Time-Series Neural Network Controller for Prostheses For Amputee Patients With Upper Limb Impairments

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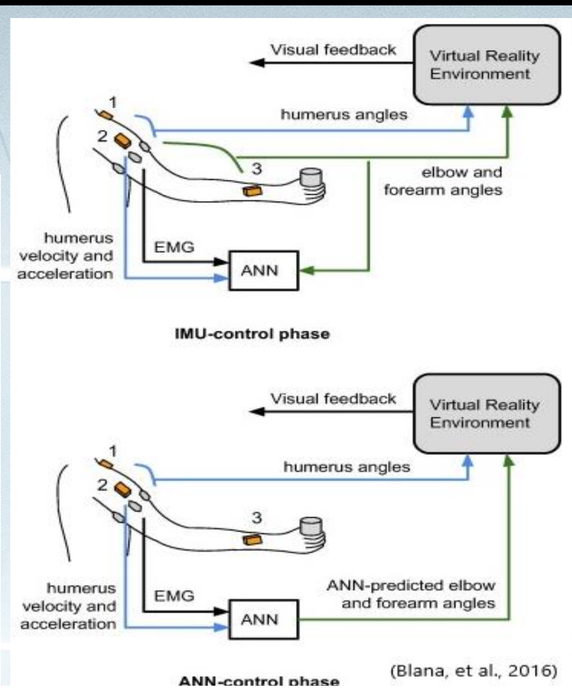
Introduction

Researchers from the Institute for Science & Technology in Medicine (ISTM) at Keele University have already recorded suitable data for a prosthetic limb controller. They recorded using 10 able-bodied participant (seven male, three female, age range 22–35 years), offline and using virtual reality environment from their upper limb muscles' movement signals [1]. Recording data from able bodied participants enables capturing 12-dimensional muscle accelerometer data, corresponding movement and ground truth of elbow and forearm. In this project, the main idea is to see if we can train a neural network (NN) controller for a person who lost their arm above the elbow. Neural network controller can take their muscles' signals and send the correct signal to the prosthetic limbs to move to elbow in the arm.



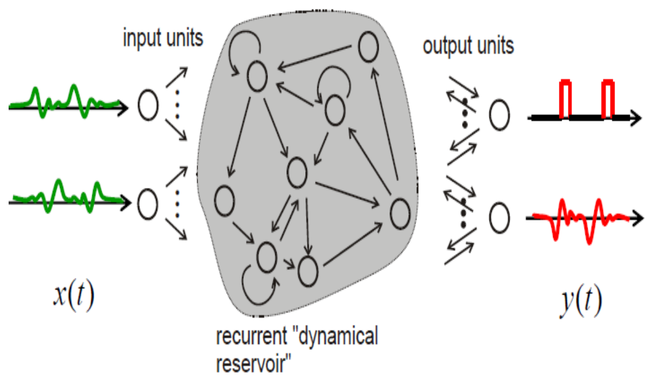
Aims And Objectives

The main aim is to explore the neural network controllers that progress time series data in order to move elbow and prosthetic limb in real time.
The way to carry out this comparative is being done by:

- Pre-preparing the data in different ways e.g. normalising, standardizing the data, for each of the normalization three different time series approaches are evaluated,
- Presenting the data to make generic and patient specific (bespoke) NN controller
- Training and testing Echo State Networks (ESN) ,
- Training and testing Time-delay neural network (TDNN),
- Training and testing Long Short-Term Memory(LSTM).

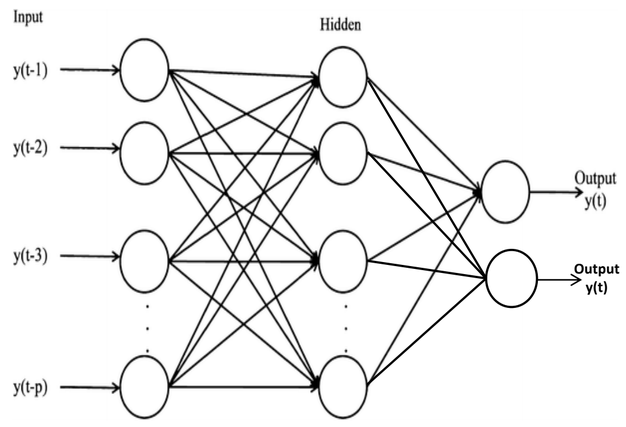
This project will compare the training and testing results from 3 different machine learning approaches.

Echo State Networks (ESN)



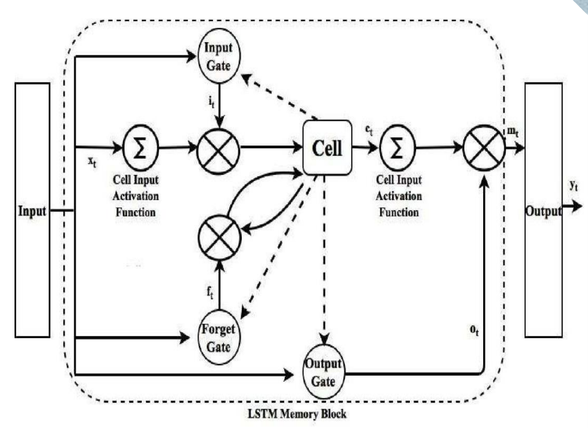
[5] In ESN, NN uses the reservoir that authentically develops dynamic short-term memory to learn the data.

Time-delay neural network (TDNN)



TDNN deals with data by controlling the delay lines where the short-term memory for data is gathered.

Long-Short Term Memory(LSTM)



[4] LSTM learns from forgetting certain parts of cells, short of tunes itself longer and shorter memory.

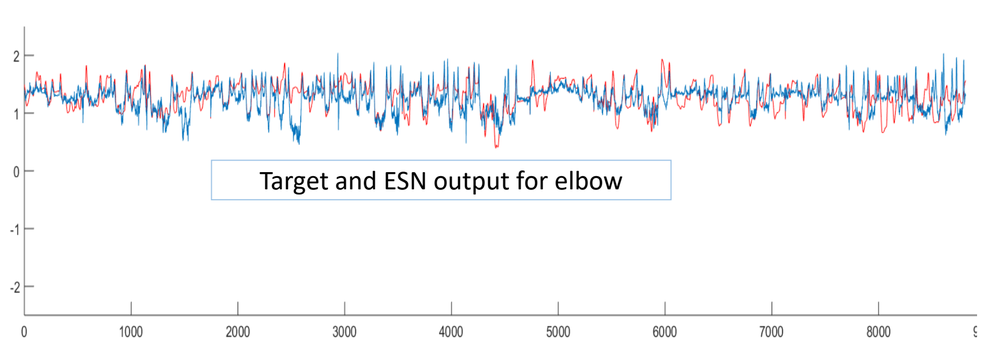
Methodology

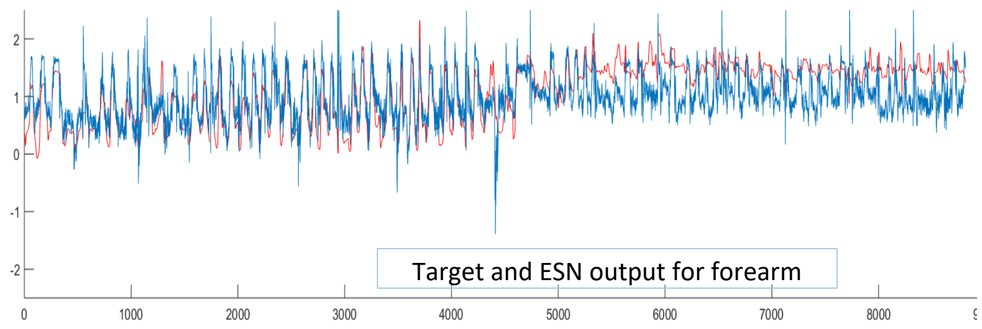
- A comparative machine learning methodology is employed in this project to see if one of the time series neural network (NN) controllers outperform the others with same data. Even if they do not outperform others, the comparative machine learning methodology will contribute to a novel finding in this area.
- The analysis will not be a linear process, but it will include iterative processes of testing and exploring how the data can be prepared for each approach and how best to compare their results. To get the most appropriate result, normalization and standardisation of the data is undertaken, and compared with the raw data.
- It includes training the neural networks to develop the best ESN, TDNN and LSTM to generic and patient-specific NN controller.
- Comparison of how effective those neural networks will be undertaken to weigh and calculate normalised root mean square error of data (NRMSE). NRMSE assesses the difference between neural network signals and target signals value showing the scope of error between two datasets [3].
- Analyses will be carried out by using MATLAB with ESN and Deep Learning toolbox.

Work Done so Far

Before developing neural network, the first thing done was to normalize data in different ways, i.e. centralize and scale the data to have a mean 0 and standard deviation 1 or range of the data [0,1] to get more occurrent result [2]. Subsequently, these datasets are used to train and test the ESN to see any meaningful result and to observe which normalization provides the best result. Different combination of datasets examined to obtain the same NN controller to apply on different subjects to see the suitability of the trained ESN. Because reservoir and hidden layers sizes play a virtual role to develop NN, different reservoir and hidden layer sizes tried and reported efficacy with NRMSE.

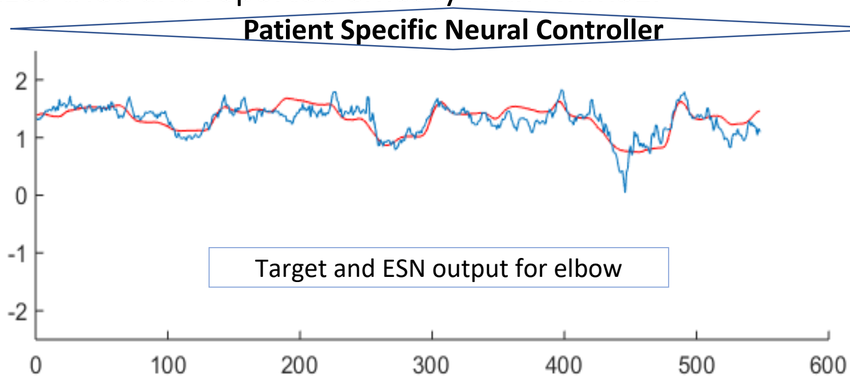
Generic Neural Controller

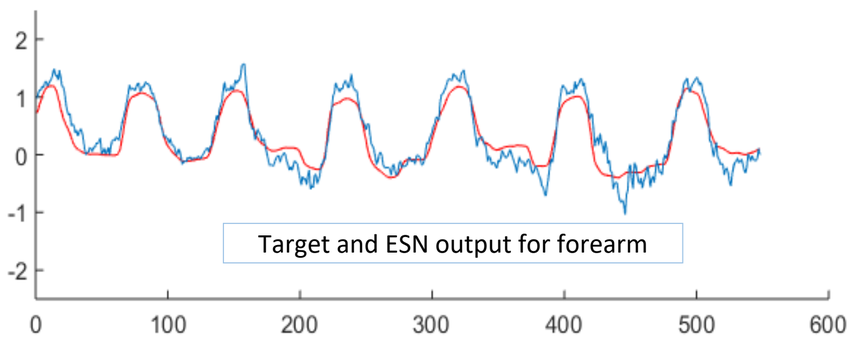




ESN is trained with subject 1-2-3's all training data's and evaluated with subject 2's all testing data to see if generic neural network that suits each subject can be created. Training NRMSE is for elbow= 1.3275, for forearm 0.99314, testing NRMSE for elbow= 1.6599 for forearm= 1.595.

Patient Specific Neural Controller





ESN is trained with part of subject 1's data to training **normalized** data and evaluate subject 1's other part of data as a testing **normalized** data. This is done to see can we produce neural network that created general and suits each subject. Training NRMSE is for elbow=0.42137, for forearm=0.20241, testing NRMSE for elbow= 0.64802 for forearm= 0.3697

Gantt Chart

Gannt Chart	Weeks													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Project Plan														
Literature Review														
Investigate and analyse property of data														
Normalising and pre-processing on data														
Train DeepESN														
Test DeepESN														
Train TDNN														
Test TDNN														
Train LSTm														
Poster														
Test LSTM														
Comparison of results														
Report														
Documentation														

After getting result from ESN, the project will carry out similar combination of data scenarios to develop TDNN and calculate the NRMSE by using MATLAB Deep Learning toolbox and own code. This comparison will allow us to see a clearer picture of which error is smaller than others and how accurate the predicted data between all NNs. After testing or during the testing TDNN, training and testing data with LSTM will continue to evaluate.
NRMSE has been calculating in each training and testing runtime, when these three NN are trained and tested with different pre-prepared and combined data, those NRMSE will be used to calculate the differences of these NNs. This will show us more occurrent and effective way to develop NN controller.

- 6 steps completed
- 3 steps work in progress
- 3 more steps need to be done

References

[1] Blana, D., Kyriacou, T., Lambrecht, J. & Chadwick, E., 2015. *Feasibility of Using Combined EMG and Kinematic Signals for Prosthesis Control: a Simulation Study Using a Virtual Eeality Environment*. Journal of Electromyography and Kinesiology.
[2] MathWorks, 2019. *Normalize* [online] Available at < https://www.mathworks.com/help/matlab/ref/double.normalize.html > [Accessed 05 August 2019]
[3] Tianfeng, C. & Draxler, R. R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature. *Geosci. Model Dev,* 7(3), pp. 1247-1250.
[4] Chauhan, S. & Lovekesh, V., 2015. Anomaly detection in ECG time signals via deep long short-term memory networks. *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)* , pp. 1-7.
[5] Day, C. & Anderson, P., 2019. *Lecture23 Echo State Networks For Time-series Processing.* Keele University.