movimentar, que é detalhado no capítulo IV. Finalmente, no capítulo V o sinal é dividido em grupos por similaridade e, por meio de uma máquina de estados, o total de movimentos possíveis é reduzido no classificador final.

As principais empresas que comercializam próteses, no mundo, são a Touch Bionics, Otto Bock, Steeper e Vicent GmbH. Todas as próteses fabricadas por elas possuem um controle sequêncial, sendo que algumas delas possuem sensores para auxiliar a movimentação da prótese ou movimentos já predefinidos [14]. Isso demonstra que o caminho para o controle natural ainda é longo, o que limita a usabilidade da prótese como apenas um membro de apoio. O controle simultâneo visa dar naturalidade ao movimento da prótese, diminuindo o seu desconforto que, pode levar ao abandono do uso da mão biônica [6, 23].

2 Importância da Informação no Sinal EMG

A busca e processamento de informações são processos cognitivos complexos que exigem a identificação, extração e organização da informação relevante. Porém, com a evolução da computação em nuvem, técnicas de classificação embasadas em Deep Learning cresceram muito, uma vez que elas vêm desempenhando melhor do que técnicas convencionais de Machine Learning. Esse aumento no uso de técnicas de Deep Learning faz com que, em diversas aplicações, sobretudo quando o volume de dados de treinamento é comparativamente grande [3], não seja necessário entender o problema ou realizar uma modelagem matemática rigorosa.

Essa abordagem gera um problema; como não houve um aprendizado do processo, o resultado fica dependendo da rede neural e do que ela foi treinada a fazer. Outro problema é que o conhecimento ganho não ser aplicável. Além disso, uma vez que modelos de deep learning são aplicados como uma caixa preta por conta de sua estrutura não linear, diversos estudos são realizados para tentar explicar o seu processo de classificação [22, 14].

Em 1948, Claude Shannon publicou um artigo chamado Teoria Matemática da Comunicação [7]. Neste artigo, Shannon descreve como a informação pode ser comunicada por diferentes elementos de um sistema. Nele, Shannon mostra como sinais e ruídos se relacionam, como o ruído adiciona uma taxa de erro ao canal. Portanto, a habilidade de separá-los para extrair informação dos dados é crucial para o processo de comunicação.

A informação é normalmente medida em bits. Um bit de informação permite a escolha de duas alternativas possíveis. Como exemplo, temos o lançamento de uma moeda, ao se revelar o resultado, é gerado um bit de informação.

A teoria da informação tem os seus próprios conjuntos de termos. Uma mensagem é o uma sequência ordenada de símbolos. Uma mensagem composta por símbolos $\mathbf{s} = (s_1, ..., s_n)$ é codificada por uma função $\mathbf{c} = f(\mathbf{s})$ em uma sequência de códigos $\mathbf{c} = (c_1, ..., c_m)$, onde o número de símbolos ou códigos não são necessariamente iguais. Esses códigos são transmitidos por um canal de comunicação para produzir saídas $\mathbf{y} = (y_1, ..., y_k)$, que são decodificadas para reconstruir a mensagem $\mathbf{s}$.

3 Introdução à Entropia

Ainda segundo Shannon [37], para que as definições matemáticas da informação sejam úteis, elas precisam obedecer às seguintes propriedades:

1. **Continuidade:** A quantidade de informação associada a um resultado aumenta ou diminui continuamente, de acordo com a mudança da probabilidade do resultado.

2. **Simetria:** O total de informação associado em uma sequência de resultados não depende da ordem em que os resultados acontecem.

3. **Valor máximo:** O total de informação com um conjunto de resultados não pode aumentar se esses resultados são igualmente prováveis.

4. **Adição:** A informação associada a um conjunto de resultados é obtida pela adição das informações dos resultados individuais.

Surpresa e Entropia

Quanto mais improvável é um resultado, maiior é a surpresa com a sua observação. Então, a quantidade de surpresa associada a um resultado aumenta caso a probabilidade do resultado diminua. Então, para satisfazer a condição de aditividade, Shannon utilizou o logaritmo de $1/p(x)$. Este parâmetro é conhecido como informação de Shannon de x, ou seja, a informação de Shannon é uma medida da surpresa. A surpresa média de uma variável X, com uma distribuição $p(X)$ é chamada entropia de $p(X)$, e é representada por $H(X)$, cuja expressão é apresentada na equação 1.

$$H(X) = -\sum_{i=1}^{n} P(x_i)log(P(x_i)) \tag{1}$$

Basicamente, entropia é a medida de incerteza. Quando a incerteza é reduzida, informação é ganha. Portanto, se a incerteza de uma variável X é resumida por sua entropia $H(X)$, se o valor de X for revelado, o total de informação ganha é, na média, exatamente igual à entropia.

Caso hajam valores consecutivos e relacionados, então eles não fornecem informação independente. Nesse caso, a sequência possui menor entropia do que o somatório das entropias individuais calculados com a equação 1. Assim, o teorema de Shannon não se aplica apenas a sequências de elementos independentes, mas também para sequências estruturadas que possuem dependências entre os seus elementos.

4 Entropia e o sinal sEMG

O sinal sEMG, assim como todos os sinais fisiológicos, é um sinal diluído, isto é, um sinal que possui muitos dados e pouca informação. Ademais, ele é um sinal em que cada sequência de amostragem possui alto grau dependência entre seus valores.

Problemas do Processamento em tempo real

Como uma boa experiência em prótese precisa de respostas rápidas, o processamento em tempo real é essencial. Radhika Menon, et al [31] mostra o impacto do tamanho da janela temporal no erro da classificação do sinal sEMG. Segundo esse estudo, quando se tem janelas muito pequenas (em média menores do que 200 ms) o erro da classificação aumenta, uma vez que o total de informação na janela diminui. Isso dificulta muito o processamento em tempo real que precisa de janelas, em 2011 Peerdeman [29] constatou que a janela de processamento precisa ser menor do que 300 ms ou o atraso se torna inaceitável para o usuário. Instintivamente nota-se a necessidade da diminuição da janela de tempo de processamento para o aumento do conforto do usuário.

Uma das dificuldades na classificação do sinal geradas pelo tamanho reduzido da janela temporal foi identificar exatamente onde o movimento começou. Isso ocorre devido às características estocásticas do sinal, quando as unidades motoras começam a ser recrutadas, o sinal de repouso e movimento é confundido.

5 Metodologia

A utilização de técnicas de reconhecimento de padrões é de grande importância para o controle de próteses mioelétricas, trazendo uma melhora nos graus de liberdade e movimentação das mesmas além da capacidade de seu controle sequêncial [13]. Tal controle consiste tipicamente na extração de características do sinal e na classificação destas características de dados segmentados no processamento de sinal para comando de um atuador. A qualidade da movimentação dessas próteses é proporcional aos processos de extração das características do sinal mioelétrico e da classificação dos padrões.

Conforme já mencionado, a maioria dos sistemas de controle empregados em mãos prostéticas é o controle sequêncial, mas, recentemente, muitas pesquisas estão sendo conduzidas para empregar o controle simultâneo [5, 11, 31, 44]. Uma das principais vantagens do controle simultâneo da prótese é aproximar a movimentação da prótese ao movimento fisiológico natural, porem isso leva a um aumento das características necessárias para se classificar o sinal, além da interferência do sinal de músculos adjacentes nos eletrodos de captura do sEMG.

Clusterização, máquina de estados e a classificação do movimento

No século XVI, Shakespeare, em suas peças, introduziu mais de 1700 de palavras ao idioma inglês. Transformou substantivos em verbos, ou verbos em adjetivos, ou conectou palavras nunca antes usadas em conjunto, misturando prefixos e sufixos criou palavras totalmente novas. Assim como o inglês consiste de sequências de letras não independentes que podem ser eficientemente codificadas como blocos independentes de sub-sequências, assim também pode ser feito como a maioria dos sinais naturais, como música, imagem, DNA, ou o EMG.

Para a classificação do sinal EMG foi realizado um janelamento no sinal, cada janela com 10ms. Após este janelamento foi realizado as seguintes etapas:

1. Seleção de características: nesta etapa diversos características, tanto no domínio da frequência quanto no domínio do tempo serão extraídas;

2. Redução de dimensionalidade: nesta etapa diversos algoritimos de redução de dimensionalidade foram avaliados para a criação de clusters de sinais de movimentos parecidos. Foram avaliados: NCA (Neighborhood Component Analysis), PCA (Principal Component Analysis), LDA (Linear Discriminant Analysis), Variational Autoencoders.

3. Clusterização do sinal: após avaliação de diversos algorítimos de de clusterização, os movimentos foram agrupados em grupos de acordo com a similaridade das características extraídas.

4. Comparação com os possíveis movimentos: após o cluster ser criado, os movimentos são comparados com os possíveis movimentos para determinada posição. Esses movimentos foram extraídos através de um processo chamado de Árvore de Decisão ou Máquina de Estados [27].

5. Classificação do sinal: com a redução das possíveis classes de movimento em intercessão com os clusters criados, diversos classificadores são criados com subconjuntos das classes totais de movimentos.

Cada janela de tempo retorna, como resposta para os possíveis movimentos, o cluster no qual o movimento pertence e a possível classificação. Essas respostas podem ser consideradas letras em uma sentença. Cada janela retorna uma sequência dependente da sequência anterior e onde, a cada uma das janelas diminui a entropia do sinal como um todo.

Para diferenciar os estados de repouso e movimento, foi utilizado um autoencoder variacional. Devido a suas características intrínsecas, ele é especializado em separar classes (movimento e repouso) em sua camada latente. Após essa separação, uma perceptron simples, foi o suficiente para classificar esses estados. Esse resultado só foi possível graças à redução de classes do classificador, que em vez de trabalhar com as 27 classes presentes no banco de dados, classificava apenas um subgrupo dessas classes.

Extraindo informação do sinal

Para extrairmos informação da eletromiografia de superfície, foi utilizada uma técnica conhecida como extração de características. O sinal foi dividido em janelas de 50 ms, onde o sinal sEMG é analisados e as características no domínio da frequência são extraídas, seguindo os principais recursos selecionados e finalmente, a rede neural classifica o movimento.

As características extraídas são:

1. Momento Espectral (Spectral Moment);
2. Amostra da Entropia (Sample Entropy);
3. KhushabaSet;
4. Comprimento de Onda (Wavelenght frequency);
5. Média da Frequência (Mean Frequency);
6. Mediana da Frequência (Median Frequency).

Dataset

No total, a base de dados utilizada possui apenas 17 pacientes e 3 repetições de cada movimento, o que impossibilitou o uso de algumas técnicas de treinamento. Com um banco de dados suficientemente grande e, uma vez criado um classificador redundante, como no caso do estudo, as diversas etapas da classificação podem ser usadas como um código e, com uma rede neural maior, e os valores das janelas de classificação podem ser previstos usando técnicas como LSTM. A relação de dependências entre as janelas de tempo também pode ser estudada para se obter um classificador melhor projetado.

6 Resultados e Discussões

Desde que as próteses mioelétricas foram desenvolvidas, o número de usuários que a rejeitam permaneceu constante [6, 23, 9], O que mostra que não houve avanço significativo neste ponto dessa área. A redução da janela de tempo para a classificação do sinal EMG permitirá que o controle da prótese seja realizado de forma mais fluida pelo usuário, aumentando seu conforto ao utilizá-la.

Com o processo de diminuição de classes para o classificador final, proposto neste estudo, foi possível uma diminuir a janela temporal de 200 ms para 10 ms mantendo o desempenho da classificação final. Outro fator muito importante gerado pela diminuição da janela de tempo foi a diminuição da complexidade da avaliação, o que resulta em economia de energia durante o processo de classificação, o que, por sua vez, aumentaria o tempo de uso da prótese, reduzindo o tempo de recargas que o usuário precisaria fazer.

Além disso, o processamento desenvolvido neste estudo pode ser usado para a classificação de outros sinais naturais que, à medida que são diluídos (muitos dados para pouca informação), são mais difíceis de classificar.

7 Conclusão

Ao fornecer informações a priori para classificação de sinais interativamente, o número de classes possíveis para classificação de sinais diminui bastante. Criar etapas de validação menos complexas também aumentou a precisão, permitindo a redução do tamanho da janela.

As técnicas apresentadas aqui apenas arranham a superfície das aplicações em que a entropia de formações pode e deve ser usada. A ideia principal é que uma sequência de redes simples cuja descrição precise de um pequeno número de bits e tenha maior probabilidade de fazer generalizações corretas do que uma rede mais complexa, porque presumivelmente extraiu a essência dos dados e removeu a redundância. Portanto, fornecer ferramentas que simplifiquem ou forneçam informações de dados é muito importante.

Infelizmente, a coleta de dados do sinal EMG pode ser estressante para o paciente. Portanto, é muito difícil obter grandes bancos de dados de sinais biológicos. Por esse motivo, este estudo foi realizado usando apenas um banco de dados, fornecido junto com a plataforma BioPatRec. Além disso, o banco de dados utilizado possui poucas repetições de movimento, o que dificulta o treinamento com algoritmos de aprendizado de máquina.

Lista de Referências

[1] Martín Abadi e et al. TensorFlow : A System for Large-Scale Machine Learning This paper is included in the Proceedings of the TensorFlow : A system for large-scale machine learning. 2016.

[2] Sebastian Amsuss, Peter M. Goebel, Ning Jiang, Bernhard Graimann, Liliana Paredes, e Dario Farina. Self-correcting pattern recognition system of surface EMG signals for upper limb prosthesis control. *IEEE Transactions on Biomedical Engineering*, 61(4):1167–1176, 2014.

[3] Jayme Barbedo. Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. *Computers and Electronics in Agriculture*, 153:46–53, 2018.

[4] Daniel A. Bennett e Michael Goldfarb. IMU-Based Wrist Rotation Control of a Transradial Myoelectric Prosthesis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2017.

[5] Stephen F. Burrough Brook e Judith A. Patterns of Acceptance and Rejection of Upper Limb Prostheses, 1985.

[6] C.E. Shannon , vol. 27, pp. , July, October,. A Mathematical Theory of Communication. *Bell System Technical Journal*, 27(April 1928):379–423,623–656, 1948.

[7] C.P. Diehl e G. Cauwenberghs. Svm incremental learning, adaptation and optimization. *Proceedings of the International Joint Conference on Neural Networks, 2003.*, 4(x):2685–2690.

[8] Strahinja Dosen, Marko Markovic, Kelef Somer, Bernhard Graimann, e Dario Farina. EMG Biofeedback for online predictive control of grasping force in a myoelectric prosthesis. *Journal of NeuroEngineering and Rehabilitation*, 2015.

[9] Biddiss EA e Chau TT.

[10] Kevin B. Englehart e Bernard Hudgins. A robust, real-time control scheme for multifunction myoelectric control. *IEEE Trans. Biomed. Eng.*, 50(7):848–854, 2003.

[11] Purushothaman Geethanjali. Myoelectric control of prosthetic hands: State-of-the-art review, 2016.

[12] IBGE. CENSO de 2010, Link: https://censo2010.ibge.gov.br/noticias-censo.html - Accessed on: Jun. 20 of 2019.

[13] Sarthak Jain, Girish Singhal, Ryan J. Smith, Rahul Kaliki, e Nitish Thakor. Improving long term myoelectric decoding, using an adaptive classifier with label correction. *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, páginas 532–537, 2012.

[14] Devinder Kumar, Graham W. Taylor, e Alexander Wong. Opening the black box of financial AI with clear-trade: A class-enhanced attentive response approach for explaining and visualizing deep learning-driven stock market prediction. *CoRR*, abs/1709.01574, 2017.

[15] McFarland. Unilateral upper-limb loss: Satisfaction and prosthetic-device use in veterans and servicemembers from Vietnam and OIF/OEF conflicts, 2010.

[16] Ministério da Saúde. Dados de nascidos vivos, Link: http://tabnet.datasus.gov.br/ - Accessed on: Jun. 20 of 2019.

[17] Max Ortiz-Catalan, Rickard Brånemark, e Bo Håkansson. BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms. *Source Code for Biology and Medicine*, 2013.

[18] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, e E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[19] Bart Peerdeman, Daphne Boere, Heidi Witteveen, Rianne Huis in 'tVeld, Hermie Hermens, Stefano Stramigioli, Hans Rietman, Peter Veltink, e Sarthak Misra. Myoelectric forearm prostheses: State of the art from a user-centered perspective. *The Journal of Rehabilitation Research and Development*, 48(6):719, 2011.

[20] IEEE Radhika Menon, Student Member, IEEE, Gaetano Di Caterina, Heba Lakany, Member, IEEE, Lykourgos Petropoulakis, Bernard A. Conway, John J. Soraghan, Senior Member. Study on interaction between temporal and spatial information in classification of EMG signals for myoelectric prostheses.

[21] Aidan D. Roche, Hubertus Rehbaum, Dario Farina, e Oskar C. Aszmann. Prosthetic Myoelectric Control Strategies: A Clinical Perspective. *Current Surgery Reports*, 2(3):44, 2014.

[22] Wojciech Samek, Thomas Wiegand, e Klaus-Robert Müller. Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models. *CoRR*, abs/1708.08296, 2017.

[23] 1. Kozin SH. Congenital disorders: classification and diagnosis. *Lippincott Williams & Williams*, páginas 1405–23, 2004.

[24] 3. Kozin SH. Upper-extremity congenital anomalies. *J Bone Joint Surg Am*, páginas 1564–76, 2003.

[25] Claude Elwood Shannon. *The Mathematical Theory of Communication by CE Shannon and W. Weaver*. 1949.

[26] Tatiana Tommasi, Francesco Orabona, Claudio Castellini, e Barbara Caputo. Improving control of dexterous hand prostheses using adaptive learning. *IEEE Transactions on Robotics*, 29(1):207–219, 2013.

[27] John J. Villarejo, Regina M. Costa, Teodiano Bastos, e Anselmo Frizera. Identification of low level sEMG signals for individual finger prosthesis. In *ISSNIP Biosignals and Biorobotics Conference, BRC*, 2014.

[28] Pauli Virtanen e et al. SciPy 1.0–Fundamental Algorithms for Scientific Computing in Python. *arXiv e-prints*, page arXiv:1907.10121, Jul 2019.

[29] Wu Yi Yang, Sheng Xing Liu, Tai Song Jin, e Xiao Mei Xu. An optimization criterion for generalized marginal Fisher analysis on undersampled problems. *International Journal of Automation and Computing*, 8(2):193–200, 2011.

[30] Aaron J. Young, Lauren H. Smith, Elliott J. Rouse, e Levi J. Hargrove. Classification of simultaneous movements using surface EMG pattern recognition. *IEEE Transactions on Biomedical Engineering*, 2013.

Abstract

The electromyographic signal is used in several areas of Medicine and Biology and has been an option increasingly explored to control robotic prostheses. Nowadays, several commercial hand-held prostheses use a sequential control mesh, which makes the prosthesis movement not so fluid and dependent on external sensors to execute movements. This work aimed to develop methods that use surface electromyography signals (sEMG) to enhance hand prostheses' real-time control. The objective was to use methods to extract characteristics, classify patterns in sEMG, and employ adaptive training to recognize hand movements with varying degrees of freedom, thus increasing user comfort and giving naturalness to movement. The proposed methods allowed the effective recognition of hand movements through various strategies that allowed simplifying the recognition process and reduced the usual moving window length in the processing of the sEMG. The classifiers were developed and tested using the databases available on the Open Source BioPatRec [25] platform; the language used for the algorithms was python, with the Scikit-learn [28], ScyPy [40] and Tensorflow [1] libraries' aid. Several statistical indicators have been applied to assess pattern recognition, both offline and online, and the results have shown significant improvement in the process of real-time pattern recognition, suggesting that the methods have good potential for future use in robotic prostheses.

Keywords: surface electromyographic signal, hand prosthesis, pattern recognition, neural networks, entropy.

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List of Nomenclatures and Abbreviations

3xCEPS First Three Cepstral Coefficients

AR Autoregressive Model

ASM Absolute value of the Summation of the expth root

ASS Absolute value of the Summation of the Square root

DWT Discrete Wavelet Transform

IBGE Instituto Brasileiro de Geografia e Estatística

EMG Electromyography

ER Entropy Representation

GMM Gaussian Misture Model

HCA Hierarchical Agglomerative Clustering

KNN K Nearest Neighbors

LDA Linear Discriminant Analysis

LSTM Long Short Time Memory

MAV Mean Absolute Value

MICI Maximal Information Compression Index

MLP Multi-Layer Perceptron

MSR Absolute value of the Summation of the The Mean

NCA Neighborhood Components Analysis

PCA Principal Component Analisys

PDF Probability Density Function

RMS Root Mean Square

sEMG Superfice Electromyography

SM Spectral Moment

SE Sample Entropy

SSC Signal Slope Change

UFS Unsupervised Feature Selection

VAE Variational Autoencoder

WFL Waveform Length

WL Wave Length

WNN Wavelet Neuro Network

ZC Zero Crossing

1 Introduction

According to the Brazilian Institute of Geography and Statistics (in Portuguese Instituto Brasileiro de Geografia e Estatística (IBGE)) [17], in Brazil, 13.2 million people declared themselves to have some type of motor deficiency, and 470,000 were victims of amputations. A hand amputation is one of the most harmful injuries and can dramatically affect a person's abilities. It is also estimated, according to IBGE, that the average annual incidence of amputations is 13.9 per 100,000 inhabitants. Besides, according to data from the Ministry of Health [24], the total number of live births in Brazil in 2015 was 3,017,668 and, it is known that from 1 to 2% of them suffer from some congenital anomaly and of these, approximately 10% have deformities of the upper limbs [24, 24, 23].

There have been great advances in man-machine interfaces, in which biomedical signals, such as myoelectric signals, play a key role. Control using the myoelectric signal is an advanced technique, subdivided into detection, processing, classification, and application of EMG signals to control human robots or rehabilitation devices. The myoelectric signals are very rich in information, from which the user's intention to move in the form of muscle contraction can be detected using surface electrodes. The surface electromyography signal is detected noninvasively from the skin surface and can be adapted for proportional force or speed control in a control scheme.

The electromyography signals have a non-stationary property, making it difficult to apply the recognition of myoelectrical patterns to control prostheses. In the literature, EMG pattern recognition is separated into two separate steps: training and test. However, the changes that happen during training, such as variation in electrode behavior, muscle fatigue, impedance changes, and psychological factors, are not considered, which often results in a drop in performance [33]. To develop methods that can take these variations into account, we performed several studies on adaptive training [2, 10, 18, 33, 39, 43].

Because EMG signal data are acquired in a short period of duration, the parameters collected contain limited information, which does not represent the entire period of use of the prosthesis. Extending data collection time becomes impractical because it would add a very large load to the user. Prosthesis systems that use myoelectric pattern recognition control are not marketed because they have unsatisfactory performance [29], precisely because of variations in test data compared to those of training. Therefore, it is necessary to develop a learning system that can adapt and account for EMG signal changes. More specifically, for the prosthesis to become as natural as possible, it is necessary to make a gradual reconfiguration of the classifier online, taking into account the real-time changes in the EMG signal.

The main companies that sell prostheses, in the world, are Touch Bionics, Otto Bock, Steeper, and Vicent GmbH. All prostheses manufactured by them have a sequential control, some of which have sensors to help drive the prosthesis or movements already predefined [14]; an example of such prosthesis, manufactured by Touch Bionics, is shown in figure 1.1. This information demonstrates that the path to natural control is still long, limiting the prosthesis's usability to only one support member. Simultaneous control aims to give naturalness to the prosthesis movement, reducing its discomfort, which is an element that can lead to the abandonment of the bionic hand [6, 23].

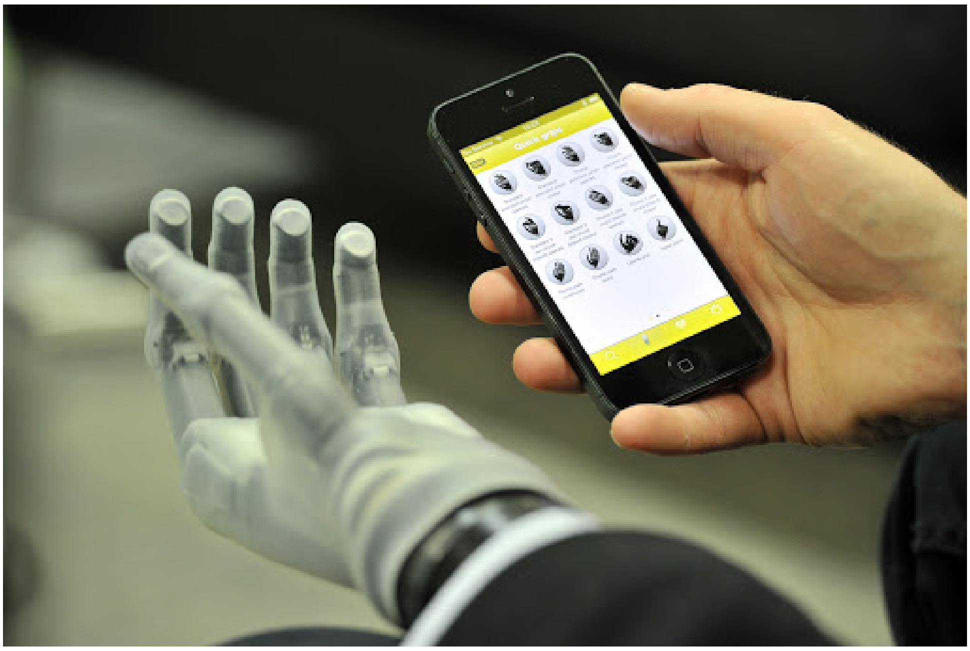

Figure 1.1. The i-limb line of hands was developed by Touch Bionics. Its proposal for easy adaptability and versatility offers great comfort for users, offering a range of commands that can be changed in a companion application. Font: Extremetech.[1]

1.1 Importance of Information in EMG Signal

The search and processing of information is a complex cognitive process that requires the identification of extraction and organization of relevant information. However, with the evolution of cloud computing, deep learning-based classification techniques have grown significantly, as they performing better than conventional Machine Learning techniques. This increase in the use of Deep Learning techniques often makes it unnecessary to understand the problem or delimit its edges.

This approach creates a problem, as there was no learning from the process. The knowledge of how to solve the problem is still insufficient, and the result is dependent on the neural network, which is usually trained to perform only one specific task. This dependency may creates the need for training new networks as complex as the primary one to solve similar problems.

In 1948, Claude Shannon published an article titled Mathematical Theory of Communication [7]. In this article, Shannon describes how different elements of a system can exchange information, showing how signals and noise relate, and how noise adds an error rate to the channel. Therefore the ability to separate these two elements is crucial to the communication process.

Information is usually measured in bits. A bit is an information element that can assume only two possible states; for example, "true" or "false" or "0" or "1".

The information theory has its own sets of terms. A message is an orderly sequence of symbols. A message composed of symbols $\mathbf{s} = (s_1, ..., s_n)$ is encoded by a function $\mathbf{c} = f(\mathbf{s})$ in a sequence of codes $\mathbf{c} = (c_1, ..., c_m)$, where the number of symbols or codes are not necessarily the same. These codes are transmitted over a communication channel to produce outputs $\mathbf{y} = (y_1, ..., y_k)$ that are decoded to rebuild the message $\mathbf{s}$.

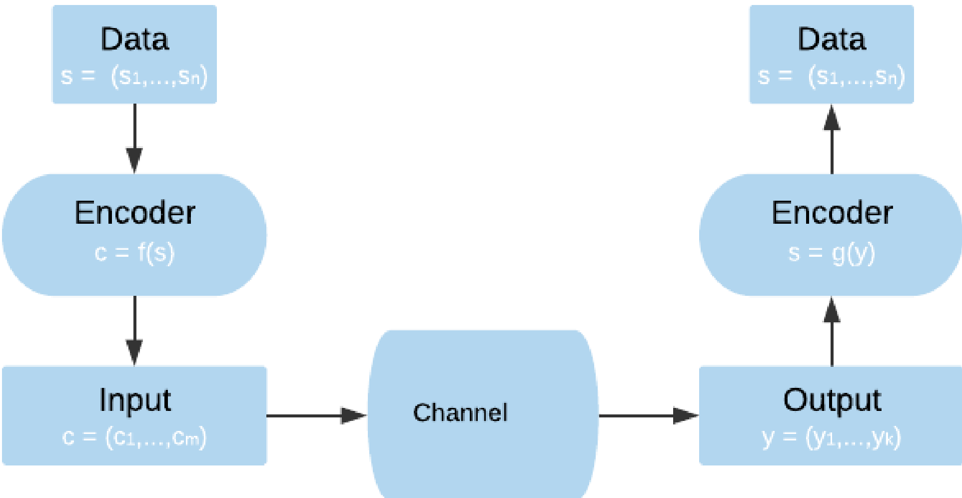

Figure 1.2. Discrete noiseless channel. The data from a source is encoded and transmitted through a communication channel. On other side, a receiver decodes the codeword and recovers the original message.

1.2 Introduction to Entropy

Also according to Shannon [37], For mathematical definitions of information to be useful, they must obey the following properties:

1. **Continuity:** The total information associated with a result increases or decrements continuously, according to the change in the result's probability.

2. **Symmetry:** The total information associated with a sequence of results does not depend on the order in which the results happen.

3. **Maximum value:** The total information with a result set cannot increase if these results are equally likely.

4. **Addition:** The information associated with a result set is obtained by adding individual results' information.

1.2.1 Surprise and Entropy

The more improbable the result, the greater the surprise with your observation. Then the total surprise associated with a result increases if the probability of the result decreases. Then, to satisfy the condition of additivity, Shannon used the logarithm of $1/p(x)$. This is known as Shannon information of x, i.e. Shannon information is a measure of surprise. The average surprise of a variable X, with a distribution $p(X)$, is called entropy of $p(X)$ and is represented by $H(X)$.

$$H(X) = \sum_{i=1}^{n} P(x_i)log(P(x_i)) \tag{1.1}$$

Basically, entropy is the measure of uncertainty. When uncertainty is reduced, information is gained. Therefore, if the uncertainty of a variable X is summarized by its entropy $H(X)$, if the value of X is revealed, the total information gains are, on average, exactly equal to the entropy.

If there are consecutive and related values, then they do not provide independent information. In this case, the sequence has less entropy than the sum of the individual entropy calculated with the Equation 1.1. Thus, Shannon's theorem applies not only to independent element sequences but also to structured sequences with dependencies between their elements.

1.3 Entropy and sEMG

The sEMG signal, like all physiological signals, is a diluted signal, i. e., a signal that has a high amount of data and little information. Moreover, it is a sign in which each sampling sequence has a high degree of dependence between its values.

Figure 1.3 exemplifies the sEMG signal measured on the forearm during a closing hand movement. The movement was repeated three times, for three seconds, with a three-second interval between the movements. As we can see from the figure, the three repetitions led to different patterns in the graph.

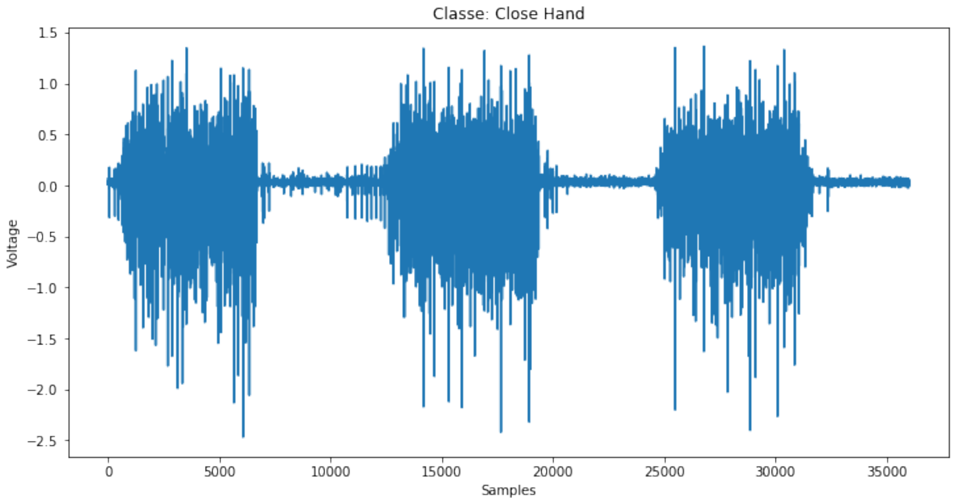

Figure 1.3. The sEMG signal, the vertical axis represents the amplitude and the horizontal axis represents the samples.

This behavior occurs because, in each contraction, different motor units are recruited, generating the corresponding sEMG signal. Other factors that may alter the measurement are sweat, muscle fatigue, and the sensors' displacement. One way to mitigate these effects is to acquire information a priori. Where each piece of information extracted facilitates the future classification of the signal.

With the use of a finite state machine, the possible movements, given a posture for the hand, were mapped and the intersection with the cluster generated a list of possible movements, greatly facilitating the classification of the EMG signal.

1.3.1 Real-time processing problems

Menon, et al [31] showed temporal window size's impact on the signal classification error for the sEMG. According to this study with very small windows (on average less than 200 ms) the classification error increase, since the total information in the window decreases. This characteristic makes it very difficult perform real-time processing with the windows. In 2011 Peerdeman [29] found that to allow for real-time processing of the sEMG signal so that the results be useful for effectively actuating a controlled prosthesis, the processing window needs to be less than 300 ms or the delay becomes unacceptable to the user. Instinctively, it is reasonable for one to expect the need for a decrease in processing time to increase user comfort.

A serious hassle caused by the decrease in the time window is the difficulty in defining the end of rest and the beginning of a movement. To overcome this problem, in this study, a clustering algorithms have been used as a way to get more information about the signal. A Neighborhood Components Analysis (NCA) algorithm has been used to reduce the dimensionality of the extracted characteristics and a hierarchical clustering algorithm grouped the closest movements.

The solution to this problem once again presented itself with a decrease in the entropy of the signal. An auto-encoder algorithm was also used for anomaly analysis by clustering the signal at rest and the motion and then, a simple perceptron classified the result.

1.3.2 Extracting signal information

In order to extract information from surface electromyography, a technique known as characteristic extraction was used. The signal was divided into windows of 50 ms, where the sEMG signal is analyzed and frequency-based characteristics are extracted, following the main selected resources and finally, the neural network classifies movement.

The extracted characteristics are:

1. Spectral Moment (Spectral Moment (SM));
2. Sample Entropy (Sample Entropy (SE));
3. KhushabaSet;
4. Wave Lenght (WL) Frequency);
5. Mean Frequency;
6. Median Frequency.

1.4 Objective

1.4.1 Main Objective

To develop an algorithm for a robotic prosthesis using the latest state of the art technologies art of myoelectric prostheses, from a proportional and simultaneous control, which allow posture recognition of the hand joints.

1.4.2 Specific Objective

When obtaining the maximum information from the myoelectric signal, the dimension of the problem is better understood, and with that its classification becomes as efficient as possible.

The objective is to use methods of extracting characteristics and classification of patterns in electromyographic signals, as well as adaptive training for the recognition of hand movements with varying degrees of freedom, thus increasing the comfort of the user and giving naturalness to movement. Through these methods, a significant improvement was achieved in the pattern recognition process.

2 Study and Proposals Overview

2.1 Introduction

Pattern recognition with the processing of myoelectric signals has been the research basis for prosthesis control in the last decade [25]. Also, the use of machines has been disseminated in the EMG signal analysis tasks, to aid in selecting of characteristics and performing classification of this signal [12, 16, 20, 22]. The project also aims to use adaptive training so that new paradigms can be created and the techniques and methods for the analysis of the myoelectric signal can be improved.

Pattern recognition techniques are of great importance for controlling myoelectric prostheses, bringing an improvement in the degrees of freedom and their movement beyond the capacity of achievable by sequential control [13]. Such control typically consists of extracting characteristics of the signal and categorizing these characteristics of segmented data in the processing signal to control an actuator. The quality of the movements of these prostheses depends directly on their ability to extract the characteristics of the myoelectric signal and to identify the intended movements.

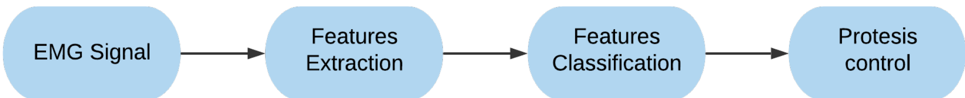

Figure 2.1. A typical flow chart used for sEMG controlled prosthese protesis.

As already mentioned, most control systems employed in prosthetic hands use sequential control but, recently, a great deal of research is being conducted to employ simultaneous control [5, 11, 31, 44]. One of the main advantages of simultaneous control of a prosthesis is that it may yield prosthesis movements that resemble normal physiological movements. However, this choice leads to an increase in the system's complexity, since it has to capture, process, and classify the signal. Additionally, the system has to deal with the interference of the sEMG signals from adjacent muscles. Moreover, there is a need for simultaneous control demanding the combined execution of several movements, such as, for example, closing and flexing the hand at the same time.

The purpose of this study takes into account the arrangement of several simple net-

Table 2.1. State of the art table of sEMG signal analysis.

Reference	Class	Channel	Features	Classifier
(Huang et al. 2005)	6 classes of movement	4 channels	Gaussian Misture Model (GMM)	GMM and Majority Vote
(Khezri and Jahed 2011)	6 classes of movement	1 channel	Mean Absolute Value (MAV), Signal Slope Change (SSC), Autoregressive Model (AR) and Discrete Wavelet Transform (DWT)	Neuro-Fuzy
(Young et al. 2013)	3 degrees of freedom	6 channels and 8 channels	MAV, Zero Crossing (ZC), SSC and Wave Length (WL)	Parallel classification strategy
(Bennett and Goldfarb 2017)	Standardized object relocation and manipulation tasks	2 channels	Normalized Signal	Result tables
(Yang et al. 2011)	6 classes of movement	4 channels	DWT	Fisher criterion, NWFE (Feature projection)
(Hartmann et al. 2015)	8 classes of movement	6 channels	Root Mean Square (RMS), ZC, SSC, WL and First Three Cepstral Coefficients (3xCEPS)	Linear Discriminant Analysis
(Duan et al. 2016)	6 classes of movement	3 channels	RMS and DWT	Wavelet Neuro Network (WNN)
(Siu, Shah, and Stirling 2016)	two grab and release sequences	7 channels	GMM and Markov	WPD e Random Forest
(Luh et al. 2016)	16 classes of movement	8 channels	Four levels of the Daubechies wavelet transform	Neural Network
(Radhika Menon et al.)	7 classes of movement	128 channels	MAV, SSC, Waveform Length (WFL), ZC	Linear Discriminant Analysis (LDA)

works to extract information and classify the sEMG signal. The figure 2.2 show the fluxogram used in this study. An autoencoder analyzes the EMG and classifies the state of rest and movement. If the movement starts, a cluster together with the state machine returns the possible movements that may be being executed. The last step is the classifier that chooses the movements among the possible ones for that state.

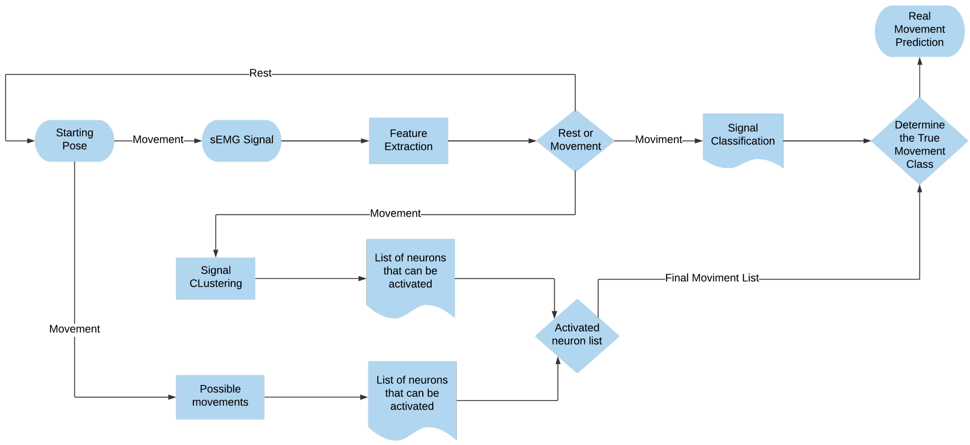

Figure 2.2. The proposed fluxogram used in this study for sEMG classification.

This dissertation presents the following chapters based on works previously published by the author in national and international conferences about this study. The next chapter presents the content of these articles.

Chapter 3 presents a strategy, proposal, and evaluation of the characteristic features for classifiers. Chapter 4 presents a study on the use of autoencoders to detect movements to improve the classification when the movements start to be executed. Chapter 5, on the other hand, shows the use of a state machine and a clustering algorithm to decrease the possible classes of movements in the final classifier to reduce the size of the time window for real-time processing.

2.2 sEMG Database

In this study, the 6mov8chUFS database, available on the BioPatRec platform, was used, and it is available on the BioPatRec platform. Seventeen subjects formed this database, six classes of individual movements were selected, such as hand opening and closing, flexion and extension of the wrist, and prono-supination of the hand, forming 27 possible movements. The signal was measured as follows: 3 seconds contraction time with 3 seconds for relaxation be-tween each repetition, repetitions of each motion. 8 bipolar electrodes (Disposable Ag/AgCl), 1 cm electrode diameter, 2 cm inter-electrode distance for the bipole. Electrodes were equally spaced around the most proximal third of the forearm.

The signal was extracted using overlapped time windows of 0.2 seconds and time increments of 0.05 seconds.

2.3 Movement Classes

The movement classes used in the "6mov8chUFS" database are formed by the linear combination of six basic open and close movements, figure 2.3, prone-supination and, finally, extension and flexion of the hand and are listed as follows:

1. Open Hand
2. Close Hand
3. Flex Hand
4. Extend Hand
5. Pronation
6. Supination
7. Open Hand + Flex Hand
8. Close Hand + Flex Hand
9. Open Hand + Extend Hand
10. Close Hand + Extend Hand
11. Open Hand + Pronation
12. Close Hand + Pronation

13. Open Hand + Supination
14. Close Hand + Supination
15. Flex Hand + Pronation
16. Extend Hand + Pronation
17. Flex Hand + Supination
18. Extend Hand + Supination
19. Open Hand + Flex Hand + Pronation
20. Close Hand + Flex Hand + Pronation
21. Open Hand + Flex Hand + Supination
22. Close Hand + Flex Hand + Supination
23. Open Hand + Extend Hand + Pronation
24. Close Hand + Extend Hand + Pronation
25. Open Hand + Extend Hand + Supination
26. Close Hand + Extend Hand + Supination

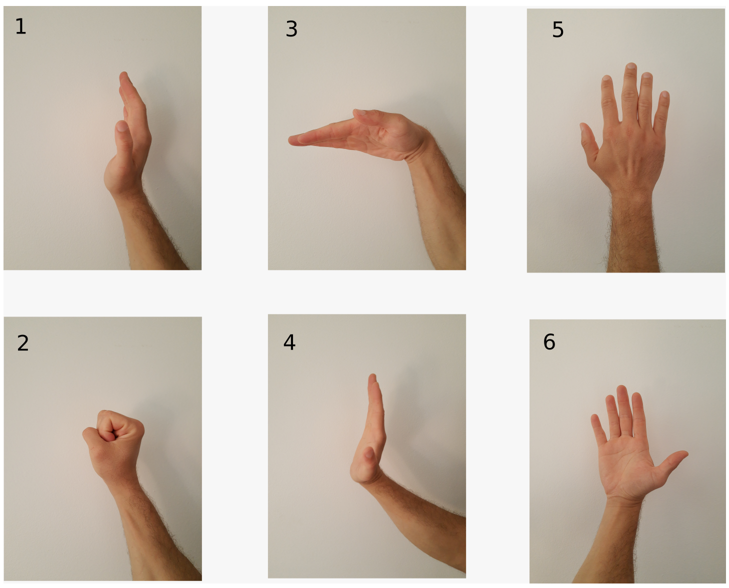

Figure 2.3. The basic six classes of movement, the 27 classes are formed by the linear combination of these six classes. 1 - Open Hand. 2 - Close Hand. 3 - Flex Hand. 4 - Extend Hand. 5 - Hand Pronation. 6 - Hand Supination

3 Proposal for the Preprocessing Algorithm and Evaluation

3.1 Introduction

Pattern recognition for myoelectric signal processing plays an important role on research for prosthetics [25]. In addition, the application of machine learning techniques has become widespread in the area of surface electromyography (sEMG) signals analysis, to enhance the feature extraction and selection as well the classification of the myoelectric pattern [16, 20, 12, 22]. Furthermore, the use of pattern recognition brings an improvement in the degrees of freedom and movement of the prosthesis beyond the capacity of its sequential control [27].

In this study, the open source BioPatRec platform was used [25, 26, 27]. With a modular and customizable concept, researchers can compare their algorithms easily and efficiently, applying them to control a prosthesis. As advantages, users, by means of this platform, can access the sEMG signals database for both sequential and simultaneous analysis, including quantitative metrics to evaluate the performance of sequential and simultaneous control in a standardized way, as well as to apply methods that the platform provides for feature extraction, feature selection, feature reduction and myoelectric pattern classification.

The objective of this work is to analyze new algorithms for feature extraction and selection methods not provided by BioPatRec platform, four additional feature extraction methods were used: the Levinson-Durbin Recursion, the Absolute value of the Summation of the Expth Root Mean, the Mean value of the Square Root and the Abso-lute value of the Summation of Square Root [34]. Additionally, an unsupervised method for feature selection (UFS) was used [9].

These additions were made for the improvement of the classification of the myoelectrical signal to provide a better performance for the simultaneous movement of an upper-limb prosthesis, aiming at increasing the user comfort and giving easing for the movement.

3.2 Methodology

For this study, the "6mov8chUFS" (Untargeted Forearm Simultaneous) [26] database was used, which is freely available on the BioPatRec platform [25]. The sEMG signal is analyzed, and the features are extracted, following the main features are selected and finally the neural network classifies the movement.

3.2.1 BioPatRec Platform

As previously mentioned, the biomedical signal analysis platform, BioPatRec, was used, using the Multilayer Perceptron Network with backpropagation, already configured on the platform for pattern classification.

3.2.2 Features Extraction

In this study were added four time-domain features described below:

(a) The Absolute value of the Summation of the Square root (Absolute value of the Summation of the Square root (ASS)) [34]: This is the first time-domain feature. For calculation of the ASS, the first step is to first execute a full-wave rectification on the sEMG data, this help in retaining the entire energy content of the signal. Next, the integral of the rectified EMG signal is calculated with respect to the current analysis window, as expressed mathematically in Eq. (1)

$$AS = \left| \sum_{n=1}^{k} (x_n)^{\frac{1}{2}} \right| \tag{3.1}$$

where k represents the analysis window, xn denote the data within the corresponding analysis window.

(b) The Mean value of the Square Root (Absolute value of the Summation of the The Mean (MSR)) [34]: This is the second time-domain feature. It provides an estimated measure of the total amount of activity in the analysis window.

$$MSR = \sum_{n=1}^{k} (x_n)^{\frac{1}{2}} \tag{3.2}$$

where k represents the analysis window, xn denote the data within the corresponding analysis window.

(c) The Absolute value of the Summation of the expth root (Absolute value of the Summation of the expth root (ASM)) [34] of the data is the third time-domain feature, as shown in Eq. (3). The ASM feature provides a comprehensive insight into the amplitude of the EMG signal since it gives an approximate measure of the power of the signal which also produces a waveform that is easily analyzable. This feature contains information from which the amplitude of the rectified EMG signal could be obtained.

$$
\begin{aligned}
ASM &= \left| \frac{\sum_{n=1}^{k} (x_n)^{\exp}}{k} \right| \\
exp &= \begin{cases} 0.50, \; if(n \leq 0.25 \times k, \; if \; n \geq 0.75) \\ 0.75 \; otherwise \end{cases}
\end{aligned}
\tag{3.3}
$$

The exp. variable can assume one of two possible values (0.50 or 0.75) based on the characteristic of the EMG signal segment under analysis. The ASM is therefore determined in the following three steps: first the summation of the expth root of all values in a given analysis window is computed; followed by the mean of the resultant values; and lastly, the absolute value of the resultant mean is evaluated.

(d) The last feature added was the Levinson–Durbin Recursion [45], it is a recursive order-update method to the calculation of linear predictor coefficients, it has applications in filter design, coding, and spectral estimation. This method was used to estimate parameters of the sEMG signal.

3.2.3 Features Selection

A method based on the Maximal Information Compression Index (Maximal Information Compression Index (MICI)), and the Entropy Representation (Entropy Representation (ER)) was applied for unsupervised feature selection, in order to obtain the best feature sets for the classification [9]. Analyzing through the MICI to obtain combinations of characteristics with lower value or high redundancy. Those redundant features come together with the rejected features, in order to obtain an updated set formed by the features that provide the highest ER value during the combination with non-redundant features.

On the other hand, principal component analysis (Principal Component Analisys (PCA)), an orthogonal linear trans-formation, that rearrange the components in the inverse order of variance It is used for dimensionality reduction in the BioPatRec platform as default, as it is a widely used technique. In that study, PCA reduced the 160 features (20 for each channel) to the 64 best features for classification.

Later in chapter5, new methods of reducing characteristics and dimensionality were tested and evaluated.

3.2.4 Neural Network Classifiers

Despite the existence of a wide variety of different pattern recognition algorithms, the Multi-Layer Perceptron (MLP) as a supervised Artificial Neural Network was chosen because of its inherent capacity of simultaneous classification [25, 27, 3].

An MLP can be used as a logistic regression classifier, where the input is first transformed nonlinearly by a learned transformation. This transformation projects the input data into a space in which it becomes linearly separable. This middle layer is called the hidden layer. For this study an MLP with 3 hidden layers with eleven neurons was used, the transference function was the softmax function.

3.2.5 Statistical Evaluation

The tests were performed on seventeen subjects of the original base "6mov8chUFS". First, the BioPatRec feature selection methods were used with and without PCA. Finally, the unsupervised feature selection algorithm (Unsupervised Feature Selection (UFS)) was used for reducing features in place of the PCA. Thus the tests were completed they were repeated by adding the new characteristic vectors proposed in this study.

The evaluation of the classifier used a cross-validation of 48 trainings with randomized datasets were per subject and for each algorithm, 24 validation sets, and 49 test sets. For this study was used unitary range normalization. The BioPatRec provides statistical tools to evaluate the proposed algorithms on the platform, thus, it has a wide variety of metrics [27] that were used to analyze the results, such as Accuracy (Class Specific), Sensitivity (Recall), PPV (Precision), F1, Specificity (Negative Condition), NPV (Negative Outcome) and Accuracy (Global).

(a) **Accuracy – Class Specific**

$$AccCS = \frac{absolute\ correct\ predictions}{total\ absolute\ predictions} \tag{3.4}$$

(b) **Sensitivity**

$$Sensitivity = \frac{TPs}{TPs + TPs} \tag{3.5}$$

(c) **PPV**

$$PPV = \frac{TPs}{TPs + FPs} \tag{3.6}$$

(d) **F1**

$$F1 = 2 \times \frac{precision \times sensitivity}{precision + sensibility} \tag{3.7}$$

(e) **Specificity**

$$Specificity = \frac{TNs}{TNs + FPs} \tag{3.8}$$

(f) **NPV**

$$NPV = \frac{TNs}{TNs + FNs} \tag{3.9}$$

(g) **Accuracy – Global**

$$AccG = \frac{TNs + TPs}{TPs + TNs + FPs + FNs}, \tag{3.10}$$

where TP means true positive, the correct activation; TN is true negative, the correct inactivation; FP is false positive, the incorrect activation; and FN is false negative, incorrect inactivation.

3.3 Results and discussion

It has been shown that the individual movements can be successfully predicted offline using pattern recognition algorithms [25, 20, 36, 14] and in this study was demonstrated an increase in terms of classification accuracy was achieved when the new features were used in conjunction with a feature reduction algorithm. Table 1 shows the results obtained using the characteristics present in BioPatRec and the use of PCA or UFS to reduce characteristics.

Table 3.2 shows the results obtained using the characteristics present in BioPatRec and those added by this study, in addition to the use of PCA or UFS to reduce the characteristics. As more characteristics are sorted, the MLP begins to diverge, but when

Table 3.1. Quantitative indicators obtained with the comparison between old features with feature reduction algorithms.

Features Selection	Accuracy Class	Sensitivity	PPV	F1	Specificity	NPV	Accuracy Global
None	83.10	85.11	92.30	0.89	99.73	99.43	99.19
PCA	92.74	94.78	94.78	0.95	99.80	99.80	99.61
UFS	90.63	92.29	95.02	0.94	99.81	99.70	99.54

selecting the most divergent characteristics, through the methods of selecting characteristics, rating the signal becomes easier. The performance of the proposed and the conventional methods present in the BioPatRec is shown by the gain in the accuracy and deviation shown in table 3.1 and 3.2.

Table 3.2. Quantitative indicators obtained with the comparison between the new features added to the old features sets with feature reduction algorithms.

Features Selection	Accuracy Class	Sensitivity	PPV	F1	Specificity	NPV	Accuracy Global
None	82.39	83.60	95.76	0.89	99.86	99.37	99.26
PCA	94.63	96.22	96.95	0.97	99.88	99.85	99.75
UFS	93.50	94.71	96.68	0.96	99.87	99.80	99.68

The below figure shows the distribution curves of the experiment, while the blue curve represents the old features the red one represent the experiment with the added features.

The difference between two means divided by a standard deviation for the data is represented with the "d" letter in the graphic.

According to Cohen and Sawilowsky:

- $d = 0.01 \implies very\ small\ effect\ size$;
- $d = 0.20 \implies small\ effect\ size$;
- $d = 0.50 \implies medium\ effect\ size$;
- $d = 0.80 \implies large\ effect\ size$;
- $d = 1.20 \implies very\ large\ effect\ size$;
- $d = 2.00 \implies huge\ effect\ size.$

The experiment was offline, and the mean training and validation time was of 34 seconds and the mean testing time was of 0.004 seconds.

The use of BioPatRec allows a fast and accurate simulation of the pattern recognition algorithms, which streamlines the process of development and testing of theories that will be applied in the control of a myoelectric prosthesis. This platform is being used in this

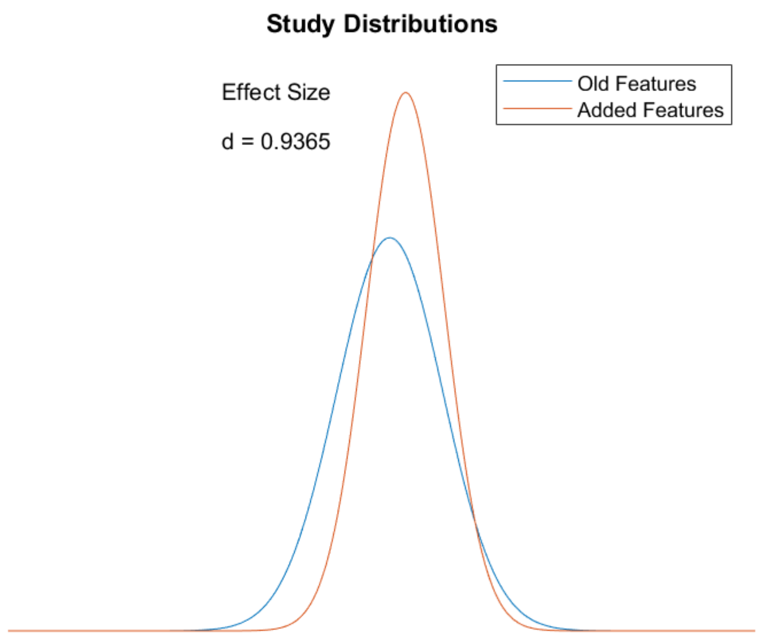

Figure 3.1. Distribution of the experiment with the old features and the added features.

study and it is hoped that it can assist in the development of an adaptive learning pattern recognition system for the control of an upper limb electrical prosthesis. In addition, the fact that the BioPatRec platform is modular allows the study to be better divided into stages, such as signal processing, extraction of characteristics, classification and the decision-making system of the prosthesis, making the process agiler.

3.4 Conclusion

The addition of the new features in conjunction with the selection algorithms improved the characterization of the myoelectric signal, which will facilitate the decision process for the control of the myoelectric prosthesis. The help of the BioPatRec platform made the work agiler and the statistical metrics helped to evaluate the effectiveness of the algorithms applied in this study. Furthermore, this study showed that simultaneous control can be considered since it improves user comfort. In addition, simultaneous control is required for more natural control of artificial limbs, and pattern recognition has proved to be an excellent means of working with the complexity generated by simulta-neous movement.

4 Autoencoder and Anomaly Detection for Movement Class Separation

4.1 Introduction

An autoencoder is a neural network that is trained to attempt to copy its input to its output. While copying the input to the output may be useless, a high-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Using the inner layer, also called latent space, we have a signal with a reduced size, more easily classified.

The Variational Autoencoder (VAE) is a generative model that estimates the Probability Density Function (Probability Density Function (PDF)) of training data. By training the model to recognize the sEMG signal it will assign a high probability value to a motion class, while the noise will receive a low probability value[42].

The VAE model can also sample examples of the PDF learned, thus generating new examples similar to the original data set. But it is important to emphasize that VAE is not a way of training generative models, but rather that the generative model is a component of VAE, generally being a deeply latent Gaussian model[32].

In the figure 4.1 are the steps to summarize the operation of a VAE. On the left side we have the model definition:

1. Let $q(z|x)$ be defined as how the signal is encoded into a distribution over the latent space;
2. Let z be A latent vector sampled from $q(z|x)$, z will contain the information describing x. The decode of it is represented as $p(z|x)$;
3. z is decoded as a signal.

On the right side we have the loss:

1. Reconstruction error: the difference between the output and the input.

2. $p(z|x)$ should be similar to the prior (multivariate standard Gaussian).

The VAE generating coefficient appears by directly sampling the latent vector from the prior distribution and decoding it into a noisy representation of x[42].

4.1.1 Model specification

4.1.1.1 Encoder layer

In Bayesian modeling, the distribution of observed variables is governed by latent variables. The latent variables are extracted from a previous density $p(z)$ and related to the observations through the probability $p_\theta(x|z)$. Deep latent gaussian models (DLGMs) are a general class of models where the observed variable is governed by a latent variable hierarchy, and the latent variables at each level of the hierarchy are Gaussian a priory[32].

Normally, in the VAE, a Gaussian distribution is used to sample the latent space.

$$p(z) = N(0, I) \tag{4.1}$$

In this way, each local latent variable is related to its corresponding observation through the likelihood $p_\theta(x|z)$, which can be seen as a probabilistic decoder. Using a hidden smaller representation z, it decodes it into a distribution over observation x.

4.1.1.2 Decoder layer

The decoder is another neural network. Its input is the latent vector z, generates the parameters for the probability distribution of the data and has weights and biases θ. The decoder is denoted by $p_\theta(x|z)$. The probability distribution is a multivariate Gaussian.

The loss function of VAE is the negative log-likelihood with a regularizer. Since it is not possible to generalize the global representation shared by all data points, we can decompose the loss function into terms that depend only on a single data point l_i. The parameters are typically the weights and biases of the neural networks represented as θ and ϕ. The total loss will then be represented by the sum of all losses l_i for all data points. The loss function l_i for the data point x_i is:

$$l_i(\theta, \phi) = \mathbf{E}_{z\ q_\theta}(z|x_i)[log(p_\phi(x_i|z))] + \mathbf{KL}(q_\theta(z|x_i)|p(z)) \tag{4.2}$$

The first term represent the reconstruction loss, and has the form of a negative log-likelihood of the i-th data point. The expectation is taken with respect to the encoder's

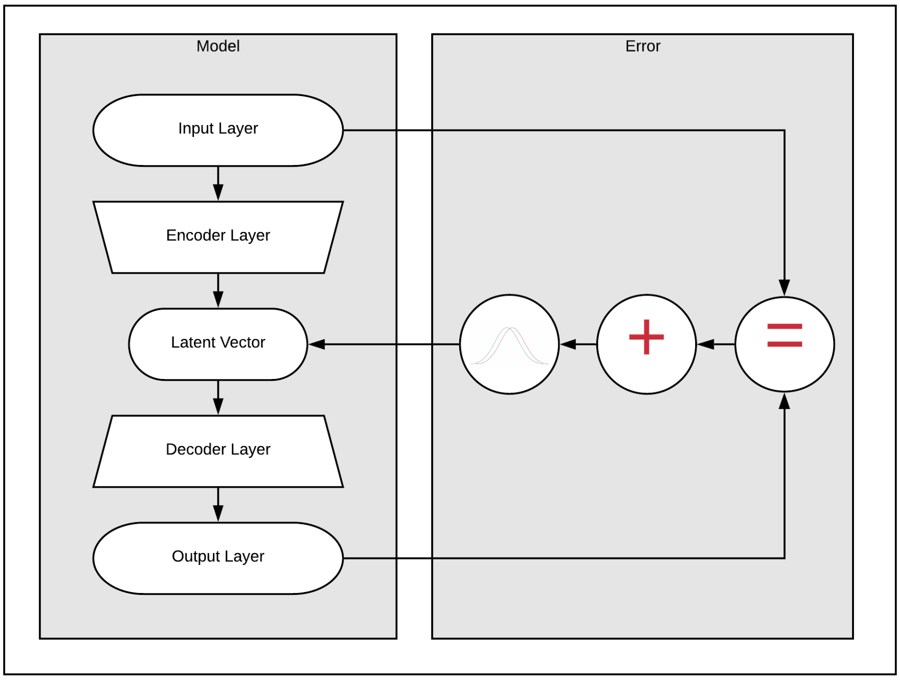

Figure 4.1. Flowchart of a variational autoencoder

distribution over the representations. This term encourages the decoder to learn how to reconstruct the data. If the decoder's output does not have similarity with the data, statistically the decoder parameterizes a likelihood distribution that does not place much probability mass on the true data. Poor reconstruction will incur a large cost in this loss function.

The second term is a regularizer. This is the Kullback-Leibler divergence between the encoder's distribution $q_\theta(z|x)$ and $p(z)$. This divergence measures how much information is lost when using q to represent p, in other words, the divergence of the approximate from the true posterior.

4.1.1.3 Inference Network

An inference network is a flexible construction for parameterizing approximating distributions during inference[8], and it is used on VAE[32, 42] to infer the optimal values of the latent variables given observed data, or to calculate the posterior $p(z|x)$. By modeling the true distribution $P(z|X)$ using simpler distribution that is easy to evaluate, e.g. Gaussian, and minimize the difference between those two distribution using KL divergence metric, as in 4.2, which tells us how difference it is p and q.

4.1.2 Anomaly Detection

The use of auto-ponder for anomaly detection is already common in the area of artificial intelligence [41, 47, 4]. In this study, a variational autoencoder was used to detect the onset of movement, which is otherwise confused with the resting state.

The test of the usability of the auto-encoder was done for the classification of the 26 classes of movement of the database, it was later retrained to detect the change of the resting state.

4.2 Methodology

4.2.1 VAE Algorithm

A simple Variational Autoencoder was used for the anomaly detection phase. The encoder stage was compose of three dense layers. The first one have 32 neurons, the second 16 neurons and the third 8 neurons. The sampling inference, which characterizes the variational autoencoder, is made on top of the last layer of the encoder step, which has 8 neurons. All layers in this phase have the Rectified Linear Unit (ReLU) as the activation function.

The decoding stage is the reverse of the encoding. It starts with 8 neurons in the first layer, 16 neurons in the second and 32 neurons in the last. The first two layers have ReLU as the activation function and the third layer, the sigmoid as the activation function.

The figure 4.2 is the dimensionless values of the autoencoder trained with two neurons in the latent layer. The figure represents the representation of the anomalies found when the patient starts to move. With that output of the latent space, a simple perceptron network is used to detect whether the patient is moving or resting.

4.3 Results

In this experiment, a 0.01s window (10 samples) was used. With this window size, normal classification methods cannot accurately classify the movements classes or even differentiate the resting state of movement. Through the use of auto-encoder as an anomaly detector, it was possible to determine the moment when the movement really started.

The figure 4.3 is the representation of the difference between the rest movement state in the latent space of the variational autoencoder. For the construction of the image the

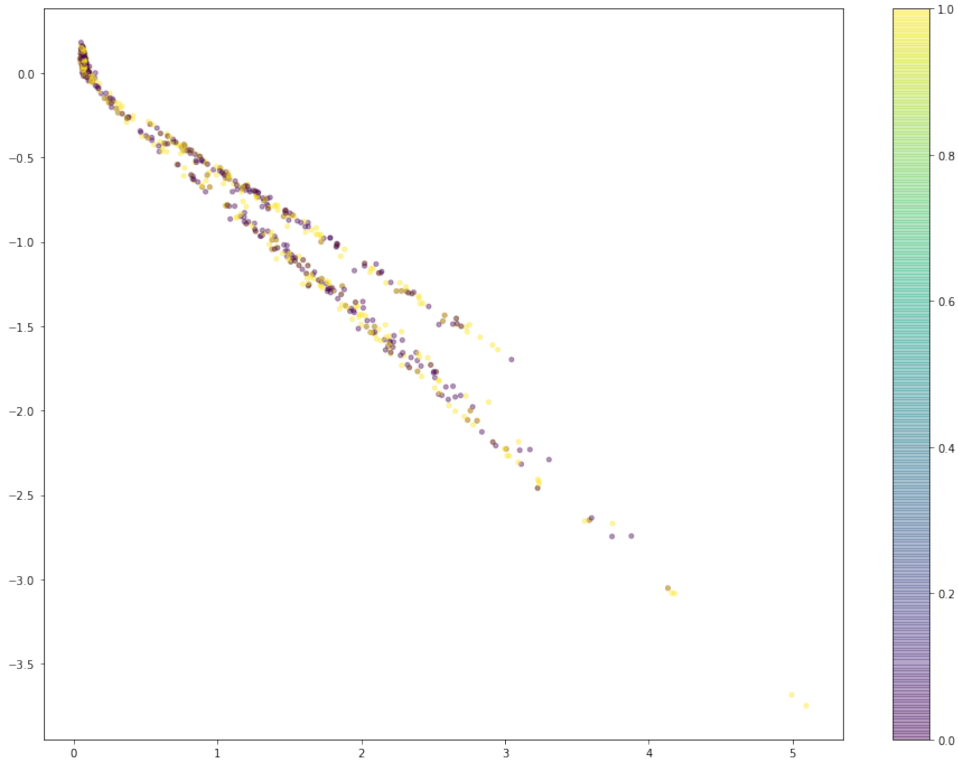

Figure 4.2. The latent space representation created by te Variational Autoencoder

latent space was dimensioned with 4096 neurons. The output of the neurons has been scaled to a 64 by 64 square shape and the image was made.

It is worth remembering that, although the detection of the anomaly only needed eight neurons to be able to perform successfully, the representation of the latent space needed to be enlarged so that the difference was visible to our eyes.

4.4 Conclusion

The results obtained demonstrate the feasibility of the variational autoenconder as an anomaly detector for the sEMG signal. Furthermore, by separating the resting state from the other classes of movement, the entropy of the system is reduced, facilitating the future classification of the other classes of movement.

By using VAE, which is specialized in separating classes in their latent space, movement detection has been simplified and its computational cost has been greatly reduced. Although the training was done only using the offline signal, simulating the acquisition of the signal online proved to be extremely efficient.

In this study, the auto encoder was used only as an anomaly detection instrument, but its use is not limited to that. As shown in figure 4.3, the autoencoder can be used to increase the separation between classes just by increasing the size of the latent space.

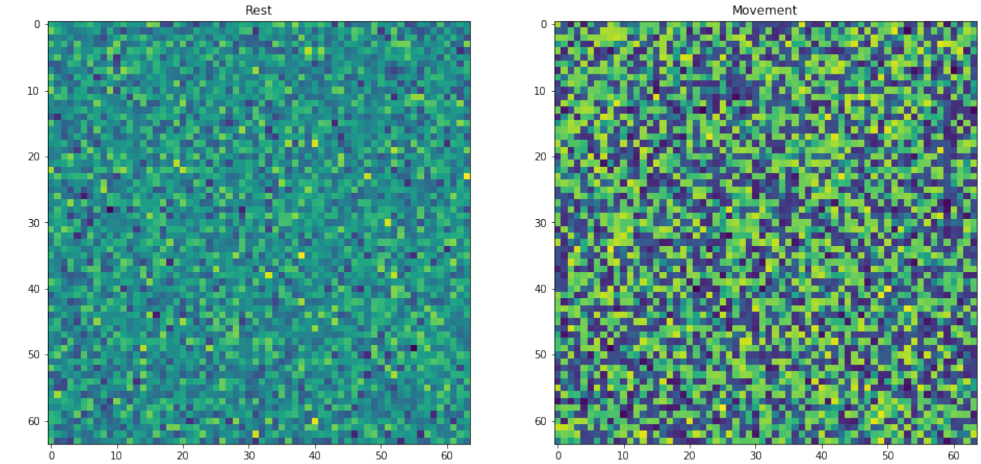

Figure 4.3. A expanded latent space, to represent the diference between the rest and the rest and the movement state. In this image the latent space was dimensioned to be 64 x 64 to facilitate the diference visualization.

This technique can be used in further studies to improve the system accuracy.

5 Entropy and Clustering Information Applied to sEMG Classification

5.1 Introduction

The EMG signal varies according to the posture, position, and force applied by the person that is performing a muscle contraction. Therefore, to have perfect control of a prosthesis, extensive training with a myoelectric unit is required. However, as these prostheses have a high cost investment, it is often not possible to offer longterm training for their use.

One of the difficulties regarding EMG signal processing for use in prosthesis control is the need for real-time processing. This creates the need for ever-smaller time windows that, in turn, have less signal information, which limits the amount of information that can be extracted from them.

In the last few years, deep learning techniques have become increasingly used, but the more complex the applications are, the more complex the neural networks become. However, the more parameters the network has, the higher the chance of having overfitting, which causes considerable deterioration to the network's generalization capacity. Otherwise, if the neural network has few parameters, it will probably not be able to represent the data accurately. Notably, the best way to achieve generalization is to seek a balance between training error and network complexity [21, 46].

In the tasks of biosignal classification, there are frequently too few biomedical signal samples to allow for the achievement of good results with deep learning [35]. Another problem associated with deep learning is the cost of training processing, which demands specific hardware and high computational cost due to the complexity of the current neural networks architectures [46]. This thesis suggests extracting maximum signal information before signal classification as a method to reduce the system complexity and create redundancy for the classification and thereby managing to decrease the time window for the real-time processing of the signal. One of the steps of the algorithm proposed includes the development of a pipeline that extracts a priori information from the EMG signal by computing the current hand and forearm postures and the similarity of the EMG signals from the forearm.

As mentioned before, one way to ensure entropy reduction (information gain) is to obtain a priori information [37]. The starting position of the hand and forearm provide a great deal of information to the classifier as it restricts possible movement classes. For this purpose, a state machine [3] that counts the possible movements from the initial classes was created. This state machine reduced by just over three times the number of classes to classify, improving the classification of the system.

A second method used in this work for entropy reduction, was the classification of signals by similarity. Therefore, a Hierarchical Agglomerative clustering (Hierarchical Agglomerative Clustering (HCA)) technique was selected. In this technique, each data point is considered an individual cluster. At each iteration, using distance, a similar pair of clusters are merged as they move up the hierarchy, until there is a formation of one cluster or K clusters.

The proposed methodology led to a substantial decrease in the size of the temporal window used for sEMG signal processing. Besides, there was also an improvement in the generalization and processing speed due to the simplification of the model used for classification.

This chapter is organized as follows: Section II shows a detailed explanation of the algorithms used. The results are listed in Section III, which also presents a detailed analysis of the experiment. Finally, there is a conclusion, where the results are summarized.

5.2 Methodology

5.2.1 The Pipeline

Initially, there is an estimation of the original positions of the hand and forearm. The possible movements are checked by analyzing the state machine; these two steps lead to a list of values associated with the neurons that are activated in the final layer of the classifier.

The second step is processing the signal with the Butterworth filter, followed by the feature extraction and standardization of the data. Furthermore, a reduced space transform created by the NCA algorithm is applied, and the signal is ready for the classification and clustering algorithms. This transformation reduces the vector of characteristics from 36 to 25 dimensions.

The third step for signal classification is to find the group to which the analyzed window belongs. The HCA clustering algorithm will provide a new list of activated neurons in the classifier. In the HCA algorithm, each observation starts in its cluster, and

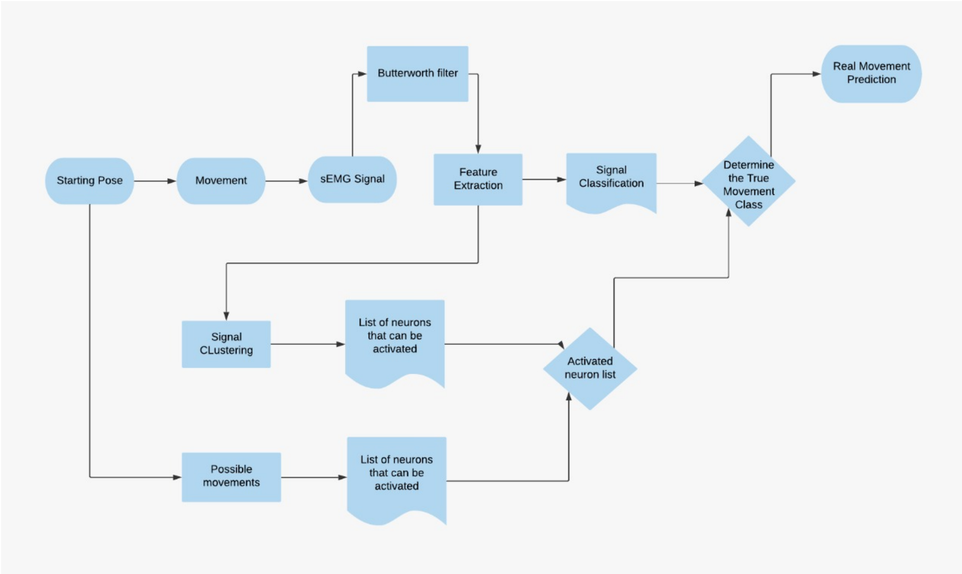

Figure 5.1. Pipeline representation: the algorithm begins at a starting position; the sEMG signal is measured and pre-processed to help to determine the movement intention; with these two information pieces, the possible next movements are determined as well as the cluster to which the class belongs; finally, the algorithm yields the movement intention.

the algorithm merges pairs of clusters when one moves up the hierarchy. The intersection between the state machine-generated list and the cluster generates the final list of neurons that can be activated.

The last step is the signal classification by the MLP and the multiplication of the result by the list generated in the previous step. The image below shows the value of neurons before and after applying the list of neurons to be used.

5.2.2 Movement Classes

The movement classes used in the "6mov8chUFS" database are listed as follows:

1. Open Hand
2. Close Hand
3. Flex Hand
4. Extend Hand
5. Pronation
6. Supination

7. Open Hand + Flex Hand
8. Close Hand + Flex Hand
9. Open Hand + Extend Hand
10. Close Hand + Extend Hand
11. Open Hand + Pronation
12. Close Hand + Pronation
13. Open Hand + Supination
14. Close Hand + Supination
15. Flex Hand + Pronation
16. Extend Hand + Pronation
17. Flex Hand + Supination
18. Extend Hand + Supination
19. Open Hand + Flex Hand + Pronation
20. Close Hand + Flex Hand + Pronation
21. Open Hand + Flex Hand + Supination
22. Close Hand + Flex Hand + Supination
23. Open Hand + Extend Hand + Pronation
24. Close Hand + Extend Hand + Pronation
25. Open Hand + Extend Hand + Supination
26. Close Hand + Extend Hand + Supination

5.2.3 Feature extraction

In order to reduce signal noise, the first step in extracting features was to use a sixth-order bandpass Butterworth filter, 80-450Hz. Additionally, a time window for sampling the signal is selected. In this study, the sampling frequency of the sEMG was 2000 Hz, with a 0.01s window (i.e., ten samples per window).

This stage was subdivided into two steps:

1. **Selection of characteristics:** to extract information from the signal four frequency domain features were used [19]:
   - Spectral Moment;
   - Waveform Length (acumulative changes in the length);
   - Mean;
   - Median;
2. **Dimensional reduction:** (NCA) [30] allowed for the dimensional reduction by helping to select the most significant features of the signal. NCA is a supervised learning algorithm for distance metric learning. It learns a linear transformation (of input data) that maximizes, in the transformed space, the average leave-one-out classification performance.

The figure 5.2 shows the study made to select the best dimensionality reduction algorithm. The methods were tested with a KNN with k =3, the method was select base on the accuracy of the knn. The plots represent the features on the dimensionality reduction algorithm space, therefore they don't have dimensions.

5.2.4 Signal Information

To extract the maximum information of the signal the processes were divided into two steps:

1. Signal Clustering: Agglomerative Hierarchical Clustering (HCA) clusterized the signal into three groups according to the similarity of the features. The HAC algorithm recursively merges the pair of clusters that minimally increases a given linkage distance [38, 15];
2. Comparison with possible movements: after the creation of the cluster, the algorithm compares movements classes with the possible movements for a given position, and the classes are extracted through a process called Decision Tree or State Machine [9].

5.2.5 Classifier Algorithm

A simple multi-layer perceptron (MLP), with three layers, was used to classify the signal. The first layer was composed of 25 neurons, the middle layer by 52 neurons and the last by 26 neurons. In the first two layers, the linear rectifier was used as

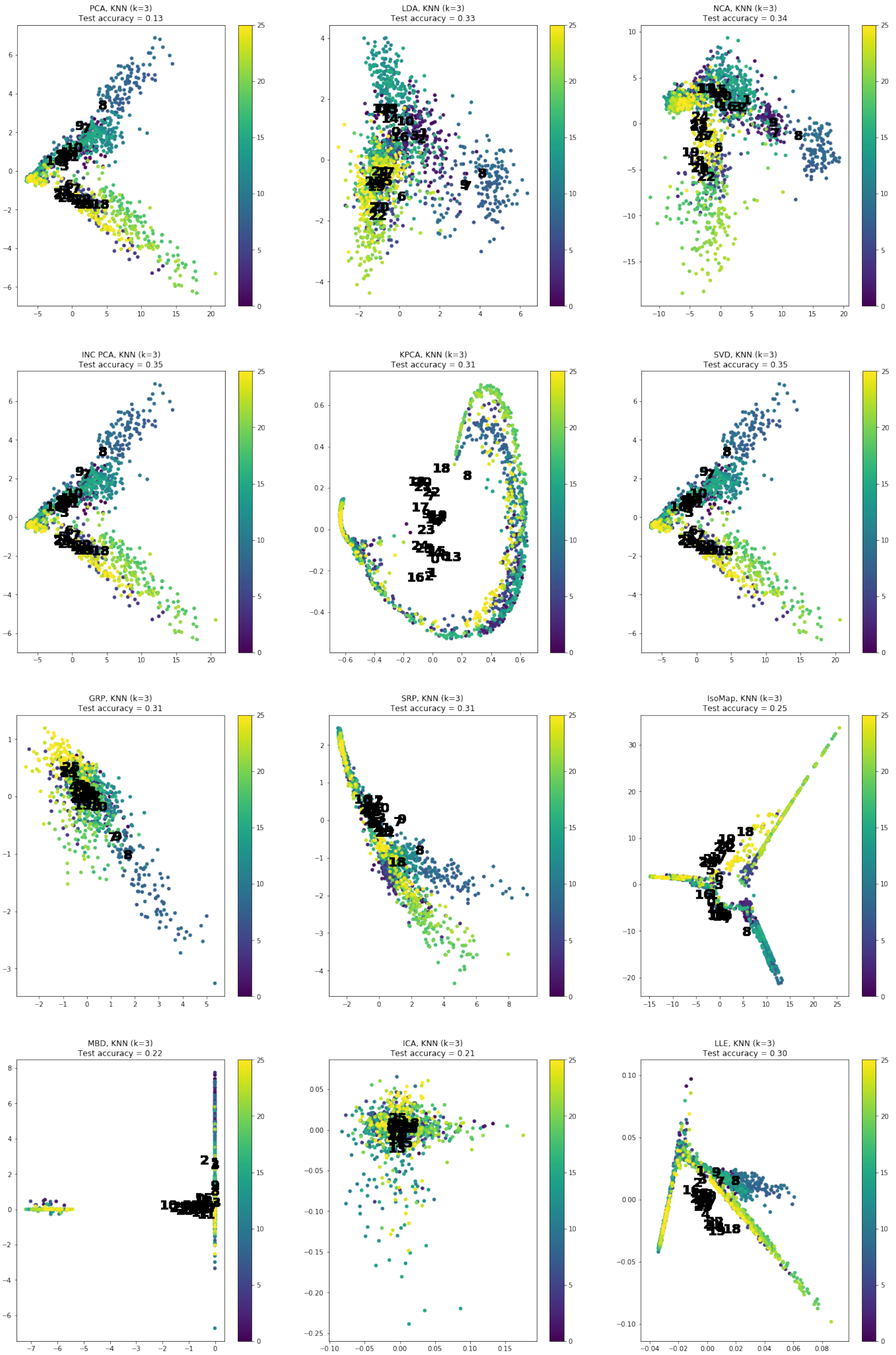

Figure 5.2. Test of diferent methodos of dimensionality reduction for the use in the classificatory algorithm. The methods were tested with a KNN with k =3.

activation function. The last layer had a softmax function helping in the classification process. A dropout function (20%), placed between the MLP layers, reduce the chance of over-fitting.The MLP was chosen because of its inherent capacity of simultaneous classification [37].

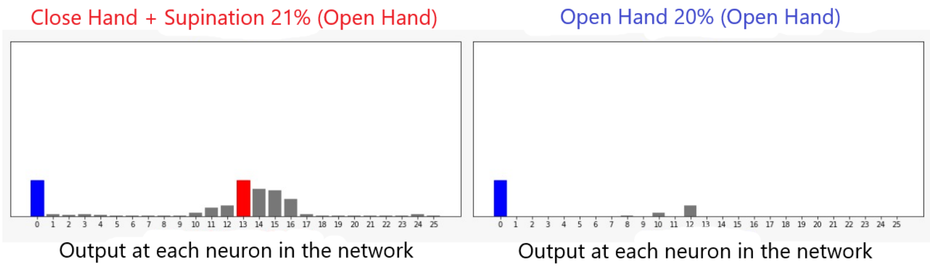

Figure 5.3. Output of the values of the MLP neurons of the last layer. The blue color mean the right classification and the red the wrong classification. The left figure is the output of the MLP and the right figure is the result with the possible classes only.

5.3 Results

A recent study [31] shows the impact of the temporal window size on the EMG signal classification error. According to this study, with very small windows, (on average less than 200 ms), the classification error increases as the total information in the window decreases. This feature makes real-time processing very difficult, since it requires small temporal windows. Moreover, in 2011 Peerdeman [29] found that the processing window needs to have less than 300 ms, or the delay becomes unacceptable to the user.

The proposals studied in this article aim to reduce this limit from 200 to 300 milliseconds by creating mechanisms that allow for using smaller windows. Through these smalltime windows, it is possible to perform real-time processing.

Because of the small size (10ms) of the window, the MLP did not achieve a good signal classification, but the selection of which neurons are active for the classification, significantly increased the accuracy. Figure 2 shows the difference in the classification using only the possible classes.

For the clustering algorithm, three data clusters were created and evaluated using a KNN (k = 3). This KNN achieved 97% accuracy by classifying the groups created, as seen in figure 5.4.

Table 5.1 shows the accuracy and standard deviation of MLP used in this article. The left side shows the results for the full MLP, and the right colulmn shows the, the results after the application of the pipeline shown in figure 5.1.

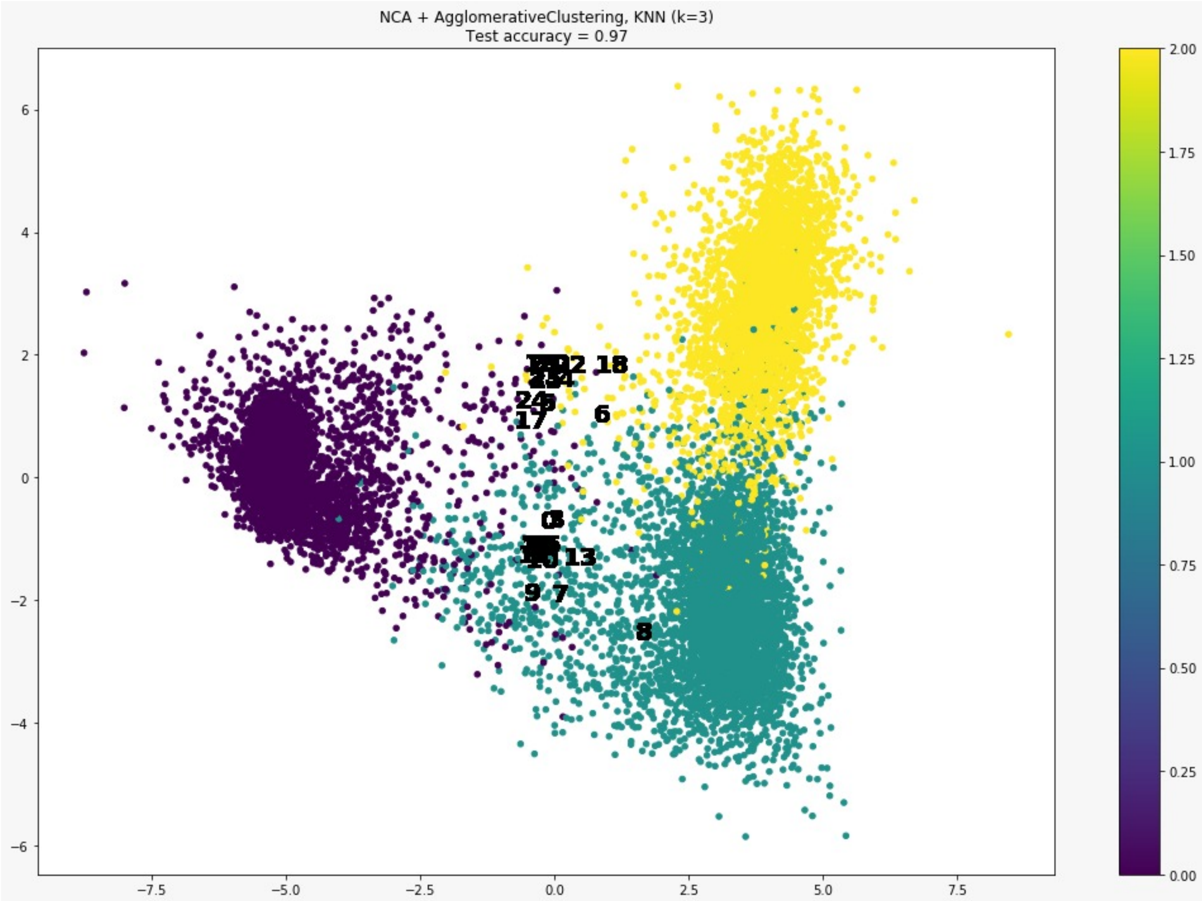

Figure 5.4. sMEG Clustering the classes by the similarity in the features extracted. After the extraction of twenty-five dimensions, the two more representative dimensions among them were used to generate the plot. A KNN was used to validate the cluster.

Although the standard deviation remained relatively unchanged, the improvement in accuracy was immense. This achievement can be reached by excluding very close classes, such as closing and flexing the hand or opening and flexing the hand, where misclassifications generally occur.

5.4 Conclusion

In this thesis, two methods were used to obtain a priori information and thus reduce signal entropy before classification. New methods can bring even more significant improvement to the system. By providing a priori information for signal classification interactively, the number of possible classes for signal classification dramatically decreases. Creating less complex validation steps also increased accuracy while allowing window size reduction. We believe that the techniques presented here only scratch the surface of the applications where information entropy can and should be used.

Table 5.1. Accuracy and Standard Deviation Comparison

	Ful MLP Output	MLP with Selectd Neurouns
Acc	0.382	0.913
Std	0.013	0.011

The main idea of this study was to create a network that is simple and, through a small number of bits, can generalize the data better than a more complex network. Therefore, it is imperative to provide tools that simplify or provide data information. Besides, a simple neural network will have faster processing time and use less energy, being cheaper to train and more efficient to apply. Thus, providing tools that simplify or provide data information is critical. Furthermore, more studies to account for the trade-off between the number of steps and the processing time of the pipeline is needed.

6 Conclusion

This study was done with the intention of raising a greater amount of information about the EMG signal. This survey serves to build a better definition of the problem. Knowing how the signal behaves it is possible to create simpler and more efficient solution. For this purpose, a processing protocol of feature extraction, clustering and classification of the myoelectric signal were followed.

As a good prosthesis experience needs quick responses, real-time processing is critical. The number of features and their choice was such as to guarantee faster signal processing. Four characteristics in the frequency domain were selected:

- Spectral Moment;
- Waveform Length (cumulative changes in the length);
- Mean;
- Median;

One of the difficulties in classifying the signal was knowing exactly where the movement started. This happens because of the stochastic characteristics of the signal, when motor units start to be recruited, the signal of rest and movement are confused. To differentiate these two states, a variational self-hiding was used. Due to its intrinsic characteristics, it is specialized in separating classes (movement and rest) in its latent layer. With a simple perceptron it was possible to ascertain the change in the user's states and activate the prosthesis movement classifier.

The last part of this study was the development of a classifier. For this, the concept of information entropy was used. The first part of the classifier was the construction of a state machine that maps the possible combinations of movement given an initial position of the prosthesis. Another step was the use of clusters to catalog nearby movements, the intersection of these two steps generates a list of possible movements. Because of the extremely small time window, without using these two steps, classification would be impossible.

Since the myoelectric prostheses were developed, the number of users who reject it has remained constant [6], Which shows that there has been no significant advance in the area. The reduction of the time window for the classification of the myoelectric signal will allow the control of the prosthesis to be performed in a more fluid way by the user, increasing his comfort when using it.

Another very important factor generated by the decrease in the time window is the decrease in the complexity of the evaluation, which results in energy savings during the classification process, which, in turn, would increase the time of using the prosthesis, reducing the amount of time of refills that the user would need to do. In addition, the processing developed in this study can be used for the classification of other natural signals which, as they are diluted (too much information for little information), are difficult to classify.

The collection of EMG signal data can be stressful for the patient, so it is very difficult to get large databases of biological signals. Because of this, this study was done using only one database, provided along with the BioPatRec platform. In addition, the database used has few repetitions of movement, which makes training with machine learning algorithms difficult. In total, this base has only 17 patients and 3 repetitions of each movement, which made it impossible to use some training techniques.

With a sufficiently large database and, once a redundant classifier has been created, as in the case of the study, the various steps of the cassification can be used as a code and, with a larger neural network and the values of the classification windows can be predicted using techniques such as Long Short Time Memory (LSTM).

One of the main future works would be the implementation of the system and tests with patients with live acquisition of the sEMG. The corelations between the time windows can also be studied in order to have a better designed classifier. New methods of reducing entropy before the classifier mustbe tested since tools that simplify or provide data information is critical.

Despite the few samples of the data set used, the methodology created in this thesis proved to be efficient for the classification of the sEMG signal. However, further studies must be carried out to find new ways to decrease the entropy of the signal before its final classification.

References

[1] Martín Abadi and et al. TensorFlow : A System for Large-Scale Machine Learning This paper is included in the Proceedings of the TensorFlow : A system for large-scale machine learning. 2016.

[2] Sebastian Amsuss, Peter M. Goebel, Ning Jiang, Bernhard Graimann, Liliana Paredes, and Dario Farina. Self-correcting pattern recognition system of surface EMG signals for upper limb prosthesis control. *IEEE Transactions on Biomedical Engineering*, 61(4):1167–1176, 2014.

[3] Mohammadreza Asghari Oskoei and Huosheng Hu. Myoelectric control systems-A survey.

[4] Caglar Aytekin, Xingyang Ni, Francesco Cricri, and Emre Aksu. Clustering and Unsupervised Anomaly Detection with l2 Normalized Deep Auto-Encoder Representations. *Proceedings of the International Joint Conference on Neural Networks*, 2018-July, 2018.

[5] Daniel A. Bennett and Michael Goldfarb. IMU-Based Wrist Rotation Control of a Transradial Myoelectric Prosthesis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2017.

[6] Stephen F. Burrough Brook and Judith A. Patterns of Acceptance and Rejection of Upper Limb Prostheses, 1985.

[7] C.E. Shannon , vol. 27, pp. , July, October,. A Mathematical Theory of Communication. *Bell System Technical Journal*, 27(April 1928):379–423,623–656, 1948.

[8] Peter Dayan. Recurrent sampling models for the Helmholtz machine. *Neural Computation*, 11(3):653–677, 1999.

[9] Denis Delisle-Rodriguez, Ana Villa-Parra, Teodiano Bastos-Filho, Alberto López-Delis, Anselmo Frizera-Neto, Sridhar Krishnan, and Eduardo Rocon. Adaptive Spatial Filter Based on Similarity Indices to Preserve the Neural Information on EEG Signals during On-Line Processing. *Sensors*, 17(12):2725, 2017.

[10] C.P. Diehl and G. Cauwenberghs. Svm incremental learning, adaptation and optimization. *Proceedings of the International Joint Conference on Neural Networks, 2003.*, 4(x):2685–2690.

[11] Strahinja Dosen, Marko Markovic, Kelef Somer, Bernhard Graimann, and Dario Farina. EMG Biofeedback for online predictive control of grasping force in a myoelectric prosthesis. *Journal of NeuroEngineering and Rehabilitation*, 2015.

[12] Feng Duan, Lili Dai, Wennan Chang, Zengqiang Chen, Chi Zhu, and Wei Li. SEMG-Based Identification of Hand Motion Commands Using Wavelet Neural Network Combined with Discrete Wavelet Transform. *IEEE Transactions on Industrial Electronics*, 2016.

[13] Kevin B. Englehart and Bernard Hudgins. A robust, real-time control scheme for multifunction myoelectric control. *IEEE Trans. Biomed. Eng.*, 50(7):848–854, 2003.

[14] Purushothaman Geethanjali. Myoelectric control of prosthetic hands: State-of-the-art review, 2016.

[15] Yuri Gloumakov, Adam Spiers, and Aaron Dollar. *A Clustering Approach to Categorizing 7 Degree-Of-Freedom Arm Motions During Activities of Daily Living.* 2019.

[16] Yonghong Huang, Kevin B. Englehart, Bernard Hudgins, and Adrian D.C. Chan. A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses. *IEEE Transactions on Biomedical Engineering*, 2005.

[17] IBGE. CENSO de 2010, Link: https://censo2010.ibge.gov.br/noticias-censo.html - Accessed on: Jun. 20 of 2019.

[18] Sarthak Jain, Girish Singhal, Ryan J. Smith, Rahul Kaliki, and Nitish Thakor. Improving long term myoelectric decoding, using an adaptive classifier with label correction. *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, pages 532–537, 2012.

[19] Luiz José, Lucas Barbosa, Paulo Roberto, Fernandes De Oliveira, Philippe Dias Araujo, Adson Ferreira, Denis Delisle-rodriguez, John Jairo, Villarejo Mayor, Suélia Rodriguez, Fleury Rosa, and Alberto López-delis. Simultaneous Myoelectric Pattern Recognition using BioPatRec Platform for Hand Prosthesis. *XXVI Brazilian Congress on Biomedical Engineering*, page 869, 2018.

[20] Mahdi Khezri and Mehran Jahed. A neuro-fuzzy inference system for sEMG-based identification of hand motion commands. *IEEE Transactions on Industrial Electronics*, 2011.

[21] Yann LeCun, John S Denker, and Sara A. Solla. Optimal Brain Damage (Pruning). *Advances in neural information processing systems*, pages 598–605, 1990.

[22] Guan-Chun Luh, Yi-Hsiang Ma, Chien-Jung Yen, and Heng-An Lin. Muscle-Gesture Robot Hand Control Based On Semg Signals With Wavelet Transform Features And Neural Network Classifier. 2016.

[23] McFarland. Unilateral upper-limb loss: Satisfaction and prosthetic-device use in veterans and servicemembers from Vietnam and OIF/OEF conflicts, 2010.

[24] Ministério da Saúde. Dados de nascidos vivos, Link: http://tabnet.datasus.gov.br/ - Accessed on: Jun. 20 of 2019.

[25] Max Ortiz-Catalan, Rickard Brånemark, and Bo Håkansson. BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms. *Source Code for Biology and Medicine*, 2013.

[26] Max Ortiz-catalan, Bo Håkansson, and Rickard Brånemark. Real-Time and Simultaneous Control of Arti fi cial Limbs Based on Pattern Recognition Algorithms. 22(4):756–764, 2014.

[27] Max Ortiz-Catalan, Faezeh Rouhani, Rickard Branemark, and Bo Hakansson. Offline accuracy: A potentially misleading metric in myoelectric pattern recognition for prosthetic control. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2015-Novem:1140–1143, 2015.

[28] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[29] Bart Peerdeman, Daphne Boere, Heidi Witteveen, Rianne Huis in 'tVeld, Hermie Hermens, Stefano Stramigioli, Hans Rietman, Peter Veltink, and Sarthak Misra. Myoelectric forearm prostheses: State of the art from a user-centered perspective. *The Journal of Rehabilitation Research and Development*, 48(6):719, 2011.

[30] Angkoon Phinyomark, Franck Quaine, Sylvie Charbonnier, Christine Serviere, Franck Tarpin-Bernard, and Yann Laurillau. EMG feature evaluation for improving myoelectric pattern recognition robustness. *Expert Systems with Applications*, 40(12), 2013.

[31] IEEE Radhika Menon, Student Member, IEEE, Gaetano Di Caterina, Heba Lakany, Member, IEEE, Lykourgos Petropoulakis, Bernard A. Conway, John J. Soraghan,

Senior Member. Study on interaction between temporal and spatial information in classification of EMG signals for myoelectric prostheses.

[32] Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. Stochastic Backpropagation and Approximate Inference in Deep Generative Models. 2014.

[33] Aidan D. Roche, Hubertus Rehbaum, Dario Farina, and Oskar C. Aszmann. Prosthetic Myoelectric Control Strategies: A Clinical Perspective. *Current Surgery Reports*, 2(3):44, 2014.

[34] Oluwarotimi Williams Samuel, Hui Zhou, Xiangxin Li, Hui Wang, Haoshi Zhang, Arun Kumar Sangaiah, and Guanglin Li. Pattern recognition of electromyography signals based on novel time domain features for amputees' limb motion classification. *Computers and Electrical Engineering*, (April), 2017.

[35] J. Raudys & Anil K. Jain Sarunas. Small Sample Size Effects in Statistical Pattern Recognition: Recommendations for Practiotioners, 1991.

[36] Jonathon W. Sensinger, Blair A. Lock, and Todd A. Kuiken. Adaptive pattern recognition of myoelectric signals: Exploration of conceptual framework and practical algorithms. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 17(3):270–278, 2009.

[37] Claude Elwood Shannon. *The Mathematical Theory of Communication by CE Shannon and W. Weaver*. 1949.

[38] Matija Štrbac, Milica Isaković, Minja Belić, Igor Popović, Igor Simanić, Dario Farina, Thierry Keller, and Strahinja Došen. Short-and long-term learning of feedforward control of a myoelectric prosthesis with sensory feedback by amputees. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2017.

[39] Tatiana Tommasi, Francesco Orabona, Claudio Castellini, and Barbara Caputo. Improving control of dexterous hand prostheses using adaptive learning. *IEEE Transactions on Robotics*, 29(1):207–219, 2013.

[40] Pauli Virtanen and et al. SciPy 1.0–Fundamental Algorithms for Scientific Computing in Python. *arXiv e-prints*, page arXiv:1907.10121, Jul 2019.

[41] L. N. Vostrova, T. A. Voronina, T. L. Karaseva, S. A. Gernega, E. I. Ivanov, A. M. Kirichenko, and M. Yu Totrova. Synthesis and anticonvulsant activity of benzimidazo[1, 2-c]quinazolines. *Pharmaceutical Chemistry Journal*, 20(6):404–406, 1986.

[42] Max Welling. Auto-Encoding Variational Bayes arXiv : 1312 . 6114v10 [stat . ML] 1 May 2014. (Ml):1–14.

[43] Wu Yi Yang, Sheng Xing Liu, Tai Song Jin, and Xiao Mei Xu. An optimization criterion for generalized marginal Fisher analysis on undersampled problems. *International Journal of Automation and Computing*, 8(2):193–200, 2011.

[44] Aaron J. Young, Lauren H. Smith, Elliott J. Rouse, and Levi J. Hargrove. Classification of simultaneous movements using surface EMG pattern recognition. *IEEE Transactions on Biomedical Engineering*, 2013.

[45] Mahdi Zeinali and Masoud Shafiee. A new Levinson–Durbin based 2-D AR model parameter estimation method. *Multidimensional Systems and Signal Processing*, 20(1):35–47, 2014.

[46] Chiyuan Zhang, Benjamin Recht, Samy Bengio, Moritz Hardt, and Oriol Vinyals. Understanding deep learning requires rethinking generalization. *5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings*, 2019.

[47] Bo Zong, Qi Song, Martin Renqiang Min, Wei Cheng, Cristian Lumezanu, Daeki Cho, and Haifeng Chen. Deep autoencoding Gaussian mixture model for unsupervised anomaly detection. *6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings*, pages 1–19, 2018.