2020

Evaluating the Use of Artificial Neural Networks in Robotic Prostheses

ELEC5032M – MODERN INDUSTRY PRACTICE

Introduction

Prosthetics used to replace missing human limbs often struggle to allow the same level of functionality as their human counterparts due to the inability to read the user's intent. Researchers have therefore begun to consider the use of artificial neural networks (ANN) to process the inputs from a variety of sensors placed on remaining muscles to try and predict the intention of the brain so that robotic prostheses can act on this intention [1…4]. In this paper, an investigation into the current state of ANN usage in robotic prostheses will be used to inform an evaluation of different types of ANN, potential errors, their severity and how they can be mitigated. This will lead to a concluding summary which will outline the developments needed to make predictive ANN usage in prosthetics reliable, accurate and safe.

Current State of the Art

Overview

Current investigations into the use of ANNs in prosthetics is plentiful and yields a wide range of results depending on the limb, quality of data, number of detected motions and the type of ANN used to classify movement. Many studies currently aim to create a system that can accurately identify intention using surface-electromyography (sEMG) [2], [3], [4], as this method is non-intrusive at the cost of accuracy. sEMG works by reading small electrical muscle signals through the skin using electrodes [5] and, due to its popularity, will be the focus of this paper. The following section will evaluate the performance of several ANN-based methods for classifying limb motions and gestures.

Prosthetic Hands

With respect to prosthetic hands, research performed in 2016 explored pattern recognition using convolutional neural networks (CNN) on sEMG signals [2]. Data was recorded from 67 different hand motions, resulting in a <2% probability of randomly guessing the hand motion. With these parameters, the accuracy when tested on people with in-tact limbs was as high as 66.59 ± 6.40% for able-bodied test subjects, dropping to 38.09 ± 14.29% for amputees [2]. The paper states that these results stem from the low (2%) chance for the ANN to randomly guess the correct gesture as this probability is proportional to the overall accuracy [2].

Another paper on using CNNs on sEMG signals in 2018 attempted to classify data from just 10 'key' hand motions seen in Figure 1 [4]. Compared to the paper in [2], this experiment has a much higher probability of guessing the correct classification at 10%, which is reflected by the results, where accuracies of 98.88% to 100% were attained depending on the specifications and parameters of the CNN [4].

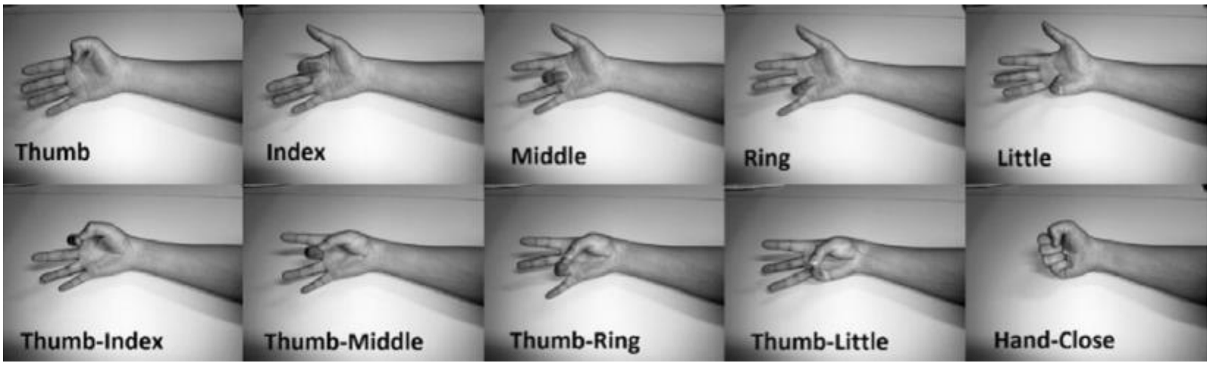


Figure 1. The classifier motions from the experiment in [4].

A paper from 2013 investigated a neural network called the "Recurrent Log-Linearized Gaussian Mixture Network (R-LLGMN)" which demonstrated superior accuracy to standard ANNs by up to 39% (93.04 ± 0.11% for R-LLGMN versus 46.52 ± 10.4%: maximum difference for a single subject) [5]. This study attempted to classify only 6 hand motions (16.66% correct guess chance) (seen in Figure 2) and uses methods proposed in 2003, showing that both R-LLGMN and older ANNs are far inferior to the modern CNN methods for classification in [2] and [4].

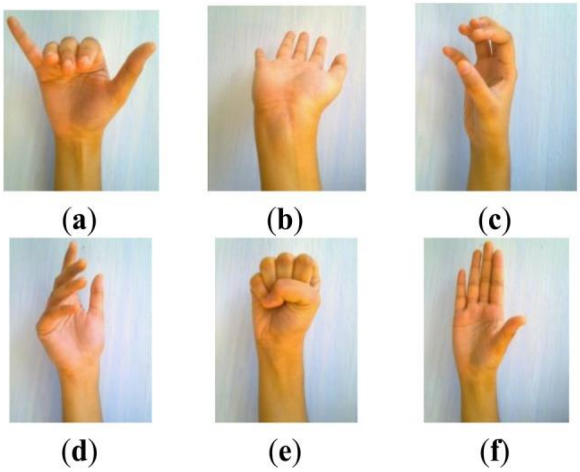


Figure 2. Motions from [5] to be classified using R-LLGMN and ANN methods. The motions depicted are (a) flexion, (b) extension, (c) supination, (d) pronation, (e) hand grasping and (f) hand opening [5].

A recent development in 2018 demonstrated the use of an extreme learning machine (ELM) compared to an ANN in classifying 6 hand gestures (16.66% correct guess chance) (seen in Figure 3) [6]. Here, it was demonstrated that an ELM system could achieve accuracies of 96.44 ± 0.31% and above compared to the 93.23 ± 5.72% accuracy of the ANN [6]. This increase in both accuracy and consistency and decrease in error spread demonstrates clear superiority of an ELM method of classification over traditional ANN methods.

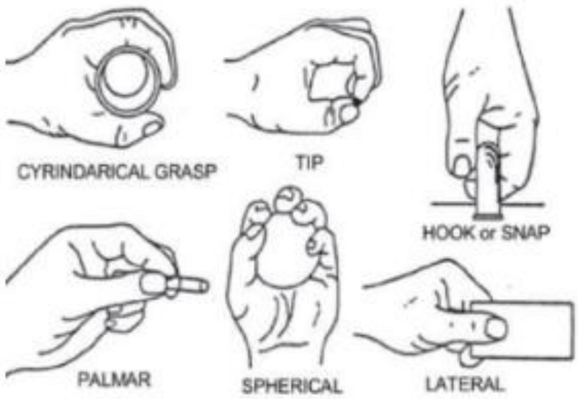


Figure 3. The 6 gestures to classify from [6].

From these examples it is evident that, due to the complexity and profusion of hand motions, a trade-off is naturally formed between the number of classifiable motions and the accuracy of the classifying network. CNN-based methods for classifying data gained through sEMG seem to produce the most desirable accuracies whilst an ELM offers high consistency and low train times [6] which could make it more appropriate for quickly tailoring prosthetics to individual users. Both methods seem to eclipse the older ANN methods due to the specialisation of modern techniques.

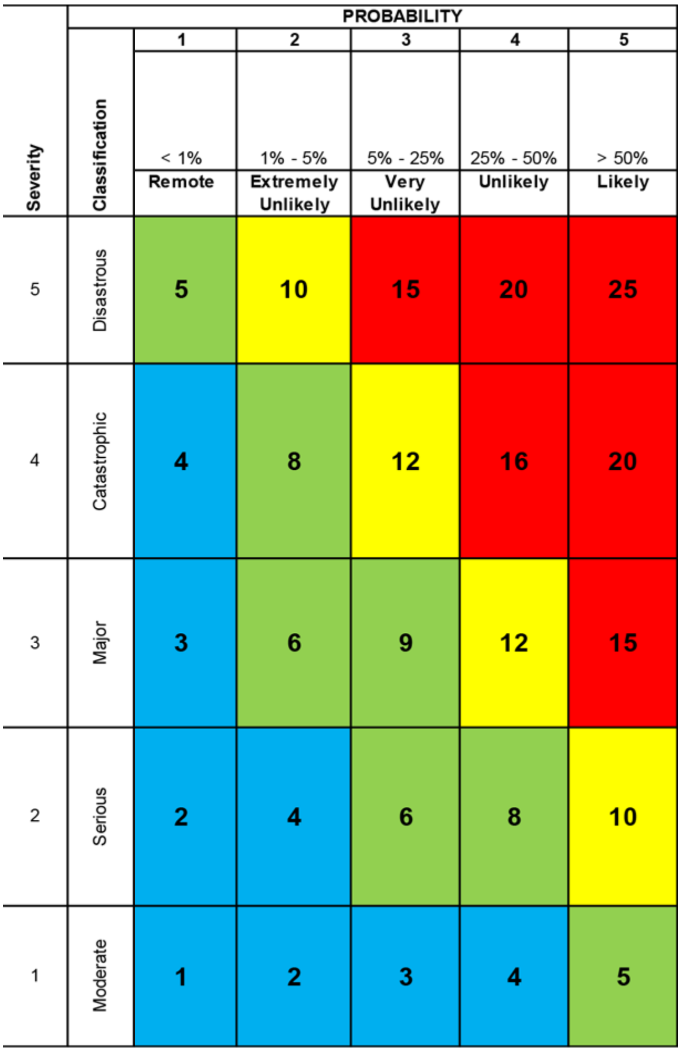
Error Effects and Mitigation

Overview

It is crucial to place the error probability in context as, while a 99% accuracy may appear good, if a patient cannot rely on a hand or leg for 1/100 motions, this could relate to several failures per day and could lead to potentially dangerous scenarios. In this section, the methods for minimising error in an ANN-based system will be explored and weighed against the severity of potential failures.

FMEA

A Failure Mode and Effects Analysis (FMEA) (seen in Figure 4.) is a common way to analyse the risk associated with the use of medical devices [7], [8]. FMEA is a technique that uses the probability of occurrence and severity of each possible failure a device can suffer to determine whether it is safe for use [7], [8]. In the context of ANN in prosthetics, a rather unique FMEA can be created where the probability of failure is constant and determined by the accuracy of the ANN whilst the severity is determined by the situation in which the device fails. For example, consider the ELM from earlier in this paper: the probability of error will be 3.56 ± 0.31% [6] in all situations, landing all failures in the 'extremely unlikely' category of Figure 4. A CNN approach, however, could be classified as 'remote' due to its high accuracy.



Severity	Classification	PROBABILITY 1: < 1% Remote	2: 1% - 5% Extremely Unlikely	3: 5% - 25% Very Unlikely	4: 25% - 50% Unlikely	5: > 50% Likely
5	Disastrous	5	10	15	20	25
4	Catastrophic	4	8	12	16	20
3	Major	3	6	9	12	15
2	Serious	2	4	6	8	10
1	Moderate	1	2	3	4	5

Figure 4. An example of an FMEA, cropped and taken from [8]. Blue denotes no action, Green denotes consideration of action, Yellow denotes action needed and Red is unacceptable.

Discussion

Given the initial investigation into ANNs in the context of robotic limbs, both ELM and CNN approaches seem to vastly outclass the other approaches in terms of accuracy and training time. Minimising train times at the cost of ~2% accuracy may initially make ELM appear superior to CNN, however the FMEA analysis suggests that CNN approaches are inherently safe whereas ELM methods need action to be taken to prevent a ‘disastrous’ event. Ultimately these devices are created to alleviate the burden placed on people’s lives as a result of the loss of a limb, placing the question on the user: would they rather be able to perform certain activities that could be considered dangerous (i.e. carrying large amounts of hot liquid) or would they prefer to get the limb quickly and guarantee that it will be accurate for them as an individual (the properties of an ELM)? In either case, improving the accuracy of an ELM approach to above 99% would seem to be the next step in improving robotic prosthetics for users as they would benefit from both the speed and accuracy of this system.

Conclusion

In conclusion, a variety of ANN techniques have been developed to classify sEMG data and generate corresponding movements in a robotic prosthetic. From the evaluated approaches, CNN and ELM approaches both offered benefits in different areas that would aid users: increased accuracy and increased consistency respectively. After performing the FMEA analysis of these approaches, neither network appeared superior and the decision for which technique is used should consider the user’s desires. The future of ANN developments for prosthetics is clear however, as if the accuracy of ELM approaches can be improved, it will be the decisive method for use in prosthetic limbs.

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