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Performance Comparison of Training Algorithms for Classification of Finger Motion from Electromyography (EMG) Signal.

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ABSTRACT – The procedure in implementing the learning process in artificial neural network (ANN) is known as training algorithm. Currently there are over a dozen algorithms commonly used for this purpose. Deciding which one to use for a given classification problem requires a proper study. This paper compares the performance of three famous algorithms, namely the gradient descent (GD), Scaled Conjugate Gradient (SCG) and the Levenberg-Marquardt (LM) algorithm in finger motion classification from Electromyography (EMG) signal. The results indicate that the choice of the training algorithm plays a significant role in the classification performance of the ANN. In this case, LM is the best, followed by SCG and GD.

1. INTRODUCTION

The implementation of the learning process in an artificial neural network is referred to as training algorithm. Currently, there are at least a dozen of training algorithms for example, gradient descent, one-step secant, Polak-Ribiére and Levenberg-Marquardt algorithm. It is difficult to know which one produces the most accurate classification for a given problem. It depends on many factors, such as the complexity, number of data points in the training set, number of neurons and layers in the network, the error goal, and types of problems either pattern recognition or function approximation i.e. regression [1].

The most basic and simplest algorithm is the gradient descent (GD). This algorithm uses the gradient vector to determine the direction of the decrease in the loss function, hence it is considered as a first order method. The main drawback of GD is due to its low accuracy and slow convergence. This algorithm will be used as benchmark in this study. An improvement in gradient descent is the Scaled Conjugate Gradient (SCG), which utilizes the second derivatives of the loss function i.e. the Hessian matrix. This produces faster convergence at the expense of more memory and computing power since the size of Hessian matrix equals to square of the size of gradient vector. The third and final algorithm in this study is the Levenberg-Marquardt (LM) algorithm, which works without Hessian matrix but with a combination of the gradient vector and Jacobian Matrix.

Previous study had shown that, for function approximation problems, LM produces lower mean square errors than any of the other algorithms. However, LM performs relatively poor on pattern recognition problems. On the other hand, SCG deliver good performances over a wide variety of problems. The reason for choosing only these two algorithms is made due to their top performances in function approximation and pattern recognition problem [2].

In this paper, the previously described algorithms will be tested for a pattern recognition problem, namely finger motion classification from Electromyography (EMG) signal. The unavoidable removal of the human lower arm due to diseases or accidents is one of disabilities that cause huge limitation in daily lives of the affected people. The interaction of the missing limb be reestablished using myoelectric control in which EMG is commonly used sensor for acquiring the action of the muscle. The ability to perform pattern recognition will give a huge contribution in explaining the muscle activity or finger movements.

The main components of this study are on the feature extraction and classification of the five finger motions from the EMG raw signals. Especially, the performance comparison between GD, SCG and LM training algorithms is of huge interest.

2. METHODOLOGY

The methodology can be divided into two stages, namely the (i) Extraction of raw signal and feature selection and (ii) Training and classification with artificial neural network (ANN).

2.1 Extraction of raw signal and feature selection

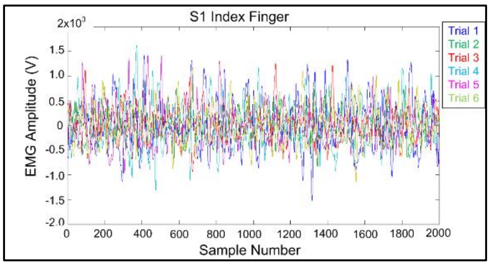
The raw signal is obtained from a published datasets repository for EMG [3]. The data collection involves eight subjects aged between 20 and 35 years that consisted of six men and two women. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) is used to sample the signal at 4000 Hz. Five classes of finger motions are gathered, namely, Rest, Thumb (T), Middle (M), Little (L), and finally Ring (R). From the raw signals, twelve features are calculated as input for the ANN, namely the Integrated EMG (IEMG), Mean Absolute Value (MAV), Modified Mean Absolute Value Type 1 and 2 (MAV1, MAV2), Simple Square Integral (SSI), Variance (VAR), Root Mean Square (RMS), Waveform Length (WL), Difference Absolute Standard Deviation Value (DASDV), Hjorth 1,2 & 3 and Autoregressive (AR) [4].

2.2 Training and classification with ANN

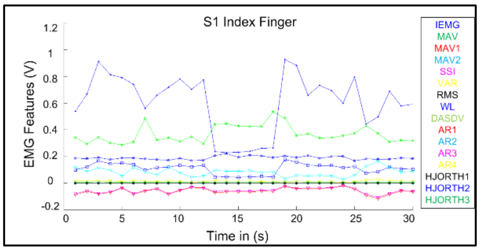
The input data for the finger movement classification is arranged in 16 x 30 matrix. This corresponds to the 16 features that have been calculated as rows and 30 as data samples that have been used as input vector in ANN. The target vector has 5 classes of finger movements. All the targets that have been used in all sample are same every of each class. The targets consist only of the value of '0' or '1' only. The 30-dataset samples of finger motion are divided into three subsets. The division of the subsets are 70% for training, 15% for testing and 15% for validation. The ANN consists of ten neurons in the hidden layer and five neurons in output layer, which is valid for all cases in the study. The implementation of ANN is performed in MATLAB using a laptop with Intel i7 2.6 GHz processors and 8 GB RAM.

3. RESULTS AND DISCUSSION

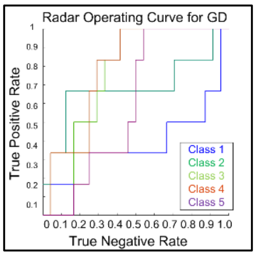
For demonstration purpose, Figure 1(a) shows the raw signals from six trials of the index finger movement obtained from Subject 1. Meanwhile, Figure 1(b) shows the calculated 12 features from the raw data. Lastly, Figure 1(c)-(e) show the Radar Operating Curve (ROC) for all classes of finger movements using different algorithms. Clearly, the worst performing algorithm is GD with area under the curve (AUC) of 12 as shown in Figure 1(c). On the other hand, LM is the best performing algorithm with the largest AUC of 27 as shown in Figure 1(e). Meanwhile, SCG performs moderately with AUC of 24 and ranked 2nd in between GD and LM as shown in Figure 1(d).



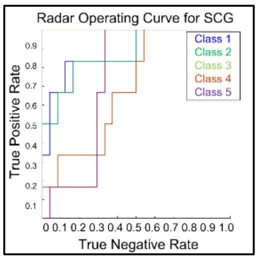
(a)



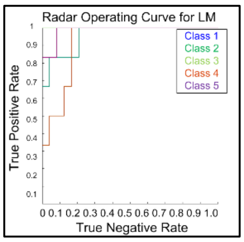
(b)



(c)



(d)



(e)

Figure 1: The results for subject 1 showing (a) the raw signal for all six trials of lifting the index finger and (b) 12 calculated features and the ROC for (c) GD (d) SCG and (e) LM algorithm.

4. CONCLUSIONS

In conclusion, the study reveals that LM algorithm is the best performing algorithm for classification of finger motion from EMG signal, followed by SCG and GD. Future work will involve more statistical analysis of the data from all subjects.

REFERENCES

[1] Cömert, Z., & Kocamaz, A. F. (2017). A study of artificial neural network training algorithms for classification of cardiotocography signals. *Bitlis Eren University Journal of Science and Technology 7(2)*, 93-103.

[2] MathWorks. (2018). *Choose a Multilayer Neural Network Training Function*. Retrieved from MathWorks: https://www.mathworks.com/help/deeplearning/ug/choose-a-multilayer-neural-network-training-function.html.

[3] Khushaba, R. N., Kodagoda, S., Takruri, M., & Dissanayake, G. (2012). Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals. *Expert Systems with Applications, 39(12),* 10731-10738.

[4] Ariyanto, M., Caesarendra, W., Mustaqim, K. A., Irfan, M., Pakpahan, J. A., Setiawan, J. D., & Winoto, A. R. (2015). Finger movement pattern recognition method using artificial neural network based on electromyography (EMG) sensor. *International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT),* 12-17.