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Artificial Neural Network Based Gait Patterns Identification Using Neuromuscular Signals and Soft Tissue Deformation Analysis of Lower Limbs Muscles

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***Abstract*—The objective of this study is to investigate the use of electromyography (EMG) signals and video based soft tissue deformation (STD) analysis for identifying the gait patterns of healthy and injured subjects. The system includes a wireless surface electromyography (EMG) sensor unit and two video camera systems for measuring the neuromuscular activity of lower limb muscles, and a custom-developed artificial neural network based intelligent system software for identifying the gait patterns of subjects during walking activity. The system uses root mean square (RMS) value of EMG signals and soft tissue deformation parameter (STDP) as the input features. In order to estimate the STD during a muscular contraction while walking, flexible triangular meshes are built on reference points. The positions of these selected points are evaluated by applying the block matching motion estimation technique. Based on the extracted features, multilayer feed-forward backpropagation networks (FFBPNNs) with different network training functions were designed and their classification performances were compared. The system has been tested for a group of healthy and injured subjects. The results showed that FFBPNN with Levenberg-Marquardt training function provided better prediction behavior (98% overall accuracy) as compared to FFBPNN with other training functions for gait patterns identification based on RMS value of EMG and STDP.**

Keywords— electromyography; soft tissue deformation; gait patterns; artificial neural network.

I. INTRODUCTION

Neuromuscular and biomechanical adaptations in gait are common due to lower limb injuries (e.g. knee or ankle injuries) [1-4]. The altered neuromuscular control may be present even in the absence of significant kinematic or kinetic changes [5]. Due to knee injuries, the activation patterns of different muscles around knee are affected which result in gait alterations in subjects. Identification of these gait abnormalities using muscle movements and characteristics is a challenging research topic as various lower extremity muscles provide control and stability during walking by contracting at certain intervals within a gait cycle.

A common technique to monitor the muscle movements is to use electromyography (EMG) which records the electrical potential generated by muscle cells when these cells are electrically or neurologically activated [6]. The surface EMG provides a non-invasive method for recording muscle activation patterns while the intramuscular EMG uses a needle/fine wire for noting the muscles activities.

The usage of surface EMG sensors has been investigated in recent studies for observing the relationship between the muscle force (quadriceps, hamstrings and brachial biceps) and root mean square (RMS) value of the electromyographic signals [7]. A linear relationship was observed between the RMS value of the EMG signal and the contraction force of the rectus femoris, vastus medialis, lateralis, biceps femoris, semitendinosus, and brachial biceps muscles. An analysis of EMG signals and force in human vastus lateralis muscle has been performed in [8] using multiple bipolar wire electrodes which describes the relationship between knee extension force and EMG signals detected by multiple bipolar wire electrodes inserted into the human vastus lateralis muscle under isometric conditions. Study of electromyography activity during sit-to-stand on vastus medialis and vastus lateralis muscle has also been used to provide information that may inform how heel height affects muscle activity around the knee joint [9]. EMG Analysis of lower limb muscles including gluteus maximus, gluteus medius, adductor longus, hamstrings, tibialis anterior, tricep surae, rectus femoris and erector spine muscles was used for developing robotic exoskeleton orthotic device [10]. In this study, the muscle activation patterns were estimated which were used to design the lower-limb exoskeletal assistive robotic systems for physically challenged persons.

However, EMG is a delicate signal which is affected by noise and crosstalk issues. Analyzing the muscle movements using EMG require expertise in terms of set-up and proper placement of electrodes [6]. A less expensive and supportive

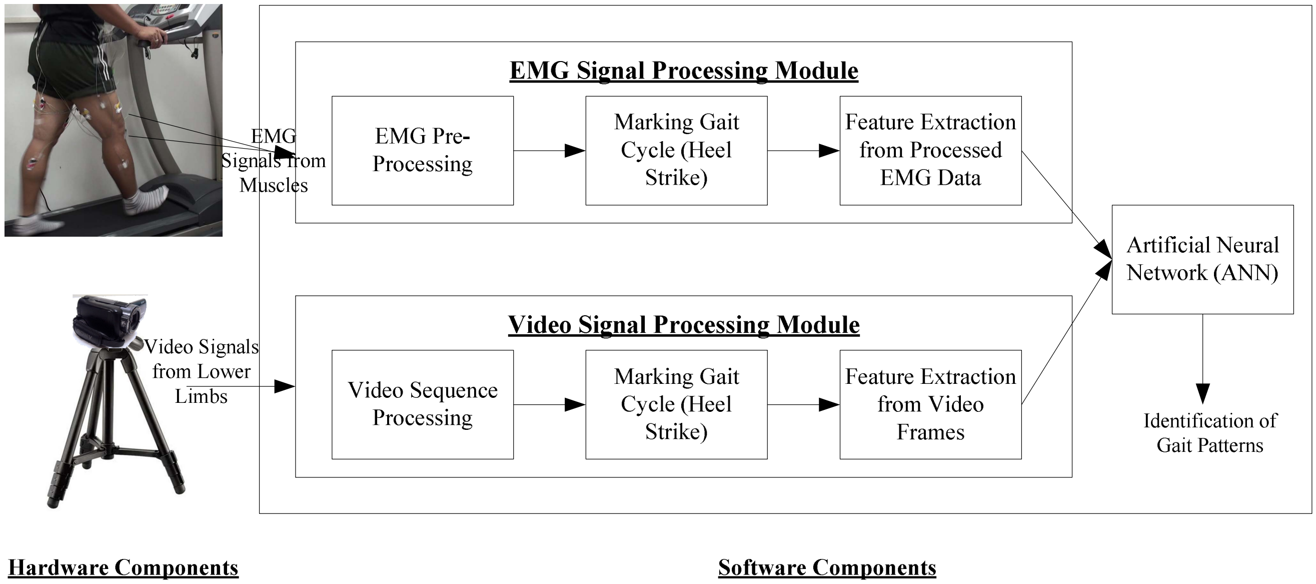

Fig. 1. General framework of the proposed method for processing soft tissue deformation and root mean square of EMG signal

method for analyzing the muscle movements is to use the soft tissue deformation (STD) analysis technique in conjunction with EMG signals [11, 12]. STD analysis can be performed in order to detect the changes in shape and size of muscles during contraction and stretching by using the video cameras. The elastic behavior of lower limb muscles can be modeled by analyzing the video sequences during the human motion.

Artificial neural network (ANN) has been used in various clinical biomechanics applications [13]. One of the most common use of ANN has been in the area of classifying or diagnosing the walking conditions using different types of parameters including ground reaction forces, foot pressure, joint angles, cadence and walking velocity [13]. However, there have been fewer efforts in gait pattern recognition using EMG signals. This study proposes a multilayer feed-forward backpropagation neural network (FFBPNN) based gait pattern identification model for healthy/injured subjects using surface EMG and video sequence analysis of lower limb muscles, EMG and video data have been collected from two lower limb muscle (vastus lateralis and vastus medialis) of healthy and knee injured subjects and feature set is generated in order to train and test the ANN for gait pattern recognition. Different types of training functions for multilayer FFBPNN have been tried and their training convergences and the classification accuracies were compared. The EMG data are processed such that RMS value of EMG signal is extracted for different gait phases. The soft tissue modelling is accomplished by using triangular meshes that automatically adapt to the lower limb body segment during the execution of a dynamic muscle contraction during gait cycle with walking on a treadmill. The aim of this initial study is to investigate the use of EMG and STD analysis for recognizing the gait patterns of healthy and knee injured subjects.

II. METHODOLOGY

A. General System Framework

The general proposed Hardware/Software co-design for identifying the gait patterns of different subjects using artificial neural network (ANN) is illustrated in Fig. 1.

1) *Hardware Components:* The system hardware includes the following major components:

a) Wireless EMG Sensors: These body mounted sensors capture the electromyography signals from lower limb muscles during walking activity. These signals are transferred to the computer through BioRadio system for further processing.

b) Video Cameras: The system used two video cameras in order to capture movements of human muscles and heel strike event during each gait cycle (GC) for walking activity.

2) *Software Components:* The software module of the system includes two major components:

a) EMG Signals Processing Module: The EMG signal module acquires signals from the sensors attached to the lower limb muscles and prepares a feature set for designing the ANN for identifying the gait patterns. It consists of three components.

(*1*) *EMG signals pre-processing*: This phase acquires the signals in raw form from EMG sensors and stores them in the database for initial processing (filtering and rectification etc.)

(*2*) *Marking the Gait Cycle*: This phase is used to identify the heel strike (HS) event from the collected data through BioRadio such that features from the EMG data shall be extracted. In order to mark the gait cycle in EMG data, the HS event was identified by using anteroposterior acceleration from a 2-D accelerometer available in BioCapture (Fig. 2) [14].

(3) EMG signals post-processing: This phase includes the processing of periodic EMG signals for extracting the RMS values from neuromuscular data based on the percentages of each phase of a gait cycle [21]. The selected features are used by the artificial neural network (ANN) for identifying the gait patterns of different subjects.

b) Video Signal Processing Module

The video signal processing modules acquire video recording of subjects during walking on the treadmill and extracts the relevant details (soft tissue deformation parameters) from frames of the video for each GC for designing the ANN for gait pattern identification. Different components of this module are described below.

(1) Video Sequence Processing: This phase includes acquiring the videos recorded from the video cameras and extracting the sequence of frames from them and storing them for further processing.

(2) Marking the Gait Cycle: As per basic characteristics of gait, this phase is responsible to find the moment of heel strike for each gait cycle from the given frames stored for each subject (Fig. 3).

(3) Feature Extraction from Video Frames: This phase provides a comprehensive environment to gain insight into images/frames of gait. It contains following steps:

(a) Gait frames segmentation: In this research, gait frames segmentation has been used to locate an object (lower limbs) and the boundaries of the object in each frame. The application of segmentation to a frame significantly reduces the amount of data to be processed and may therefore filter out information that may be regarded as less relevant.

(b) Threshold: It is important to filter the frames in order to smooth out any noise picked up during video recording. This is essential because noise introduced into a frame can result in false output from the soft tissue detector. Also with a specified threshold value, a better intensity value can be given to a frame. For calculating the threshold value, an auto threshold method was adapted in this research [15-17].

(c) Select region of interest (ROI): The selection of ROI from gait frames was an important step in order to locate the specific muscle of interest for this study. An ROI was selected by creating a cropped image from the threshold frame. The size of the ROI was set to 114×109 pixels for each muscle.

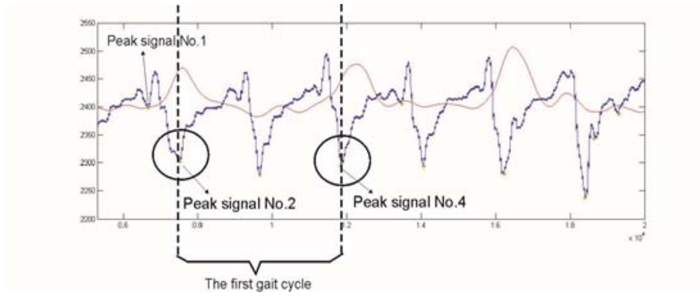

Fig. 2. Heel strike detection of EMG signals using anterioposterior acceleration from accelerometer data

Fig. 3. Heel strike event in a gait cycle

(d) Motion Estimation: As the gait cycle is a dynamic movement, thus, in this research a block matching motion estimation algorithm was implemented in order to achieve sub pixel accuracy without interpolation [18]. In conventional block matching motion estimation algorithms, sub pixel motion accuracy is achieved by searching the best matching block in an enlarged (interpolated) reference search area. This, however, is computationally expensive as the number of operations required is directly proportional to the interpolation factor [18]. This method integrates the block matching algorithm and optical flow method to estimate the motion. Motion vectors are determined by a two-stage algorithm, with the first stage being a single layer block matching, and the second stage being a first order optical flow by solving a 2×2 linear system [18].

(e) Incremental Delaunay Triangulations (IDT): In order to estimate the STD during a muscular contraction while walking, flexible triangular meshes are built on reference points. The positions of these selected points, during the walking are evaluated by applying the block matching motion estimation technique as described above. Mesh generator based motion estimation algorithms automatically select features in a reference frame s_k and estimate the corresponding

feature position in a second frame s_{k+1} to get motion vectors. These feature points are then used as nodes of a mesh. Each node n has a source position $p_{n,k}$ in the reference frame s_k and a target position $p_{n,k+1}$ in the second frame s_{k+1}. The motion of every other pixel of the image is interpolated using surrounding mesh nodes. In case of a triangular mesh, three nodes are used for the motion vector interpolation providing six parameters for an affine transform [19]. Fig. 4 illustrates the mesh generator based motion estimation. Hence, the Soft Tissue Deformation Parameter (STDP) at frame *i* is calculated as follows (1)[11, 12] :

$$STDP_i = \frac{\sum_{k=1}^{M}(a_i^k - a_{i-1}^k)}{M} \tag{1}$$

where M is the number of triangles which forms the meshes and a_i^k is the area of the single triangle k at the frame i.

c) Artificial Neural Network (ANN): The outputs from both software modules are used to design the ANN for detecting the gait patterns of different subjects. The feed-forward back-propagation paradigm of ANN has been used in this research which is a supervised learning method based on the generalization of least mean square error (LMS) algorithm. It uses gradient descent method to minimize the cost function, which is the mean square difference between target and actual net output. The inputs to the ANN are the RMS and STDP values for two selected muscles (vastus lateralis and vastus medialis) and the output is the class/type of the subject.

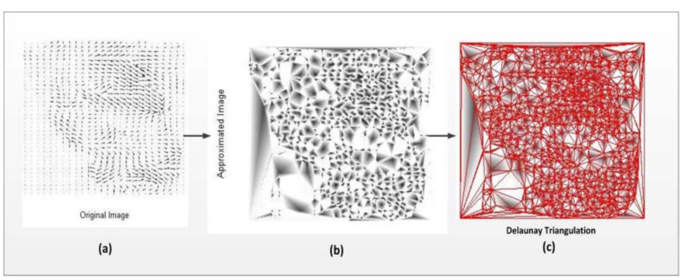

Fig. 4. Mesh generator based motion estimation. (a). Original image motion vector. (b). Approximation image. (c). Delaunay triangulation.

B. Participants

Four male participants (2 healthy soldiers and 2 soldiers having knee injury) were recruited for this study. The average age, height and weight of the subjects were 24 years, 168.4 cm and 69 kg, respectively. The participants were recruited from Ministry of Defense Brunei Darussalam. Ethical procedures were carried out according to the guidelines approved by Graduate Research Office and Ethics Committee at Universiti Brunei Darussalam.

C. Experimental Setup

The EMG signals were recorded using BioCapture physiological monitoring system consisting of BioRadio and USB receiver. The BioRadio records the EMG signals, does initial processing and then wirelessly transmits them to the computer using USB receiver. For this study, the sampling rate to collect EMG signals was set to 960Hz at 12 bit A/D conversion. In order to record surface EMG signals, foam snap electrodes were placed on two lower limb muscles including vastus medialis (VM) and vastus lateralis (VL). SENIAM EMG guidelines were followed for skin preparation and electrodes placement [20]. The raw EMG signals for selected lower extremity muscles were band-pass filtered (20-480Hz) using 4th order Butterworth filter for removing the noise/motion artifacts and generating the required features set.

In order to capture a video sequence for 2-dimensional analysis, two video cameras (Canon Legria HFM41 HD Camcoder and Sony HDR-XR520 Handycam) were set up so that the data from subjects in the narrow sagittal and frontal plane could be recorded at 29 frames per second (fps) with a resolution of 1920×1080 pixels per frame. The cameras were placed on a level tripod, perpendicular to the center of the pathway at a distance of 2 meters. One video camera (set in the sagittal plane) was used to record the muscles movements during walking activity. The other video camera was placed in the frontal in order to record the gait image from the first event of the gait cycle, which the timing of the heel is landed on the ground.

D. Data Collection and Feature Extraction

The gait data from each subject were collected while he was walking on a treadmill at a speed of 4km/h for the duration of around 15-20 seconds. The data collection was performed indoors, with lighting at a constant level. The procedure for data collection was as follows; first each subject was requested to walk on the treadmill at the specified speed and EMG data were recorded using BioCapture system while he was wearing EMG sensors. Three trials were performed for recording the EMG data. Each subject was then requested to walk again on the treadmill at the specified speed and this time the muscle movements data were recorded using video cameras (without covering the muscles with electrodes). Thus, for same speed EMG and video data were collected for multiple gait cycles from each subject. Fig 5. shows video frames of a subject walking on treadmill.

In total, 48 walking trials were completed, yielding 12 gait cycles for each subject and there were 384 events of gait cycle for subsequent data analysis. This was a very important step as the total result depends on the accuracy and quality of the gait captured.

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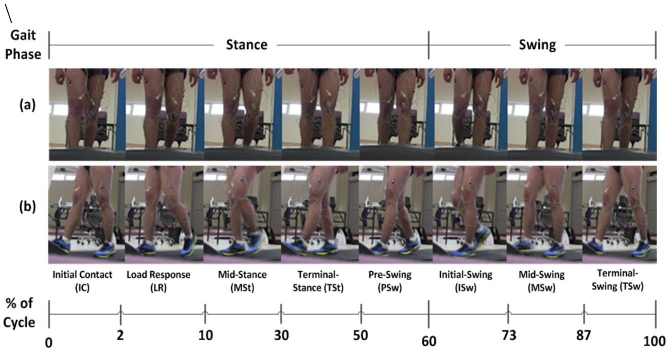
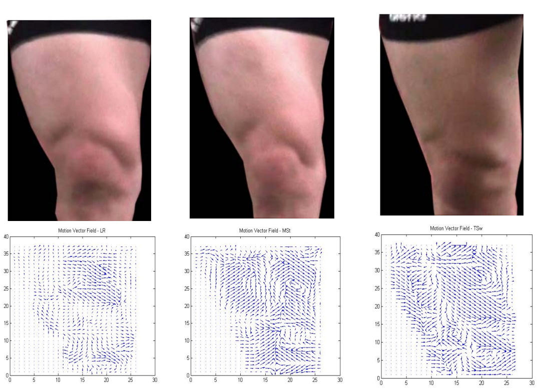


Fig. 5. Video sequences recording for one gait cycle with walking on treadmill at speed of 4 km/hour. (a). Front side camera. (b). Right side camera

All post-processing and analysis were carried out off-line using the MATLAB programming environment. There were 3 video files recorded per subject (one for each trial). One video file usually contained 118-122 frames and all video files yielded average 357 frames after walking three times. Each gait cycle was contained on average 29 frames with 4 gait cycles in each video file. In total, after three trials of walking for all subjects, there were 1430 frames for 48 gait cycles for processing.

In order to extract the features (RMS and STDP) from EMG and video frames, the gait cycles were marked using HS detection and gait phases were identified using the percentage value for each phase [21]. There are seven phases during a gait cycle but the selected muscles are active mostly in three gait phases namely load response (LR), Mid-Stance (MSt) and terminal swing (Tsw). So the features were extracted for these gait phases only. RMS values for pre-processed and normalized EMG data were calculated for these three phases (2).

$$EMG_{RMS} = \sqrt{\frac{1}{T_2 - T_1}\int_{T_1}^{T_2} [EMG(t)]^2 dt} \qquad (2)$$



(a) (b) (c)

Fig. 6. Motion vectors estimated applying motion estimation without interpolation algorithm. (a) frame 5 (b) frame 12 (c) frame 29

The STDP calculations were performed on each frame captured during three selected phases of each gait cycle. For each gait cycle, 29 frames were divided by the percentage value of each event, e.g. Load Response (LR) consists of 10% of GC time then dividing 29 by 10 gives 2.9 frames for LR. This value was then rounded off which means there were 3 frames of 29 frames of LR for which the STDP values were computed as described in next section.

1) Motion Vectors Estimation: The first step for the generation of a triangular mesh from an image was the choice of a set of points to be triangulated [12].

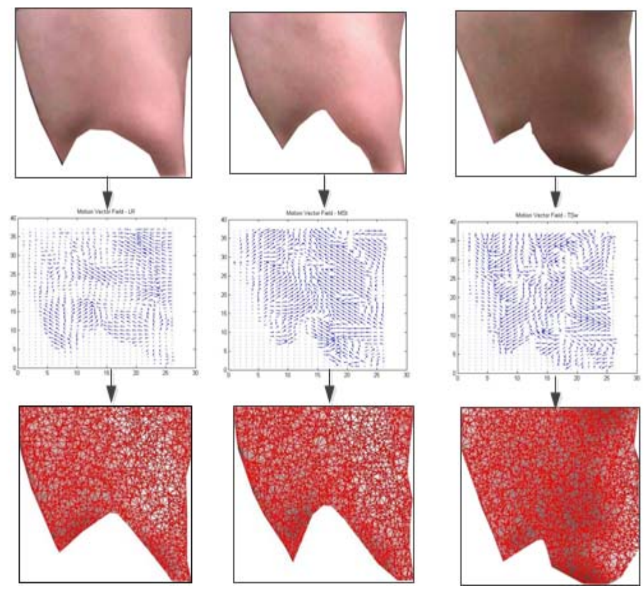


Fig. 7. IDT Mesh Generator

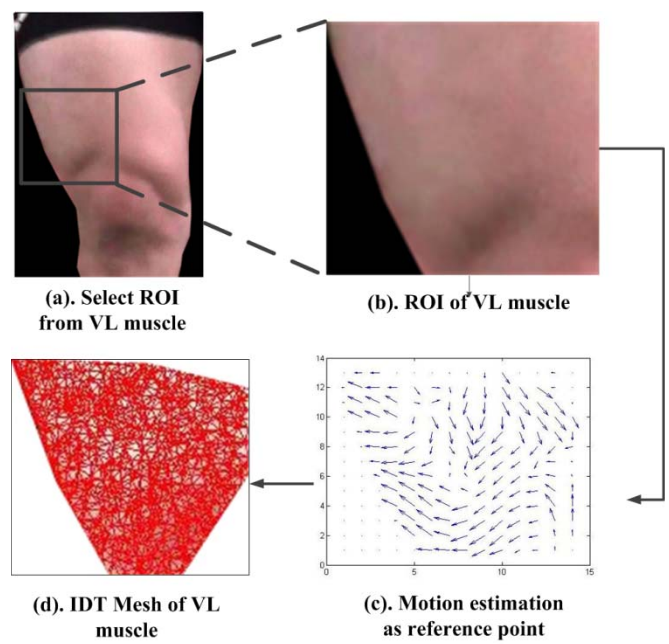


Fig. 8. IDT Mesh processing.

The input data for a triangulation process was a set of points that were linked by edges which had to be preserved after the triangulation. The estimation of soft tissues deformation during dynamic muscular contraction has been carried out by using flexible triangular meshes built on reference points [12]. The positions of these selected points, during the walking were evaluated by applying the motion estimation technique based on the motion estimation without interpolation [18]. This motion estimation technique was used in order to extract the motion of the selected points on the body segment. The estimated positions of the selected points have been considered as reference for the construction of the triangular mesh.

The video of a gait cycle was composed of 29 frames and the spatial resolution was 51pixels/cm. In order to test the functionality of the method, three relevant frames of the video sequences (frame 5/LR, frame 12/MSt and frame 29/TSw) have been taken into account. 114 pixels of the first frame have been chosen as reference points. These pixels have been selected on the lower limb surface. Their motion in the sequence has been estimated by applying the motions estimation without interpolation algorithm. The sample results can be seen in Figure 6.

2) IDT Mesh Generator: The meshes of the subsequent frames have been fixed on the reference points. The pixel interval has been automatically set in order to obtain the number of nodes of the net of the first frame. Fig. 7 shows the meshes on the related frames. In this research, the calculation of soft tissue deformation refers VL and VM. Based on the results of Fig. 7, a region of interest (ROI) of two muscles was selected separately to get the new selected points. Fig. 8 shows a sample of selected ROI at frame 5 of VL muscle and the processing done by motion estimation algorithm. In order to quantify the soft tissue modification during the frames, the obtained triangular meshes are analyzed and the STDP at each frame is calculated by using (1).

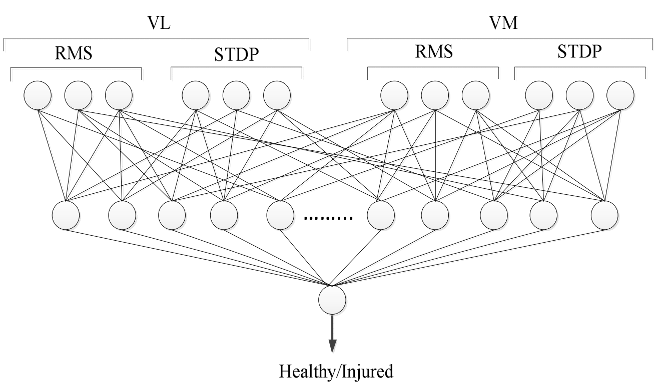


Fig. 9. ANN Architecture for Gait Patterns Identification using RMS and Soft Tissue Deformation Inputs of healthy/injured subjects.

E. Gait Pattern Identification using Artificial Neural Network

For identification of gait pattern based on RMS of EMG signals and STDP, the multilayer FFBPNN has been used in this study [22]. A general architecture for ANN for twelve input parameters and one output parameter used to identification gait pattern for the healthy and injured subjects is shown in Fig. 9. The inputs to the network were the root mean square (RMS) values of EMG signal and STDP for two muscles: vastus lateralis (VL) and vastus medialis (VM), for the selected gait phases. The network was trained based on sequence of the above parameters for the healthy and injured of each subject and then tested on data from both also. In order to estimate the status, the input parameters were first normalized between the ranges of 0 to 1 so that appropriate activation functions could be used. FFBPNN with four different training functions (Gradient Descent (GD), Levenberg-Marquardt (LM), Random Order Weight/Bias (ROWB) and Scaled Conjugate Gradient (SCG)) were designed and tested using MATLAB 7.0 [23, 24, 25]. The input vectors and target vectors were randomly divided into training (80 percent of input/output data for adjusting the network according to its error) and testing (20 percent of input/output data for providing an independent measure of network performance) sets. Each of the networks was trained with 12 inputs, 20 hidden layer *tansig* neurons and a single *tansig* output neuron for gait pattern of healthy/injured (1/0) subjects. A 10-fold cross validation was performed to test the performance of FFBPNNs with different training functions.

III. RESULTS

In order to observe the relationship between RMS value of EMG signals and STDP, the correlation between these two variables was computed. The coefficient of correlation is a measure of the strength and direction of the linear relationship between two variables (EMG Parameter and STDP) that are defined as the (sample) covariance of the variables divided by the product of their (sample) standard deviations. For assuring RMS value of EMG signals and STDP can be used for identification of gait patterns, the correlation between two parameters was tested for each muscle from different phases of gait cycle. Based on the average value from 12 gait cycles for each subject, Table I and Table II show the correlation between EMG RMS and STDP values for VL and VM muscles, respectively. The average values of coefficient of correlation for VL and VM muscles for all subjects were found as 0.760391 and 0.811655, respectively.

Based on the values of coefficient correlation, root mean square (RMS) and STDP from two different muscles of four subjects were used to design artificial neural network. The FFBPNNs were designed, trained and tested for all subjects walking at 4 km/h. The targeted mean square error was 0.001 for higher precision. Initially, two multilayer FFBPNNs with Levenberg-Marquardt (LM) training function were designed separately for RMS values of EMG and STDP values. The first FFBPNN was trained and tested using only RMS value of EMG for all subjects. This network converged to a mean square error of 0.0014759 with an average accuracy of 99.66% at training phase and 98.6% at test phase for healthy subjects. For injured subjects, the average accuracy was 54.18% for training phase and 100% for test phase. Additionally, a FFBPNN was designed using only STDP values which converged to a mean square error of 0.0036694 with an average accuracy of

TABLE I. COEFFICIENT OF CORRELATION BETWEEN RMS AND STDP VALUES FOR VASTUS LATERALIS MUSCLE FOR ALL SUBJECTS

Subject	Coefficient of Correlation
Healthy Subject 1	0.7047
Healthy Subject 2	0.8582
Injured Subject 1	0.7509
Injured Subject 2	0.7275

TABLE II. COEFFICIENT OF CORRELATION BETWEEN RMS AND STDP VALUES FOR VASTUS MEDIALIS MUSCLE FOR ALL SUBJECTS

Subject	Coefficient of Correlation
Healthy Subject 1	0.8109
Healthy Subject 2	0.8672
Injured Subject 1	0.8101
Injured Subject 2	0.7582

99.63% during training phase and 99% for test phase for healthy subjects. For injured subjects, the average accuracy was 54.91% at training phase and 100% at test phase.

In the second step, multilayer FFBPNN with four training functions were designed for combined RMS and STDP features. Fig. 10 illustrated the convergence curves for different training functions used in this study. The overall performances (average classification accuracy) of all training functions are shown in Fig. 11. The maximum training (100.00%) and testing (98.50±4.11) classification accuracies were achieved by using Levenberg-Marquardt training function. While the next highest average training (99.68±1.62) and testing (97.50±5.39) classification accuracies were obtained by using Scaled Conjugate Gradient training function. Table III shows the average accuracy of multilayer FFBPNNs for healthy and injured subjects, separately, during training phase and test phase.

IV. DISCUSSION

This preliminary study shows that the use of root mean square (RMS) of EMG signals and soft tissue deformation parameter (STDP) with FFBPNN provides assistance in making an objective and informed decisions about identification of gait patterns from lower limb muscles. The methods used in this study demonstrate that the comprehensive information about muscle contraction during a gait cycle can be obtained using combination of neuromuscular signals and soft tissue deformation analysis of muscles.

The system has been tested for a small group of subjects and shows promising results. The results shown in Table I and Table II depict that there is a positive high correlation between the RMS values of EMG data and STDP values of VL and VM muscles for healthy and injured subjects. It suggests that video frames based analysis of muscle movements can also be used as a supporting tool to observe the neuromuscular alterations in injured subjects.

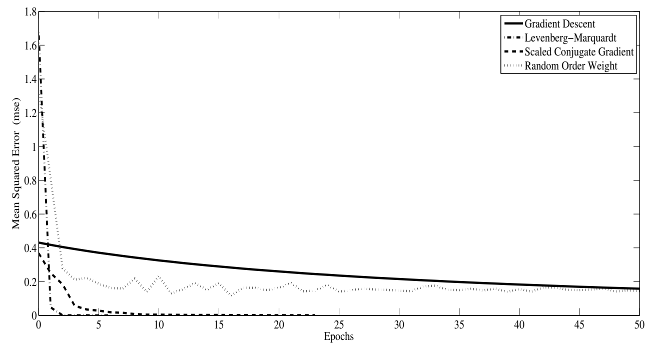


Fig. 10. The curve of network error convergence

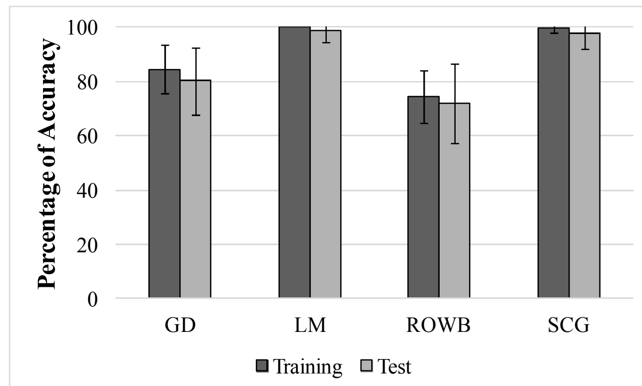


Fig. 11. Performance of comparison using four classifiers

TABLE III
AVERAGE ACCURACY OF MULTILAYER FFBPNN FOR HEALTHY AND INJURED SUBJECT BASED ON COMBINED RMS AND STDP FEATURES

Method	Healthy		Injured	
	Training	*Test*	*Training*	*Test*
GD	69.1±18.34	62.2±24.76	98.7±3.54	98.2±6.42
LM	100.0±0	97.0±8.23	100.0±0	100.0±0
ROWB	100.0±0	95.2±11.05	49.2±18.81	48.6±27.3
SCG	99.2±4.18	95.0±10.78	100.0±0	100.0±0

The use of FFBPNN with different training methods has also proved to be helpful in objective identification of gait patterns. The identification accuracy results were improved for injured subjects when combined RMS and STDP features were used. The difference in targeted and actual values suggests that further estimation accuracy requires considering more input parameters. It also indicates that RMS of EMG signals and STDP have a strong correlation in terms of acquiring strength of muscle contraction. The accuracy of the network can further be improved by including large data set and using more features both from EMG signals and STDP.

The accuracy of results depends on number of factors including position of video cameras in different planes, placement of EMG sensors on different body parts and muscles during movement, techniques used for data processing and the type of features extracted from data. The limited feature set has been used for training FFBPNN which can be further enhanced by inclusion of more features e.g. time-frequency domain features for EMG signals. Additionally, all these data for each gait phase can also be stored and later reused to compare the performance of same or difference subjects.

In this study, the system has been applied for vastus lateralis (VL) and vastus medialis (VM) muscles which can be generalized using common features at different lower limb muscles. As the gait patterns of individuals vary and designing a completely autonomous system is far challenging which requires further investigations in terms of features and the type of intelligent mechanism used for classification.

V. Conclusion

This study demonstrates that the combined parameters; root mean square values of EMG signals and soft tissue deformation parameter are very useful for identification of gait patterns of healthy and injured subjects based on artificial neural network. Based on the muscles movements captured through EMG sensing device and video cameras, the trained FFBPNN can differentiate and classify the gait patterns of the subjects. This study also evaluates the modification of the body segment shape during contraction and stretching of muscles using video sequence analysis. The proposed method analyzes the video sequences recorded during the execution of dynamic muscle's contractions and models the soft tissue by using incremental triangular meshes that automatically adapts to the body segment. The alterations of the body lower limb have been evaluated in terms of STDP. The obtained results are promising and the proposed method can be extended to other applications in human movement analysis. The future study will focus on enhancing the motion capture system to optimize the human movement analysis together with human musculoskeletal modeling using high-precision motion capture cameras and solutions.

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