A new Multiple ANFIS model for classification of hemiplegic gait

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Abstract. Neuro-fuzzy system is a combination of neural network and fuzzy system in such a way that neural network learning algorithms, is used to determine parameters of the fuzzy system. This paper describes the application of multiple adaptive neuro-fuzzy inference system (MANFIS) model which has hybrid learning algorithm for classification of hemiplegic gait acceleration (HGA) signals. Decision making was performed in two stages: feature extraction using the wavelet transforms (WT) and the ANFIS trained with the backpropagation gradient descent method in combination with the least squares method. The performance of the ANFIS model was evaluated in terms of training performance and classification accuracies and the results confirmed that the proposed ANFIS model has potential in classifying the HGA signals.

Keywords. Adaptive neuro-fuzzy inference system; Fuzzy logic; Hemiplegic, Gait analysis

1. Introduction

Human gait analysis is particularly attractive to model because of its importance in everyday life and its complexity as a total body movement. In particular, pathological gait in humans following disease or injury is the subject of much contemporary research. For the rehabilitation process, quantification of gait is necessary for monitoring of functional recovery. The process of motor system recovery is qualitatively classified into stages by the Brunnstrom method [1]. The accelerometry technique is widely used clinically to investigate body motion of gait in healthy and post-stroke hemiplegic patients. The study of gait analysis through the accelerometric records is one of the most important tools for the diagnosis of locomotion defects. Sekine and co-authors demonstrated that the wavelet transform method was effective for classifying walking types for young subjects but not for elderly subjects, since gait changes with age [2,3]. In particular, locomotion is slower for elderly people than for young people. The amplitude of impact acceleration at heel-strike decreases with age. Elderly people also shuffle during locomotion and complexity of acceleration increases. Therefore, it is difficult to classify the post-stroke hemiplegic patient’s walking type by using the former methods. The techniques have been used to classify gait and diagnosis to gait disorders using the, frequency domain features, time frequency analysis, and WT [2, 4-7]. The wavelet based approach has been found to be a useful tool for analysis of nonstationary biological signals and the results of the studies in the literature have demonstrated that the WT is the most promising method to extract features from the gait signals [8-12]. In this respect, in the present study the WT was used for feature extraction from the HGA signals.

This study aims an assessment of gait after stroke that is useful as a support of diagnosis and therapy considerations. Our previous study on classification of HGA signals has been done by using fuzzy logic approach [13]. That study showed us the possibility of discrimination of subjects as healthy or patient using fuzzy logic. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Neuro-fuzzy systems are fuzzy systems, which use artificial neural networks (ANNs) theory in order to determine their properties by processing data samples. A specific approach in neuro-fuzzy development is the ANFIS, which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a

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data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [14,15]. Successful implementations of ANFIS in biomedical engineering have been reported, for classification [16,17]. Successful classification of patients to correct Brunnstrom stages, because of unstable signal behavior, was found extremely difficult. Classifying patients becomes increasingly difficult linearly according to hemiplegia's severity. Our results suggested that combination of artificial intelligence techniques may be suitable to assess the hemiplegic gate. In this article we try to explain an ANFIS classification application for hemiplegic gate to correct Brunstromm stages by using WT coefficients.

2. Materials and Method

Decision making was performed in two stages: feature extraction of HGA signals using the WT (28 extracted features as ANFIS inputs) and classification using the ANFIS classifier trained with the hybrid learning algorithm. In this section we restrict ourselves to explain how the HGA data collected for the datasets. For description of the used datasets and further details please refer to reference [18]. The complete dataset consist of five sets (denoted H, STVI, STV, STIV, STIII) each of them contains three subject's anteroposterior (×) acceleration signals. After the accelerometer device had been calibrated it was fixed on an acrylic plate that had two slits for a waist belt. It was fastened by an elastic waist belt to the subject's back in the lumbosacral region of the vertebral column, close to the subject's center of gravity while standing. Set H have been taken from recordings of healty elderly volunteers. Sets STVI, V, IV and III have been taken form post-stroke hemiplegic patient recordings.

3.MANFIS

3.1 Neuro-fuzzy system

Neuro-fuzzy system is a combination of neural network and fuzzy system in such a way that neural network learning algorithms, is used to determine parameters of the fuzzy system [20]. ANFIS is a neuro-fuzzy model proposed by Jang [11]. The structure of ANFIS with five layers is shown in Fig. 1. x and y are the inputs for ANFIS. Note that the input layer is not calculated as an ANFIS layer.

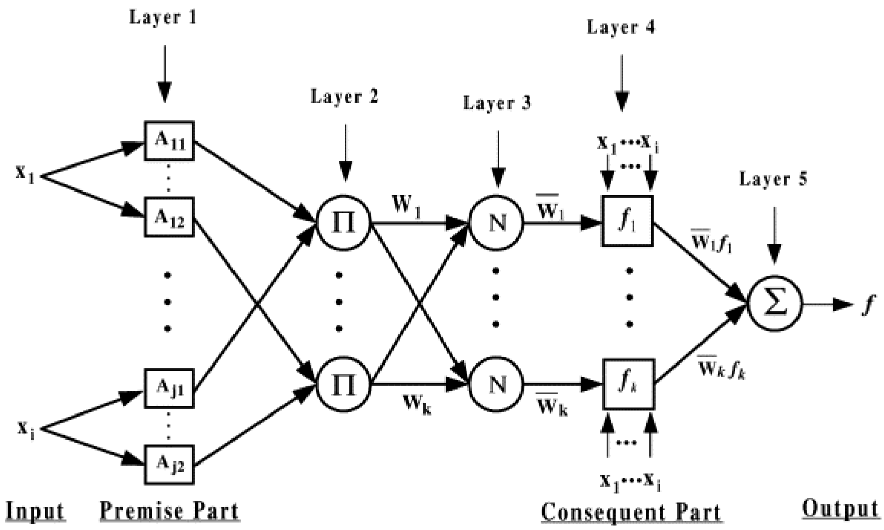

Figure 1. ANFIS Architecture

For learning rule of ANFIS, hybrid learning algorithm which combines the gradient descent and least-squares method is used to find a feasible set of parameters. Table 1 shows the hybrid learning procedure for ANFIS.

Table 1. Two passes in the hybrid learning procedure for ANFIS

	Forward Pass	Backward pass
Premise Parameters	Fixed	Gradient Descent
Consequest Parameters	Least squares estimate	Fixed

However, ANFIS itself only suitable for single output system. For a system with multiple outputs, ANFIS will be placed side by side to produce a Multiple ANFIS (MANFIS). The number of ANFIS required depends on the number of required output.

3. Results and Discussion

Spectral analysis of the HGA signals was performed using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. The frequency band of normal gait signals is approximately 4-512 Hz. It is generally accepted that the frequency corresponding to step cycle is approximately 2 Hz, and almost all variance of the signal is in the band below 17 Hz. Sekine and co-authors suggested to use scales 6 and 7 for discrimination of walking patterns of healty subjects since these scales closely related to the impact acceleration, and the rest can accepted as a noise [8]. In this study, because the complexity of HGA signals we used the scales 7 to 1 instead of 6 and 7. The HGA signals were decomposed into details D1-D7. Generally, tests are performed with different types of wavelets and one which gives maximum efficiency is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 4 (db4) madeit more suitable to detect changes of the HGA signals. Therefore, the wavelet coefficients were computed using the db4 in the present study. A rectangular window, which was formed by 512 discrete data, was selected so that the HGA signal considered being stationary in that interval. For each HGA segment, the detail wavelet coefficients (d^k k=1, 2, 3, 4, 5,6,7) at the first, second, third, fourth, fifth, sixth, seventh levels (259+133+70+38+22+14+10) and approximation wavelet coefficients (a^7) at the seventh level (10 coefficients) were calculated by using db4 wavelet. Then 556 wavelet coefficients were obtained for each HGA segment. Figure 2 illustrates details (D6-D7) of a healthy eldery gait signal. In order to reduce the dimensionality of the feature vectors, statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time-frequency distribution of the HGA signals: Maximum of the wavelet coefficients in each sub-band, Minimum of the wavelet coefficients in each sub-band, Mean of the wavelet coefficients in each sub-band, Standard deviation of the wavelet coefficients in each sub-band. These feature vectors, which were calculated for D1-D7 and A7 frequency bands, were used in classifying the HGA signals. The MANFIS classifier were trained with hybrid learning algorithm when 28 features (dimensions of the extracted feature vectors) representing the HGA signals were used as inputs. The max, min, sd and mean features of signals for seven level accepted as inputs.

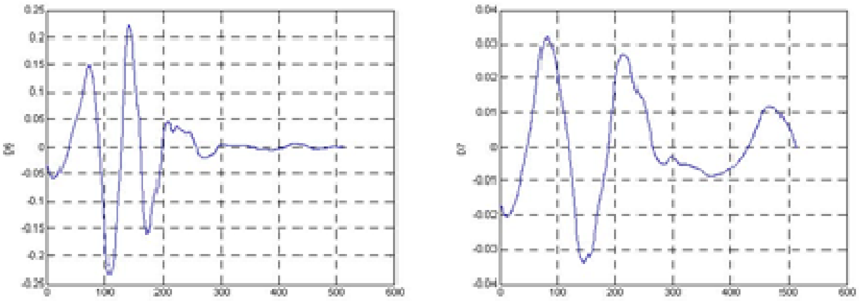

Figure 2. D6 and D7 coefficients of gait signal taken from healthy elderly subject

We prepared three sets each of them consists 20480 samples for each group. Then we wrote a short computer programme to produce 40 segments with 512 samples from these sets. After these steps 600x28 dimension matrix was obtained. MANFIS used 8400 traning data in 500 training epochs. At the end of the 500 training epochs average training error was found as 0.0079. After training period, 8400 testing data were used to validate the accuracy of the ANFIS model for classification of the HGA signals. In classification, the aim is to assign the input patterns to one of several classes, usually represented by outputs restricted to lie in the range from 0 to 1. In this application there were five classes as mentioned above: healthy elderly (H), Brunnstrom stage VI (STVI), Brunnstrom stage V (STV), Brunnstrom stage IV (STIV) and Brunnstrom stage III (STIII). The test performance of the classifiers can be determined by the computation of sensitivity, specificity and total classification accuracy. The ANFIS model's test performance was defined after comparing the real diagnosis results and FIS results. After our first attempts the avarage test error was found as 6.82. The training results were shown in Figure 3.

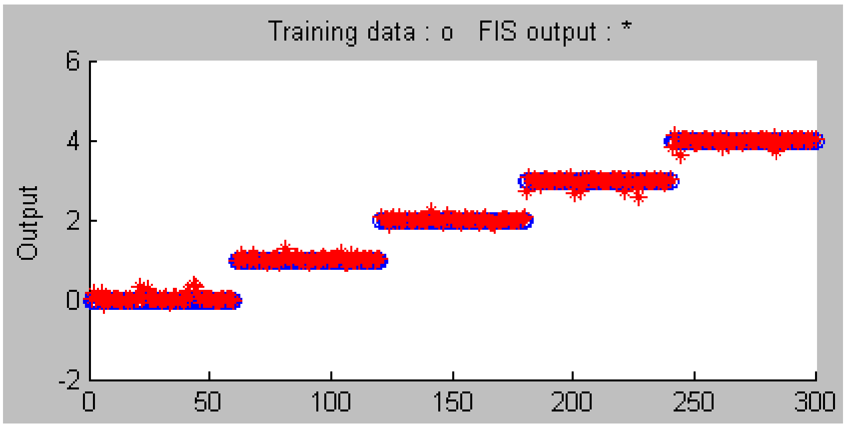

Figure 3. Training result of MANFIS

According to this test error point the classification of subjects to correct groups was not satisfactory. Finally the total classification accuracy was obtained as %84. As similar our previous study the main problem is here still to classify STIII patients. Successfull classification of this group patient to correct Brunnstrom stages, because of the complexity of signal is extremely difficult. Even the test result of system has not satisfactory yet, it is pleasent for us that this result belong to first attempt of study and it confirmed that the proposed ANFIS model has potential in classifying the HGA signals. We therefore have concluded that the proposed ANFIS model can be used in classifying the HGA signals by taking into consideration the misclassification rates. We believe that if we increase ANFIS moduls for each group the results will be better.

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