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Research paper

Detection of muscles diseases based on EMG signal by using locally recurrent neural networks (LRNNs) techniques

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Abstract

Muscle diseases occur in all age groups and can cause serious physical disability. The effect of such diseases is severe when children and young adults are affected. The needs of these patients are numerous and complicated and are frequently inadequately met. Some muscle diseases respond well to medical treatment, whereas many physical disabilities can be improved or prevented.
This paper presents the implement of The Locally Recurrent Neural Networks (LRNNs) to detect the muscles diseases based on real measurement of electromyography (EMG) signals. The LRNNs training achieved by using Levenberg-Marquardt back propagation (LMBP) to get high accuracy through the identification and recognition process. Many processing applied with EMG signal through LRNNs before recognition the diseases. Finally design the simulation of this work by using Graphical User Interface (GUI) through MATLAB. Satisfactory results are obtained with the case study of real implement on human arm muscles.

Keywords: *Locally Recurrent Neural Networks (LRNNS); Electromyography (EMG) Signals; Graphical User Interface (GUI); Levenberg-Marquardt Back Propagation (LMBP).*

1. Introduction

Electromyography activity is recorded from contracted arm muscles upon execution of the instruction from the brain. Electromyography (EMG) is used to recognize the activities developed by individual muscles while crossing the bones of the body. Muscle refers to the tissue of the body that primarily functions as a source of power. Muscles in the body are of three types. Muscles responsible for moving extremities and external areas of the body are called "skeletal muscles." Heart muscles are called "cardiac muscles." Muscles in the walls of arteries and bowels are called "smooth muscles."
Nerve is a fiber that connects the brain and spinal cord with various parts of the body (also called receptor organs). Nerves conduct impulses from the brain/spinal cord to these receptor organs as well as from the receptor organs back to the brain/spinal cord [1-3].
EMG is a technique used to evaluate and record the electrical activity produced by skeletal muscles. EMG is performed using an instrument called an electromyography to produce a record called an electromyogram. Electromyography detects the electrical potential generated by muscle cells when such cells are electrically or neurologically activated. The signals can be analyzed to detect medical abnormalities, activation level, and recruitment order or the +biomechanics of human or animal movement [5], [6].
Many common medical conditions, such as diabetes, can cause nerve damage. In such cases, the longest nerves are usually affected first, thus the term peripheral neuropathy. Even when diabetes is controlled with diet or oral and injectable medications, nerve damage often occurs. An EMG/NCS can evaluate the severity and monitor any progression of a peripheral neuropathy [7-9].
Myopathy is a disease that is localized to the muscle and Muscle-supporting structures. Myopathies are hereditary (inherited from a mother or father) or acquired (from infection or underlying medical conditions). A patient will usually present with proximal muscle weakness and perhaps myalgia (muscle aches). An EMG/NCS can localize the disease process in such cases to aid diagnosis [10-12].
Focal Neuropathies occur when a single nerve suffers damage at a specific site along its course. An infinite number of possible focal neuropathies exist in the body, but the most common example is carpal tunnel syndrome. Carpal tunnel syndrome occurs when the nerve to the hand is squeezed at the wrist, causing numbness, tingling, and pain. An EMG/NCS evaluates the severity and location of such focal neuropathies [13], [14].
EMG has many characteristics, but the most effective for recognition the diseases are:
Amplitude is determined by the presence of active fibers within the immediate vicinity of the electrode tip. Low-pass filtering by the volume conductor attenuates the high-frequency spikes of remote SFAPs. Thus, the Motor Uint Action Potential (MUAP) amplitude does not increase for a larger Motor Uint (MU). However, MUAP amplitude will increase if the tip of the electrode is located near a cluster of re-innervated fibers. Large MUAP amplitudes are frequently observed in neurogenic diseases [15].
Rise time is an increasing function of the distance between the electrode and the closest active muscle fiber. A short rise time in combination with small MUAP amplitude might therefore indicate that the amplitude is reduced because of fiber atrophy rather than a large distance between the electrode and the closest fiber [16].
Number of phases indicates the complexity of the MUAP and the degree of misalignment between SFAPs. In neurogenic diseases, polyphasic MUAPs arise because of slow conduction velocity in immature nerve sprouts or slow conduction velocity in re-innervated but still atrophied muscle fibers. Variation in muscle fiber size also causes polyphasic MUAPs in myopathic diseases [17].

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Three types of recording devices are commonly used: strip chart recorders, multi-channel analog tape recorders, and computer-controlled data recorders. In each case, the frequency response of the recording device must be at least equal that of the EMG signal being recorded. For surface EMG signals, the frequency response is generally considered to be 10 Hz to 500 Hz, whereas needle (fine-wire) recordings directly from the muscle may produce signals in the range of 2 Hz to 1,000 Hz [18].

The EMG signal is measured either non-invasively with surface electrodes or invasively with wire or needle electrodes. Typical EMG signal levels are in the region of 400 μV to 3 mV (depending on many factors). Thus, the measured EMG signal is almost always pre-amplified, amplified, and conditioned to yield a format that is most convenient for answering the clinical or scientific question of concern. The detection electrode for EMG is typically bipolar, and the EMG signal is amplified differentially. The waveform of the observed action potential will depend on the orientation of the detection electrode contacts with respect to the active fibers. EMG can be recorded from the skin surface or by placing an electrode directly within the subject's muscle, which this is usually referred to as a fine-wire recording [19], [20].

Surface EMG is generally recorded with either passive or active electrodes placed on intact skin surface over the subject's muscle, whereas fine-wire recordings use a wire electrode that is inserted into the muscle by a trained (and, in most cases, licensed) professional. Each electrode type has specific advantages and disadvantages. As regards recording the EMG signal, the amplitude of the MU action potential depends on many factors, including the diameter of the muscle fiber, the distance between active muscle fiber and the detection site (adipose tissue thickness), and filtering properties of the electrodes themselves. The objective is to obtain a signal free of noise (i.e., movement artifact, line frequency interference, etc.). Therefore, the electrode type and amplifier characteristics serve a crucial function in obtaining a noise-free signal [21-24].

The conventional neural networks of Multi-Layer Perceptron (MLP) type have been increasingly in use for recognition and also for other signal processing applications. Those networks work very well as an effective classifier for random signal with stationary spectra, while their phoneme discriminating power deteriorates considerably for consonants which are characterized by variations of their short-term spectra. This may be attributable to a fact that feedforward multi-layer neural network are inherently unable to deal with time varying information like time-varying spectra of EMG signal. One way to cope with this problem to incorporate feedback structure in the networks to provide them with an ability to memorize incoming time-varying information. Incorporating feedback structure in feedforward networks are results in so-called LRNNs, which have feedback connections between units of different layers or connections of self-loop type [24-28].

This paper contains an introduction and general concepts, background of EMG signal physiology of signal, fundamentals of signal, measurement system of real EMG human muscle signals, and design of detection system based on EMG signal by using LRNNs and taking the human arm as case study. Simulation results for all components of system design are discussed, and the GUI design is explained to demonstrate the simulations and present the program. Finally, the conclusion and suggestions for future work are given.

2. Design the NN for recognition of muscles diseases

Real EMG signal was measuring from muscle by using practical measuring unit such as Micromid system or Delsys system. The recognition system of diseases based on LRNNs by using EMG signal consists of three stages:

The first stage, time series data for EMG is measured by electrodes then processing will be applied to this signal such as filtering, amplification and amplitude normalization.

2.1. Filtering the EMG signal

There are two basic filters that can be applied to EMG signals: high-pass and low-pass. Other filters such as notch and band-pass filters are just combinations of these two basic filters. Figure 1, shows zoom in of window for EMG signal for Biceps EMG signal about time (0-0.45 msec).

Actual EMG data has frequency 10-15 Hz or higher, depending on the activity (10 Hz for normal walking and 15 Hz for more rapid movements). Clinical EMG data is usually low-pass filtered at 300-600 Hz for surface EMG, or 1,000 Hz or higher for fine wire EMG recordings because of including the measuring environment. The choice of whether to filter the data or not, and the filter points to use, depends partly on the quality of the raw data and partly on the intended use of the processed data Figure 1, display the effect of low pass (625,1250) Hz and high pass (2500Hz) filters on EMG signal.

2.2. Amplitude normalization

The timing of muscle activity can be easily determined from the raw EMG. The onset and cessation of EMG activity can then be correlated to the stance and swing periods of gait. The difference in the EMG amplitude of a single muscle represents varying levels of activity. As more muscle strength is required, additional motor units are added, thus visually the EMG signal has larger amplitude and becomes denser.

Normalization of the EMG signal amplitude is required when attempting to compare the signals from different muscles. One simple method of amplitude normalization is to normalize each of the displayed EMG channels to the maximum of the signal throughout the current trial within the channel. Thus, the muscle effort can then be displayed as a simple percent of the maximum achieved by that muscle in the current trial. This is a simple method that works very reliably for most common EMG signals. This type of EMG signal normalization is called Maximum Amplitude Normalization is considered in this work by Equation (1).

$$s_n(k) = \frac{s(k)}{\max\left(s(k)\right)_{k=1:N} + K_n * \max\left(s(k)\right)_{k=1:N}}; \quad K_n = 0.45; \tag{1}$$

Where: S_n: represents the normalized signal. K_n: represents the gain for tolerance of the signal normalization, obtained by trial and error.

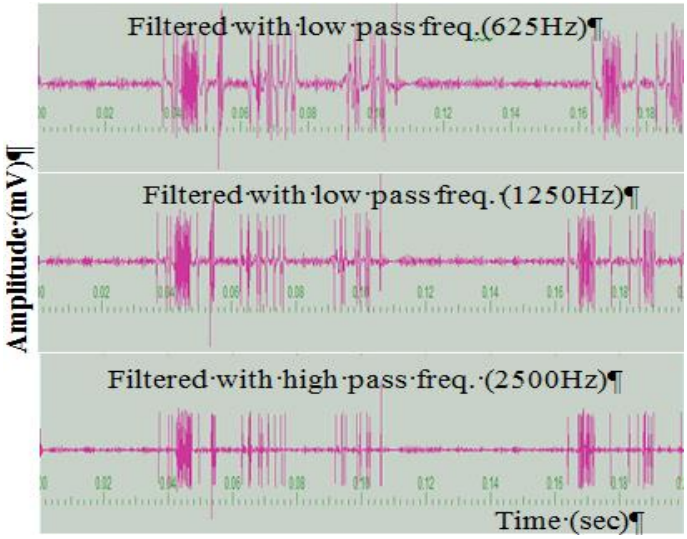


Fig. 1: Filtered EMG Signal.

An alternative normalization method is to make an individual recording from each muscle, while the subject is attempting to generate a maximum contraction for the individual muscle (or muscle group). Each EMG channel is then normalized to the max-

imum amplitude of the recorded EMG signal during the test. This method is more complex and time consuming than the simpler Amplitude Normalization method but is considered to provide a more accurate comparison of the recorded EMG signal. The type of EMG signal normalization is called Maximum Voluntary Contraction Normalization (MVC) [8].

There are needle type electrodes and surface type electrodes to measure EMG signal. The needle (insertion)-type electrode can measure EMG from a specific muscle because of sticking muscle directly. But, it is not preferable for the subject and in danger of sick contagion. As compared with this, the surface-type electrode is preferable for the subject and not in danger of sick contagion and pain. On the other hand, it is difficult to use in practice.

The second stage is identification on LRNNs Figure 2, by EMG signal, it is done by parallel form of identify NN, where the data of EMG arrangement by set with diminution (P×I). The network consist of an i/p Layer (I), hidden Layer (M) and output Layer (N). The weight matrix consists of WI_{mxi} and WO_{nxm}, the characteristic of the network is that the units in hidden layer are connected with themselves and each other.

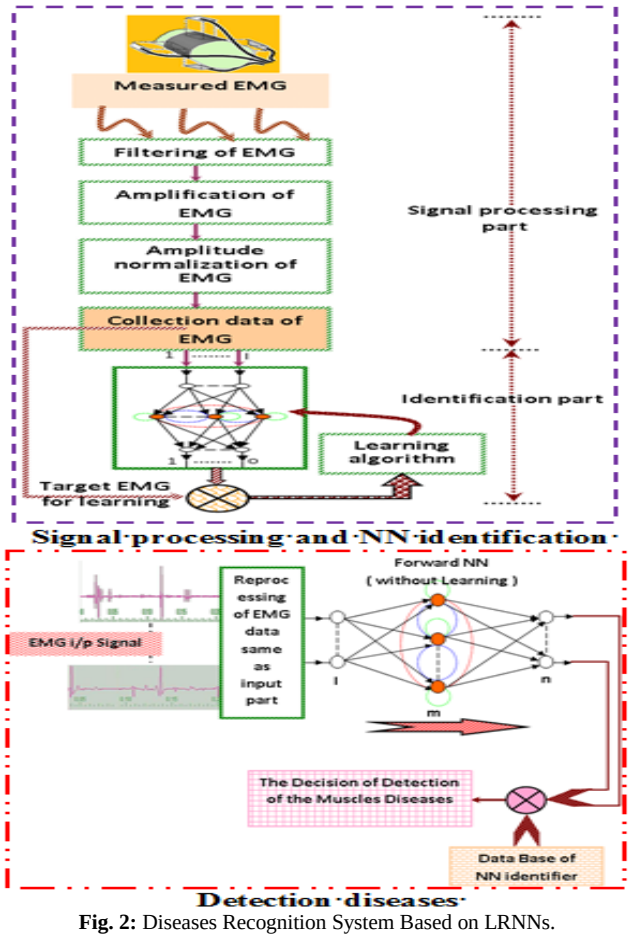


Fig. 2: Diseases Recognition System Based on LRNNs.

However, the information in such units at one time can only be transferred until being replaced by new data after finite steps, i.e. the units in hidden layer only memorize the information for finite time which is the key difference from the fully recurrent BP. Thus, the network here is called finite recurrent back propagation network. Hence at the time (t) the input to the (ith) hidden units are:

$$\left.\begin{aligned} AHi\,(t)=\sum_{k=1}^{I} WT_{ik}\, I_k+\sum_{k=1}^{m} WH_{ik}\, f\,(AH_k(t-1)); \\ i=1,2.....m \end{aligned}\right\} \tag{2}$$

The activation function (f) is a sigmoid, that is:

$$f(x)=\frac{1}{2}+\frac{1}{(1+\exp(-x))} \tag{3}$$

The output of the network is a weighted sum of the hidden unit o/ps:

$$O_i(t)=\sum_{k=1}^{m} WO_{ik} f\,(AH_k(t)); \qquad i=1,2,....n \tag{4}$$

The net is trained by minimization of the total error, which is evaluated as:

$$\left.\begin{aligned} E(t)=\sum_{p=1}^{pp}\left(\frac{1}{2}\sum_{i=1}^{n} e_{ip}(t)^2\right), \quad \& \\ E(t)=\sum_{p=1}^{pp}\left(\frac{1}{2}\sum_{i=1}^{n}\left(T_{ip}(t)-O_{ip}(t)^2\right)\right) \end{aligned}\right\} \tag{5}$$

Where; (pp) is the sample length, $T_{kp}(t)$s are the target values that the output of the (K_{th}) unit in output layer while inputting the (pth) sample match at time (t). This can be fulfilled by a gradient descent procedure adjusting (w) along the negative of ∇w E (t).

In this paper the dimension of LRNNs used is (7-11-2) and the adaptation of weight is achieved by Levenberg-Marquardt modification algorithm. It is an approximation to Newton's method. Suppose that we have a function V(x) we want to minimize with respect to the parameter vector, (x) then Newton's method would be:

$$\Delta x=-\left[\nabla^2 V(x)\right]^{-1}\nabla V(x) \tag{6}$$

Where $\nabla^2 V(x)$ is the Hessian matrix and ∇V(x) is the gradient. If we assume that V(x) is a sum of squares function

$$V(x)=\sum_{i=1}^{N} e_i^2(x) \tag{7}$$

Then it can be shown that:

$$\nabla V(x)=J^T(x)e(x) \tag{8}$$

$$\nabla^2 V(x)=J^T(x)J(x)+S(x) \tag{9}$$

Where J(x) is the Jacobian matrix:

$$J(x)=\begin{bmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_n} \\ \frac{\partial e_2(x)}{\partial x_1} & \frac{\partial e_2(x)}{\partial x_2} & \cdots & \frac{\partial e_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_N(x)}{\partial x_1} & \frac{\partial e_N(x)}{\partial x_2} & \cdots & \frac{\partial e_N(x)}{\partial x_n} \end{bmatrix} \tag{10}$$

$$S(x)=\sum_{i=1}^{N} e_i(x)\nabla^2 ei(x) \tag{11}$$

For the Gauss-Newton method it is assumed that S(x)≈0, and the update (1) becomes:

$$\Delta x=\left[J^T(x)J(x)\right]^{-1}J^T(x)e(x) \tag{12}$$

The Marquardt-Levenberg modification to the Gauss-Newton method is:

$$\Delta x=\left[J^T(x)J(x)+\mu I\right]^{-1}J^T(x)e(x) \tag{13}$$

The parameter μ is multiplied by some factor (β) whenever a step would result in an increased V(x). When a step reduces, μ is divided by β. Notice that when p is large the algorithm becomes steepest descent (with step 1/μ), while for small μ the algorithm becomes Gauss-Newton. The Marquardt-Levenberg algorithm can be considered a trust region modification to Gauss-Newton.
The key step in this algorithm is the computation of the Jacobian matrix. For the neural network mapping problem the terms in the Jacobian matrix can be computed by a simple modification to the back propagation algorithm. The performance index for the mapping problem is given by [8]. It is easy to see that this is equivalent in form to (2), where:

$$x = \begin{bmatrix} w^1(1,1)w^1(1,2)\cdots w^1(S1,R)b^1(1) \\ \cdots b^1(S1)w^2(1,1)\cdots b^M(SM) \end{bmatrix}^T \quad (14)$$
$$,and: \quad N = Q \times SM$$

Standard back propagation calculates terms like:

$$\frac{\partial \hat{V}}{\partial w^k(i,j)} = \frac{\partial \sum_{m=1}^{SM} e_q^2(m)}{\partial w^k(i,j)} \quad (15)$$

For the elements of the Jacobian matrix that are needed for the Marquardt algorithm we need to calculate terms like:

$$\frac{\partial e_q(m)}{\partial w^k(i,j)} \quad (16)$$

These terms can be calculated using the standard back propagation algorithm with one modification at the final layer:

$$\Delta^M = -F^M(n^M) \quad (17)$$

Note that each column of the matrix in (16) is a sensitivity vector which must be back propagated through the network to produce one row of the Jacobian.
A summary for the Marquardt modification to the back propagation algorithm thus proceeds as follows:

1) Present all inputs to the network and compute the corresponding network outputs (the standard BP algorithm), and errors ($e_q = t_q - a_q^M$). Compute the sum of squares of errors over all inputs (V(x)).
2) Compute the Jacobian matrix (using Equations (10, 11).
3) Solve Equation (12) to obtain Δx.
4) Recomputed the sum of squares of errors using: ($x + \Delta x$).If this new sum of squares is smaller than that computed in step (1), then reduce μ by β, let (x=x+Δx).:, and go back to step (1). If the sum of squares is not reduced, then increase μ by β and go back to step (3).
5) The algorithm is assumed to have converged when the norm of the gradient (Equation (4)) is less than some predetermined value, or when the sum of squares has been reduced to some error goal [8].

The Third stage is test recognition system that is done by taking new raw EMG signal and recollecting this data using the same procedure in signal processing part as shown in Figure 2. After that, setting the NN by biases and weight to identify NN in second stage above, enter the new data to forward NN. The output of the recognition NN is compared with output of the identify NN, the difference between them is entered to check for amplitude in order to decide human arm muscle diseases, where the identification of NN is done by all muscles of human arm.

3. Implementation of GUI for simulation the detection of muscle disease

This package consists of 18 main windows, starting with the first window, which is called the "Main window of GUI," and ending with the "Exiting window," as shown in Figure 3. This design consists of 18 windows that can be divided three groups: the first group executes the instruction for call program was writing by using MATLAB editor. This program is used for signal processing, identification of NN, and detection of muscle diseases. The second group comprises windows of the GUI package used for displaying the help files that explain the basic idea and fundamental concepts. The third group is used to manage the GUI package and includes the exit and starting windows



Fig. 3: GUI Windows for System Design.

The starting window of GUI is shown in Figure 3, which explains the idea of the work as well as how to start the research and some problems in this system. The next button is used to move on to the structure of the system window, as shown in Figure 4:(1)–(5).



Fig. 4: (1)–(5): Structure of the Simulated System.

The system has two main parts. One explains the current this division, whereas every button will move to a new window of the system. The properties of every part are shown in Figure 4(2). The package stores photos and movies of some selected subjects, as listed in Figure 4: (3)–(5).

The next step in the GUI is real measurement of EMG signal, which has two main sources for real EMG signals and EMG characteristics. The GUI is shown in Figure 5: (1)–(2).
In thus work, the real EMG signal measured by using the device in AL Ramadi city are stored in the format (filename. TRC) [Figure 5 (1)]. These data can be read and collected by the program EMG lab. The practice data from the hospital are arranged by table for every muscle with three cases: no resistance (no activity of muscle), low resistance (mild), and high resistance. The real value for muscle parameters can be obtained by studying the anatomy of muscles in detail.
To start the process of the detection of muscle diseases, we go to step three in the first window of the designed GUI, as shown in Figure 6. The start button in Figure 6(2) is selected to choose real EMG signal samples. These samples are analyzed by EMG lab, and then the disease is detected in NN, as shown in Figure 6(1). To obtain the data on EMG signals, a specific human arm muscle must be selected.
The applied of NN called by the GUI window is shown in Fig. 6(2). The identification process is based on the choice in terms of collecting the data base for NN reorganization [Fig. 6(3)]. Figure 7:(1)-(3) presents the samples of identification of LRNNs for real EMG signals (Deltoid, Flexor Crapi Radail , Extensor Crapi Ulna muscles).

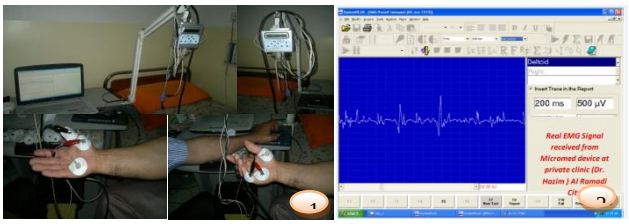


Fig. 5: (1)-(2): Real Measurement of EMG Signals.

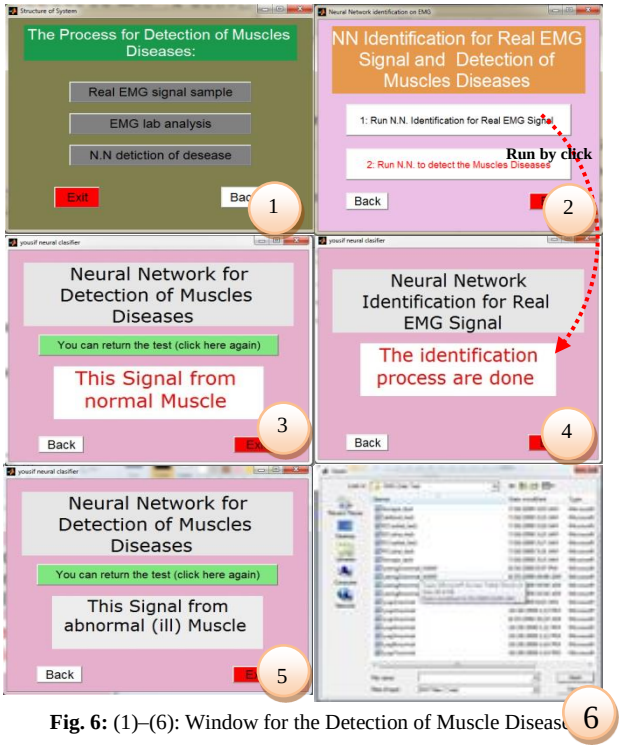


Fig. 6: (1)–(6): Window for the Detection of Muscle Disease

After the identification process, the final stage is the testing window to obtain the final decision on the selected signal. The project can be completed by exiting, as shown in Figure 6: (4)–(6). The "exit window" is shown in Figure 3(2). All windows from 1 to 17 have the option for exit and for returning to the same exit point.

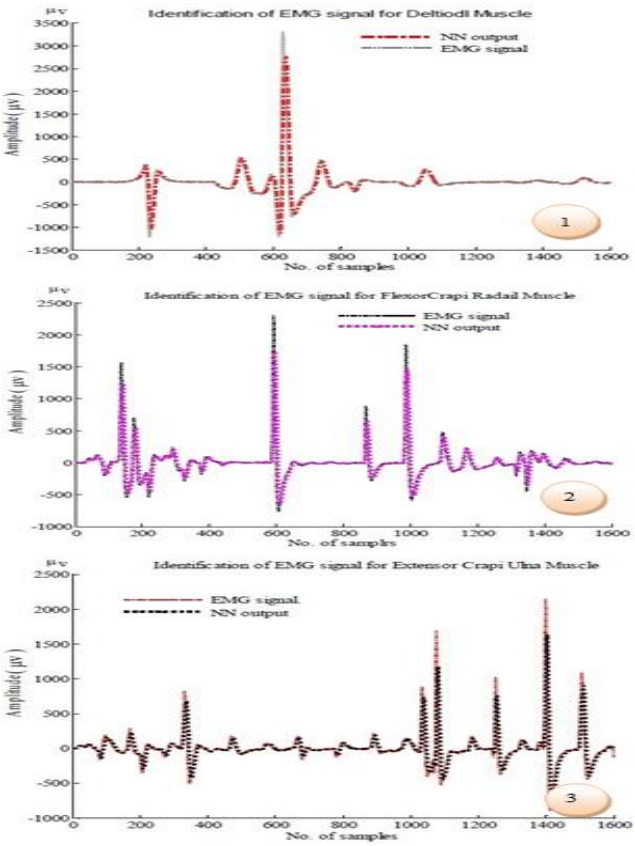


Fig. 7: (1)-(3): Identification of LRNNs for Real EMG Signals.

4. Conclusion

The results are obtained through real measurements and simulation with analysis explains high-accuracy NN detection was used to distinguish human arm muscle EMG signals. Muscle diseases were detected based on EMG signals using LRNNs, which is an efficient method because of its simplicity and accuracy. The design of the proposed package is based on the GUI technique, which gives the capability to connect all three parts under consideration, simulate individual parts by transportation among them, and finally present the three parts simultaneously as one animation system. Moreover, this package includes instructions with explanations presented in notes and graphs, thus enabling this package to be used as an educational tool for human muscle diseases detection.
Real-time monitoring and analysis of EMG signals, extraction of all important features from captured EMG required for correct diagnosis of different neuromuscular diseases, and patient data management enable remote clinicians to follow patient progress. The developed GUI can be easily modified to suit clinician needs.

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