Neural Network-Based approach for Hemiplegia Detection via Accelerometer Signals

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***Abstract*—This article introduces a method that can automatically classify the hemiplegia type (right or left side of the body is paralyzed) between healthy and non-healthy subjects. The proposed method utilizes the data taken from the accelerometer sensor of the RehaGait mobile gait analysis system. These data undergo a pre-processing and feature extraction stage before being sent as input to a scaled conjugate gradient backpropagation (SCG-BP) trained neural network. The proposed system is tested using a custom-created dataset containing 10 healthy and 20 patients suffering from hemiplegia (right or left). The experimental part of the system utilized 7 sensors placed on the left and right foot, the left and right shank, the left and right thigh, and the hip of each subject. Each sensor captured a 3-dimensional (3D) signal from 3 different device types: accelerometer, magnetometer, and gyroscope. The system utilized and split into 2-second windows only the accelerometer data, achieving a classification accuracy of 87.71%.**

Keywords—accelerometer, backpropagation, feature extraction, neural network, scaled conjugate gradient,

I. Introduction

Hemiplegia is a condition that affects people who have suffered a severe stroke and causes damage to a portion of the brain. The human central nervous system is an extensive network with interconnected neurons having feedback and feed-forward communication types. The 2 sides (left and right) of the central nervous system are interconnected together at every level of the neuraxis. When a part of the brain is damaged, the communication loss of the damaged part affects the entire brain. The normal operating parts of the brain do not receive information from the damaged area. Also, they are prone to erroneous brain signals and misinformation generated as an outcome of the lesion. For this reason, the stroke victim will face difficulties in both body sides, which will be extended to some degree in all brain functions. The outcome from these difficulties will be motor impairment, affecting the patient's balance and movement coordination [1-3].

The current study aims to automatically detect the hemiplegia type (right or left side of the body is paralyzed) in a group of hemiplegic and non-hemiplegic subjects. The purpose behind creating such an automated tool is to provide a supplementary diagnostic tool that will help the doctors diagnose the 2 hemiplegia types mentioned above. The automatic detection is achieved by placing 7 sensors in 4 different body parts of the patient. These body parts are the left and right foot, the left and right shank, the left and right thigh, and the subject's hip. The sensors are part of the RehaGait mobile gait analysis system by HASOMED [4, 5]. The advantages of the RehaGait mobile analysis system include:

- Monitoring the patient's condition with the utilization of an integrated video capture function.
- Determining the damaged areas.
- Evaluating the gait pattern.
- Identifying asymmetries in the lower limbs.
- Mobile use without the need for a gait lab.
- Movement freedom.
- Graphical representation of the results.

Each sensor captured a 3-dimensional (3D) signal from 3 different device types: accelerometer, magnetometer, and gyroscope. The proposed system utilized the accelerometer data which were split into 2-second windows and underwent a pre-processing and feature extraction stage. Then, the extracted features were sent as input to a scaled conjugate gradient backpropagation (SCG-BP) trained neural network. The neural network was trained using a custom-created dataset comprised of 10 healthy and 20 patients suffering from hemiplegia (right or left).

Existing works are focused on various aspects of hemiplegia. Abaid et al. [6] proposed a gait phase detection method which utilizes gyroscope data taken from the subject's feet. The authors tested the algorithm in a dataset containing data from healthy children and children with hemiplegia. Patil et al. [7] used a convolutional neural network (CNN) to analyze the gait characteristics of human subjects. The system can distinguish between healthy and hemiplegic subjects by taking into consideration their posture and walking pattern. Cai et al. [8] tested a number of machine learning methods for detecting common compensatory movement patterns in stroke patients with hemiplegia using a pressure distribution mattress. The k-nearest neighbor (KNN) and support vector machine (SVM) classifiers managed to achieve the highest accuracy in the binary classification problem of detecting compensation during all reaching tasks. SVM achieved a

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good classification performance in the multiclass classification problem of compensatory movement patterns during 3 types of reaching tasks (trunk lean-forward, scapular elevation, and trunk rotation). Park et al. [9] created a wearable inertial signal measurement module for simplifying hemiplegia's measurement and diagnosis. The module can observe leg motion caused by gait using a 3-axis acceleration sensor and 3-axis angular velocity sensor. Aguilera and Subero [10] used data mining techniques and classification algorithms to investigate kinematic, kinetic, and electromyographic (EMG) data from children having spastic hemiplegia with the purpose of finding useful gait patterns. Suzuki et al. [11] used a non-linear SVM to investigate the relationship between grip strength and self-care activities in post-stroke hemiplegia patients. Azlan et al. [12] created a hand gesture recognition system based on the Leap Motion controller for hemiplegia patients. The system aims at encouraging patients' motor function. Goyal et al. [13] developed a number of gait features for detecting 4 severe neurological disorders (Parkinson's disease, diplegia, hemiplegia, and Huntington's chorea) in videos. Nozaki and Watanabe [14] used an artificial neural network (ANN) to automatically detect movement state in stride for estimating stride length of a hemiplegic gait. Pandit et al. [15] utilized transfer learning in the Inception v3 CNN to classify 4 walking styles (regular walk, hemiplegic gait, diplegic gait, and Parkinsonian gait). The CNN used the accelerometer and gyroscope data transmitted from 4 wireless body adhering modules which were converted to images. Potluri et al. [16] used a wearable system combining a plantar pressure measurement unit with inertial measurement units (IMUs). The data received from this system were introduced to a stacked long short-term memory (LSTM) neural network which was responsible for detecting human gait abnormalities. The abnormalities include hemiplegic, Parkinsonian and sensory-ataxic gaits. Ji et al. [17] captured the tibialis anterior muscle's acceleration signals from 2 different subject groups (healthy and hemiplegic). The recordings were done during ground walking, and 2 core gait events were detected (heel strike and toe-off) by a continuous wavelet transform algorithm having different mother wavelets. Lemoyne and Mastroianni [18] utilize the internal accelerometer of an Apple iPhone in combination with a software application to create a wireless accelerometer platform. The platform utilizes automated pre-processing in a functionally autonomous environment to quantify hemiplegic gait disparity. Chattopadhyay and Nandy [19] used a sensor-based method utilizing a wearable IMU placed at subject's shank for detecting abnormal (hemiplegic and equinus) gait patterns. The IMU sensor contains a 3-axis accelerometer and gyroscope, which provide acceleration and angular velocity of a human foot. The proposed system also uses a hidden-Markov model to represent bipedal human gait. Manca et al. [20] used hierarchical cluster analysis to classify the gait patterns of 49 hemiplegic patients having equinus foot deformity. The cluster analysis revealed 5 groups showing homogeneous dysfunction levels during gait. Pagorelc et al. [21] created a system for early automatic recognition of health issues related to gait. The proposed system contains a series of body-worn tags and wall-mounted sensors. It can classify the subject's gait into 5 categories (normal, hemiplegic, Parkinson's disease, pain in the back and pain in the leg) using machine learning methods. Nieto-Hidalgo et al. [22] used a computer vision algorithm to extract features from gait recordings taken from a smartphone camera. The extracted features are entered as an input vector to a classification algorithm which classifies them into 5 different gait types (normal, diplegic, hemiplegic, neuropathic and parkinsonian). Li et al. [23] proposed a method for identifying 2 neurogenerative diseases (hemiplegia and Parkinson's disease) from a person's gait. The method uses a Kinect motion sensor to capture the joints' trajectories from a 3D human skeleton. Adhikary et al. [24] used wearable sensors comprised of a 3-axis accelerometer and a 3-axis gyroscope for capturing the motion signatures produced during walk. The captured signals include healthy individuals and individuals suffering from hemiplegia, osteoarthritis, rheumatoid arthritis and knee ligament fracture. The proposed system utilizes various machine learning algorithms to classify each case. Luo et al. [25] used the Kinect motion sensing input device to capture normal and hemiplegic gait data. Then, they utilized the random forest algorithm for the classification and analysis of hemiplegic gait. Although the above methods managed to get very good results, they are not focused on detecting the hemiplegia type (right or left).

This paper is structured in 5 main sections (Introduction, The SCG-BP Algorithm, The System Architecture, Experimental Results, and Conclusion). The Introduction section includes the problem's description and the motivation behind this problem, followed by a literature review. The SCG-BP Algorithm section contains a detailed description of the SCG-BP neural network training algorithm used for the classification task. The System Architecture section contains an extensive analysis of the proposed system. The Experimental Results section analyses the outcome of the proposed approach in the custom-created dataset. Finally, the last section contains a summary of the proposed method.

II. The SCG-BP Algorithm

The SCG-BP algorithm was developed by Møller [26] in 1991. It is a conjugate gradient type of learning algorithm, which is suitable for large-scale problems according to the general opinion of the numerical analysis community [27-29]. Its advantages include simplicity and speed since it is fully automated without needing any critical parameter tuning from the user's perspective. Moreover, it eliminates the time-consuming line search, which alternative methods use. The elimination of the time-consuming line search is achieved by utilizing a Levenberg-Marquardt approach [28] which scales the step size.

SCG-BP calculates a numerical approximation close to the 2nd order derivatives when calculating the error energy for the next training epoch. The calculation of the Hessian matrix is omitted because it is computationally intensive and slows down the training process. During the k^{th}epoch, it calculates a new search direction (d^k) and a new step size (a_k). Then, it utilizes the formula depicted in (1) for finding new weights to the neural network [30].

$$E(W_k + a_k d_k) < E(W_k) \quad (1)$$

The Taylor expansion [31] depicted below gives the quadratic approximation to $E(W_k)$ in a neighbourhood of a point W_k.

$$E(W_k + z) \approx E(W_k) + E'^{(W_k)^T} z + \frac{1}{2} z^T E''(W_k)^T \quad (2)$$

In the above formula, the hessian $E''(W_k)$ is not computed, and the 2nd order derivative O_k is estimated as seen below.

$$O_k = E''(W_k) d_k \approx \frac{E''(W_k + \sigma_k d_k) - E'(W_k)}{\sigma_k} \quad (3)$$
$$for\ 0 < \sigma_k \leq 1$$

In the above 2nd order derivative, W_k describes the weight vector for the k^{th} epoch and $E'(W_k)$ is the error energy's gradient. $E(W_k)$ is the total error energy and σ_k denotes the incremental change in the weight vector regarding the 2nd order derivative approximation [30].

The SCG-BP algorithm combines the trust-region case of the Levenberg Marquardt approach with the conjugate gradient method for the calculation of the next step size. The indefiniteness of the $E''(W_k)$ is managed by the utilization of the control variable c_k as seen below.

$$O_k = \frac{E'(W_k + \sigma_k d_k) - E'(W_k)}{\sigma_k} + c_k d_k \quad (4)$$

The indefiniteness of $E''(W_k)$ is checked by computing in parallel the term $\delta_k = d_k^T O_k$.

At each epoch the c_k is adjusted according to the sign value of δ_k. If $\delta_k \leq 0$ then a slight increase to c_k is applied and O_k is recalculated. Finally, in every iteration, the weight vector is adjusted according to formula (5).

$$W_{k+1} = W_k + a_k d_k \quad (5)$$

The weight update procedure continues until the stopping criteria have been met [30].

III. The System Architecture

The proposed system architecture utilizes the RehaGait mobile gait analysis system by HASOMED [4, 5]. RehaGait contains 7 sensors placed at 4 different body parts of the patient (left and right foot, the left and right shank, the left and right thigh, and the subject's hip). Each sensor contains an accelerometer, a magnetometer, and a gyroscope. The present research uses the signals received from the accelerometer, which were split into 2-second windows and underwent a pre-processing and feature extraction stage. The signals were transmitted wirelessly to a laptop computer that had the MATLAB 2018a environment. MATLAB was responsible for the pre-processing, feature extraction, and classification tasks. The pre-processing stage involved smoothing the signal using a low pass filter.

In the feature extraction stage, 4 time-domain features and 2 frequency-domain features were extracted. The first time-domain feature was the mean (μ) which can be seen in equation (6).

$$\mu = \frac{1}{N} \sum_{i=1}^{N} A_i \quad (6)$$

In this equation, N is the number of scalar observations, and A denotes a random variable vector. The second feature was the standard deviation which can be seen below.

$$S = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (A_i - \mu)^2} \quad (7)$$

In this equation, N is the number of scalar observations, A_i denotes a random variable vector A and μ is the mean of A. The third feature is the kurtosis of a distribution defined below.

$$k = \frac{E(x-\mu)^4}{\sigma^4} \quad (8)$$

In this formula, $E(t)$ is the expected value of quantity t, μ defines the mean of x and σ defines the standard deviation of x. The fourth feature was the peak-magnitude-to-RMS ratio seen in formula (9).

$$RMS = \frac{\|A\|_\infty}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} |A_i|^2}} \quad (9)$$

The frequency-domain features were the acceleration energy and the acceleration signal energy. The first feature is defined in equation (10) where A_i denotes the i^{th}spectral line of the acceleration signal and N are the total lines.

$$Eng = \frac{\sum_{i=1}^{N} A_i^2}{N} \quad (10)$$

The second feature is the acceleration signal entropy seen in formula (11) where p_i defines the probability of the A_i value occurring in the amplitude spectrum.

$$Ent = -\sum_{i=1}^{N} p_i \log_2 p_i \quad (11)$$

After completing the feature extraction process, these features were sent as an input vector to an SCG-BP trained neural network. The neural network classified the input data into 3 categories (healthy, left hemiplegia, and right hemiplegia) using a custom-created dataset. The dataset was divided into training and testing using the k-fold cross-validation method. The architecture of the proposed system is visualized in Fig. 1.

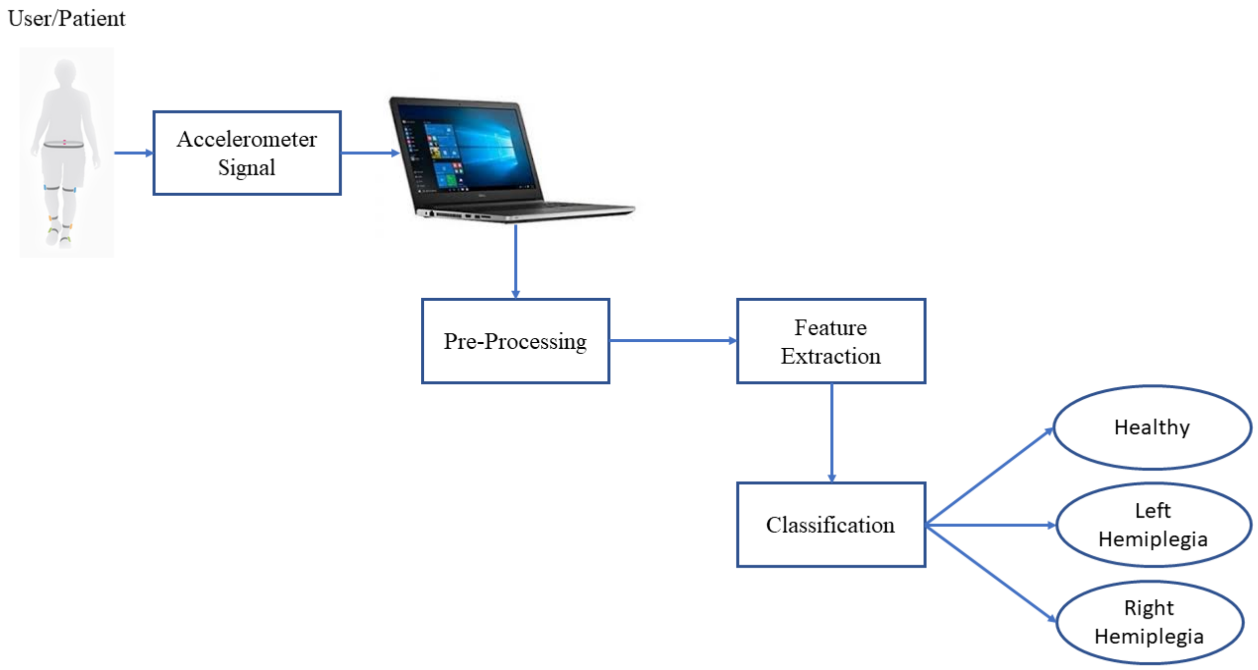

Fig. 1. The system architecture. Initially, the signals received from the accelerometers were sent to a laptop having the MATLAB 2018a environment for undergoing a pre-processing and feature extraction process. After completing the feature extraction, the data are sent to a neural network trained with the SCG-BP algorithm, which classifies them into 3 categories (healthy, left hemiplegia, and right hemiplegia).

IV. Experimental Results

The proposed system was tested in a custom-created dataset containing 10 healthy subjects and 20 patients suffering from hemiplegia. Regarding the patients, 8 had left hemiplegia, and 22 had right hemiplegia. The signals were received to a laptop having the MATLAB 2018a environment using a wireless connection. The experimental part utilized the signals received from the accelerometer, which were split into 2-second windows and underwent a pre-processing and feature extraction stage. The pre-processing step involved using a low-pass filter, while the feature extraction stage used the features described in section 3. The selected features formed the feature vector, which was introduced to a neural network trained with the SCG-BP algorithm. The neural network contained one hidden layer having 100 neurons with the sigmoid $\left(y = \frac{1}{1+e^{-x}}\right)$ activation function and 3 output neurons with the identity $(y = x)$ function. Each input dimension introduced to the network contained 6 features × 7 accelerometers × 30 subjects = 126 entries, while the output layer had 3 classes. The neural network structure can be seen in Fig. 2.

The experiments were repeated 10 times with the purpose of avoiding any bias due to random initialization of the hidden weights and biases. The dataset was divided into training and test sets. The former received 80% of the data, while the latter received 20% of the data. During training, the 10-fold cross-validation method was used to avoid overfitting. The experimental results showed an average of 87.71% accuracy on the test data over all experiment runs.

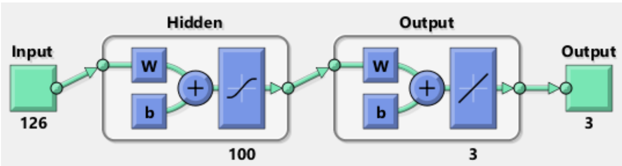

Fig. 2. The neural network structure. The network contains one hidden layer having 100 neurons with the sigmoid activation function and 3 output neurons with the identity function.

Conclusion

This paper presented a method for automatic identification of the hemiplegia type (right or left). The proposed approach receives data from the accelerometer sensor of the RehaGait mobile gait analysis system. The proposed method showed a very good classification accuracy (87.71%) on the test data in a custom-created dataset containing 10 healthy subjects and 20 patients suffering from the right or left hemiplegia type.

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