Analysis of Genetic Algorithm Optimized Neural Network System for Human Gait Recognition

Saima Farooq¹, Simranjit Kaur², Satnam Singh Dub³
Department of ECE
IKGPTU, Pathankot, Punjab, India

Abstract:
This paper explores a gait recognition method with binary silhouette-based input images and Genetic Algorithm Optimized Artificial Neural Network (GA-NN) classification. The performance of the recognition method depends significantly on the quality of the extracted binary silhouettes. A fuzzy correlogram based method is employed for background subtraction and Frame Difference Energy Image (FDEI) reconstruction is performed to make the recognition method robust to partial incompleteness of silhouettes. Feature extraction process uses extracted features directly for classification while the indirect method maps the higher-dimensional features into a lower-dimensional space by means of a Frame-to-Exemplar-Distance (FED) vector. The FED uses the distance measure between pre-determined exemplars and the feature vectors of the current frame as an identification criterion. The extracted features are fed to the GA optimizer for feature fitness evaluation and NN-based classifier which models human gait to compute similarity scores and carry out identification. This work achieves an overall accuracy for all database datasets with difference in recognition time as the dataset sample bulk increases and the GA optimization and ANN trains and learns itself from increased number of samples. As expected, the results using this approach are better, owing to a basic trade-off between complexity and efficiency. The approach is computationally more extensive with a better overall performance, while the indirect approach tends to be computationally less intensive at the cost of recognition performance. Also this approach is less vulnerable to noise and distortion compared to the indirect approach. Surprisingly, the results obtained by using the FED vector show that in this case, the overall performance is actually slightly lesser in the case of FDEI reconstruction as compared to the use of direct binary silhouettes. It is also seen that the recognition performance depends to a certain extent on the specific gait sequences. The algorithms used in this work produce relatively better results in the case of CASIA Dataset-A.

Keywords: MATLAB, gait recognition, GA-NN, FDEI, FED, CASIA Database.

I. INTRODUCTION

The process of pattern recognition in the gait biometrics is particularly important. The patterns can differ from each other a lot, and even the samples can be significantly different from the templates. The Artificial Neural Networks can be applied as a universal approximator to recognize the patterns with more flexibility. However the topology of the networks determines the processing time and complexity of the hardware of the physical environments. The Genetic Algorithms can be used with success in optimization problems like in this situation; the topology of the neural network is more optimal if we apply the Genetic Algorithms. The Hybrid Genetic Algorithm-Neural Network (GA-NN) technique is used as in combination of both Genetic Algorithms and Neural Networks for optimization of artificial neural networks with genetic algorithms for gait pattern recognition. Biometric systems are becoming increasingly important, as they provide more reliable and efficient means of identity verification [1]. Individual gait is dependent on many variables such as surface properties, confidence, mood, quantity and quality of sensory information (e.g. light levels, noise, and distractions), any chemical effects on the body (such as alcohol or medication), energy levels, mental alertness and muscle fatigue. Walking mainly consists of the ability to maintain the equilibrium and the ability to initiate and maintain a rhythmic stepping motion – locomotion. In conjunction with these two abilities, there are other many contributing factors involved in walking such as the skeletal system with the joints as well as neuro-muscular system. Although the human gait varies from individual to individual, some basic stages are common for all normal gaits.

We divide human gait into gait cycles, which consists of a repeated sequence of events and is the time between two equal events in the walking cycle, such as the heel to heel strike of the right foot[2] [3]. Human gait has common patterns of movements and describes a rhythmic and periodic motion by which the body moves step by step in the required direction. A period of the gait cycle exists between the successive heel strikes, and the gait motion in space and time satisfies spatial and temporal symmetry. To extract the gait motion, body angles of each segment are extracted from gait silhouette images. A simplified 2D stick figure with six joint angles is used to represent the human body structure for recovering and interpreting the human movement.

Figure 1. Normal gait cycle [3]
The gait cycle is composed of main phases, stance and swing. The stance phase is the period where the foot is in contact with the ground and equates to 60% of the cycle when walking.

**Stance**
1. Heel strike - The point when the heel hits the floor.
2. Foot flat - The point where the whole of the foot comes into contact with the floor.
3. Mid stance - Where we are transferring weight from the back, to the front of our feet.
4. Toe off - Pushing off with the toes to propel us forwards.

**Swing**
1. Acceleration - The period from toe off to maximum knee flexion in order for the foot to clear the ground.
2. Mid-swing - The period between maximum knee flexion and the forward movement of the tibia (shin bone) to a vertical position.
3. Deceleration - The end of the swing phase before heel strike.

When running, a higher proportion of the cycle is swing phase as the foot is in contact with the ground for a shorter period. Because of this there is now no double stance phase, and instead there is a point where neither feet are in contact with the ground, this is called the flight phase. As running speed increases, stance phase becomes shorter and shorter. The extensive research activity on gait analysis for recognition and clinical purposes resulted in a large set of features to characterize the human gait signature. Extraction of kinematic that describes body movements during gait, relies on: dynamic features locating the coordinates of points such as hip joint, knee, and foot and tracking them in each frame [4]. The data is modeled according to biomechanical structure of the human body in order to analyze it and form the gait signature. Static features related to body geometry such as height and length and width of different body segments combination of static and dynamic gait features is used to achieve better recognition rate [5]. Gait recognition aims essentially to address this problem by identifying people based on the way they walk. Gait recognition has 3 steps. The first step is pre-processing, the second step is feature extraction and the third one is classification. This study introduces one more step of feature optimization using Genetic Algorithms before the ANN classification step that is essential to increase the ANN Performance, Accuracy and Recognition Rate thus creating an hybrid GA-NN. Here mentioned is a new method for recognizing humans by their gait using GA Optimized features as inputs to Multi Layer Perceptron (MLP), which in turn is used to recognize humans by their gait patterns. The process of pattern recognition in the biometrics is particularly important. The patterns can differ from each other a lot, and even the samples can be significantly different from the templates. The Artificial Neural Networks can be applied as a universal approximator to recognize the patterns with more flexibility. However the topology of the networks determines the processing time and complexity of the hardware of the physical environments. The Genetic Algorithms can be used with success in optimization problems like in this situation; the topology of the neural network is more optimal if we apply the Genetic Algorithms. This system is to apply an algorithm which aims to correct the topology to optimize the ANN or in other words to enhance the effectiveness of the process. The Artificial Neural Networks (ANN) are used widely for pattern recognition. The MATLAB (Matrix Laboratory) has a built in toolbox, although we used tailor made algorithm in order to have the most possible variable parameters. Practically, the more the parameters we have, the more complicated to find and optimize those. There are some parameters that can be found experimentally, but there are some which are independent from each other and it is difficult to define searching space, thus we are introducing a combination method of two soft-computing methods i.e. Genetic Algorithms (GA) and Artificial Neural Networks (ANN) as a deep-learning tool.

II. LITERATURE REVIEW

Kooksung Jun et. al. propose that in skeleton-based abnormal gait recognition, using original skeleton data decreases the recognition performance because they contain noise and irrelevant information. Instead of feeding original skeletal gait data to a recognition model, features extracted from the skeleton data are normally used. However, existing feature extraction methods might include laborious processes and it is hard for them to minimize the irrelevant information while preserving the important information. To solve this problem, an automatic feature extraction method using a recurrent neural network (RNN)-based Auto-encoder (AE) is proposed [6].

Chi Xu et. al. in this paper propose a pair-wise spatial transformer network (PSTN) for cross-view gait recognition, which reduces unwanted feature misalignment due to view differences before a recognition step for better performance. The proposed PSTN is a unified CNN architecture that consists of a pair-wise spatial transformer (PST) and subsequence recognition network (RN). More specifically, given a matching pair of gait features from different source and target views, the PST estimates a non-rigid deformation field to register the features in the matching pair into their intermediate view, which mitigates distortion by registration compared with the case of direct deformation from the source view to target view. The registered matching pair is then fed into the RN to output a dissimilarity score [7].

Chenshu Wu et. al. publish that interests in monitoring and recognizing gait have surged significantly over the past decades. Traditional approaches rely on camera array, floor sensors, or wearables, none of which are suitable for continuous and ubiquitous everyday use. In this paper, authors present GaitWay, the first system that monitors and recognizes an individual's gait speed through the walls via wireless radios. GaitWay passively and unobtrusively monitors gait speed by a single pair of commodity Wi-Fi transceivers, without requiring the user to wear any device or walk on a restricted walkway. GaitWay automatically identifies stable walking periods, extracts physically plausible and environmentally irrelevant speed features, and accordingly recognizes a subject's gait. Built upon a distinct rich-scattering multipath model, GaitWay can capture one's speed >10 meters away behind the walls [8].

Guoheng Huang et. al. publish that the information contained in gait frames is different, and the contribution of different frames to recognition tasks is also different. However, each frame has the same degree of attention in the input layer; this prevents the network from focusing on key frames. Therefore, authors propose a key frame extraction module via information weighting, make network can pay more attention to the high contribution frame at the input layer, and the extraction of the distinctive features is improved. Moreover, the range of motion in different parts of the human body is
different; the temporal and spatial correlation of local feature between silhouettes is different. Based on the discovery, authors propose a Local Features Flow Regulation module to calculate the correlation coefficient of the local features of each silhouette, and the regulation coefficient is generated by the correlation coefficient. The regulation coefficient is applied to regulate the flow of local features; this enables the network to capture areas with more spatial and temporal features. Through the extraction of frame-level features and the interaction of local features between frames, the network can extract the most discriminative features from global to local flexibly. During training, each horizontal part is trained separately. The training can adjust the regulation coefficients, and the network is more flexible and expressive [9].

Jingran Su et. al. publish that gait information has gradually attracted people’s attention due to its uniqueness. Methods based on deep metric learning are successfully utilized in gait recognition tasks. However, most of the previous studies use losses which only consider a small number of samples in the mini-batch, such as Triplet loss and Quadruplet Loss, which is not conducive to the convergence of the model. Therefore, in this paper, a novel loss named Center-ranked is proposed to integrate all positive and negative samples information. We also propose a simple model for gait recognition tasks to verify the validity of the loss [10].

Kun Hu et. al. publish that Freezing of gait (FoG) is one of the most common symptoms of Parkinson’s disease (PD), a neurodegenerative disorder which impacts millions of people around the world. Accurate assessment of FoG is critical for the management of PD and to evaluate the efficacy of treatments. Currently, the assessment of FoG requires well-trained experts to perform time-consuming annotations via vision-based observations. Thus, automatic FoG detection algorithms are needed. In this study, we formulate vision-based FoG detection, as a fine-grained graph sequence modelling task, by representing the anatomic joints in each temporal segment with a directed graph, since FoG events can be observed through the motion patterns of joints. A novel deep learning method is proposed, namely graph sequence recurrent neural network (GS-RNN), to characterize the FoG patterns by devising graph recurrent cells, which take graph sequences of dynamic structures as inputs. For the cases of which prior edge annotations are not available, a data-driven based adjacency estimation method is further proposed. To the best of our knowledge, this is one of the first studies on vision-based FoG detection using deep neural networks designed for graph sequences of dynamic structures [11].

Ying Zhang et. al. publish that artificial intelligence is the hot topic of research recently and pattern identification is one of the important aspects. For human recognition, gait recognition is a novel popular way for its advantages in remote surveillance. This paper gives the present methods of gait recognition in walking information acquiring, feature extraction and recognition. In the end, future development outlook is given [12].

Maryam Babaei et. al. state that gait is a biometric property that can be used for human identification in video surveillance. Basically, different gait features require motion of a person walking over one complete gait cycle. For example, in Gait Energy Image (GEI), average of silhouette images over one complete gait cycle is computed. However, in reality, there might be a partial gait cycle data available due to occlusion. In this paper, authors propose a Generative Adversarial Network (GAN) in order to address the problem of gait recognition from incomplete gait cycle. Precisely, the network is able to reconstruct complete GEIs from incomplete GEIs. The proposed architecture is composed of (i) a generator which is an auto-encoder network to construct complete GEIs out of incomplete GEIs and (ii) two discriminators, one of which discriminates whether a given image is a full GEI while the other discriminates whether two GEIs belong to the same subject [13].

III. METHODOLOGY

The Pre-processing is performed on the acquired images so as to optimize them for feature extraction. This process involves getting rid of redundant information, and maximizing the relevant information. In this work, pre-processing sequentially involves the steps of background subtraction, morphological operations, gait period estimation, and Frame Difference Energy Image (FDEI) reconstruction. For identification, only the static and dynamic information contained in the silhouette of the human subject figure is required.

Thus, background subtraction and extraction of silhouettes constitutes the first crucial pre-processing step. As in all pre-processing algorithms, this algorithm should not be computationally extensive so as to increase the time taken for entire process but at the same time it should be efficient enough to produce acceptable results. It is important to underline that for gait recognition, only the silhouette of the subject is needed. Thus the output image should be a binary image with the outline of the human subject. All other features of the subject, such as color of clothing, is irrelevant, since the identification has to rely on gait or motion data only. Thus, this step takes grayscale images as input and produces binary silhouette images as output. The CASIA Gait Database readily comes with pre-processed binary silhouette. The pre-processing of gait video in this database employs fuzzy-correlogram based method for background subtraction.

Thus, a correlogram captures the spatial relation between a pair of pixels in addition to the intensity information. Since taking all the 256 intensity levels individually increases the complexity, grouping the intensity range into / bins (l <= 256) reduces the correlogram size to / X l. But a regular correlogram involves crisp assignment of bins and is vulnerable to quantization noise. For example, due to slight illumination changes or artifacts or other errors leading to localized intensity changes with steep gradients, a particular pair of pixels may contribute to the neighboring bins instead of the actual bins where they should belong.

To alleviate this problem, a fuzzy membership function is introduced into the correlogram in to create a Fuzzy Correlogram such that each pixel pair contributes to every bin with a finite and definite probability, while having major belongingness or maximum probability in the adjacent bins. In the fuzzy correlogram, the membership matrix M is obtained by employing fuzzy c-means algorithm.

Also, lesser number of bins are used (c) as compared to the regular correlogram (/2) which leads to a further reduction in computational complexity. Since it is region-based, the fuzzy correlogram based background subtraction method performs well in case of dynamic backgrounds too. The broad outline of gait recognition process is shown in figure below.
GA Optimized MLP: The non-linear property of multi-layered neural networks is useful for analysis of complicated gait variable relationships which have traditionally been difficult to model analytically. Hence, an enhanced multi layer perceptron structure for training multi-layered neural network, based on selective retraining and a dynamic adaptation of learning rate and momentum, is employed to recognize the gait. An automated pattern recognition system minimally contains an input subsystem that accepts sample pattern vectors and a decision-maker subsystem that decides the classes to which an input pattern vector belongs. If it also classifies, then it has a training phase in which it learns a set of classes of the population from a sample of pattern vectors, namely, it partitions the population into the subpopulations that are classes. As described above, a multi-layered feed-forward neural network is employed here to train and recognize the human gait. Figure below shows the network architecture used within this study. To train the network, the chosen structure is the enhanced Multi Layer Perceptron (MLP) with one input and output layer and two hidden layer. Also, the nodes of output layer are divided into two groups, and information about a maximum output node of each group is used to decode the output to an identification code of gait.

In the MLP the size and number of the hidden layers is usually determined to an exact problem. However in our algorithm the number of hidden layer is variable, but fixed to two. The amounts of the neurons in each hidden layers are the researched variables of the Genetic Algorithm (GA), which will be introduced soon. In the ANN it is necessary to give summation and activation functions in each neuron. The character of the activation function has effect on the outcome, the input function is the most common form, whereas a threshold function assumes the value of 0 or 1, and it is less sensitively changing close to the extreme values. In this algorithm the activation function form has been chosen fixedly.

The ANN recently has been used for separation, but as the capacity of network is bigger the complexity of the distinction is more. The advantage of the ANN compared to other classification method is the capability to learn. A neural network is learning about its environment through an iterative process of adjustments applied to its synaptic weights and thresholds, similar like in the human brain. Eventually the ANN is the computational ‘copy’ of the human brain. The perceptrons are working as the natural neurons, which linked to each other with an organized network. If a link between two neurons is used more likely, then it is getting stronger (weights are higher), so it will have a more effective impact in the decision making. Just like biological brain, this artificial one is able to recognize objects, processes or patterns, but only those ones which have been taught in advance. The level of similarity can be changed in the matching phase or during the training it is even possible to teach more genuine templates to increase the recognition efficiency. The training is necessary but without appropriate test, it is worthless. The test result validates the ANN and its reliability. Generally the usage of the ANN is separated to the following steps:

1. Network setup
2. Training phase
3. Testing phase
4. Operating phase

There are some critical setting points in the training phase as well. First of all, it has to be decided how we would like to train. The training here means that, there are an initial weight matrices with random values that symbolize the strength of the links. Actually the starting weight matrices are crucial, because any similarity or regular pattern can lead the learning phase into local minima, which sabotages the training. Regarding to this phenomenon we used random generator to set the starting weight. During the training, the algorithm investigates the training patterns, which are mathematically extracted vectors from biometric samples, or like in our algorithm they are synthesized with a minutiae generator to decrease the environmental failure effects. As all the vectors have been taught then we get result from the output layer. The training is actually a process how the desired and obtained output could get closer to each other. According to Genetic Algorithm structure all the populations are trying to survive and multiply their genome, which is actually an endless competition. The better adapting strings have the better chance to survive – in a concrete environment or task –, and the degree of the adaptation measured by the fitness value. The biometric devices usually qualified with failure rates, which are able to measure the goodness of a device. Here error values are used as to determine fitness value for the Genetic Algorithm. Lower the error higher the fitness. As the strings are competing which each other, there are three type of modification across the population (selection, crossover, mutation). The bigger the
fitness values among the strings the higher the probability of selection into the next generation. The crossover depends on some initial regulation and a random generated probability; it is crossing string fragments into a new whole string. The mutation has an exact small probability that can change a bit in the binary code in each chromosome. The mutation of the probability can be changed if it is necessary. There are several types of selection and crossover methods. The tournament selection type is chosen for selection, when for every place in the new population two old strings are competing with each other. They are chosen randomly and the fitter win ever. The crossover is chosen to uniform and the pairing is random, like the position of the crossing point. The probability of the crossover also can be changed depending on the goodness of the GA test’s result. The applied structure of the GA is shown in figure below.

![Figure 4. Ga optimization structure](image1)

The applied form of the GA for optimization of the ANN still needs some fine tuning. There were some previous decision about the basic architecture like the type of the selection and crossover. The crossover type have been changed through the tuning, because we experienced it is favorable to let chance to copy the whole chromosome not only a fragment. The exact point of the brake is determined by a random generator.

![Figure 5. Ga-NN optimization of gait features](image2)

The FED vector can be seen as the observed manifestation of the transition across exemplars or stances (a hidden stage of a neural network processing a feature vector to weight vector). The whole process can be seen as an enhanced GA Optimized Multi Layer Perceptron (MLP) algorithm for training multi-layered neural network, based on selective retraining and a dynamic adaptation of learning rate and momentum with exemplars representing the layers, and an ANN can be used to model the statistical characteristics of the process according to the observed FED vectors which are employed to recognize the gait. Thus the FED vectors represent the observation symbols of the GA-NN, which in turn are also called weight vectors of GA-NN. The ANN parameters as well as exemplars of all the persons in the database are available, along with a probe gait sequence. The objective is to reveal the identity of the subject in the probe gait sequence by using GA-NN to find weight vectors that have the maximum probability of generating that particular sequence. Initialization for the parameters remains the same as in the training step while initial value for weight vector is obtained using the exemplars of each person in the gait database. For each person in the database, we already have the weight vectors parameters and exemplar vectors; MLP is used to compute the likelihood or probability that the probe sequence was produced by the weight vector of that person. A ranking is carried out using the degree of repetition of feature vectors and weight vectors for recognition. Figure below illustrates the training procedure and recognition procedure for a GA-NN respectively in the form of flowchart.

![Figure 6. Flowchart: Ga-Nn Based Gait Recognition](image3)

IV. RESULT ANALYSIS

Output 1: The User-Interface Designed in MATLAB GUIDE
The designed user interface for GA-NN Human Gait Analysis using MATLAB GUIDE is shown in figure as under:

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27847

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The GA-NN optimized Gait Recognition application is tested on three different datasets of CASIA Gait database. Each dataset consists of 20 classes where each class corresponds to an individual subject or person. The Dataset 1 also referred to as Dataset 80 consists of a total of 80 gait sequences with 4 gait sequences per class. The Dataset 2 also referred to as Dataset 160 consists of a total of 160 gait sequences with 8 gait sequences per class. The Dataset 3 also referred to as Dataset 240 consists of a total of 240 gait sequences with 12 gait sequences per class.

Table 1. Result Analysis Parameters: GA-Nn Gait Recognition

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Gait Sequences</th>
<th>Training Angle</th>
<th>Training Time</th>
<th>Avg. Recognition</th>
<th>% Accuracy</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset 1</td>
<td>80</td>
<td>0°</td>
<td>2072s</td>
<td>0.81282s</td>
<td>100%</td>
<td>0</td>
</tr>
<tr>
<td>Dataset 2</td>
<td>160</td>
<td>45°</td>
<td>4371s</td>
<td>0.110183s</td>
<td>86.25%</td>
<td>13.75%</td>
</tr>
<tr>
<td>Dataset 3</td>
<td>240</td>
<td>90°</td>
<td>7033s</td>
<td>0.147176s</td>
<td>6.25%</td>
<td>93.75%</td>
</tr>
</tbody>
</table>

Analysis Graph 1: Total Gait Sequences
The graph shows comparison of total no. of gait sequences in each of the three datasets. The Dataset 1 contains 80 Gait Sequences. The Dataset 2 contains 160 Gait Sequences. The Dataset 3 contains 240 Gait Sequences.

Analysis Graph 2: GA-NN Training Gait Angles
The graph shows comparison of training gait angles applied in each of the three datasets. The Dataset 1 is trained at 0° gait angle. The Dataset 2 is trained at 45° gait angle. The Dataset 3 is trained at 90° gait angle.

Analysis Graph 3: GA-NN Optimized Training Time
The graph shows comparison of GANN training time in seconds for each of the three datasets at different gait angles. As the number of images for each dataset increases the training time for the dataset also increases.

Analysis Graph 4: Input Id Vs Recognized Id for 03 CASIA Gait Sequence Datasets
The graphs show comparison of Input Gait Sequence Id and Output Recognized Id for each of the Dataset 1, Dataset 2 and Dataset 3 for which the optimization and training was done at 0°, 45° and 90° respectively.
VI. CONCLUSION

The major objective of this work is to implement an efficient algorithm for the reliable identification of humans using their gait data. The experimental results provide a preliminary platform for satisfactory gait identification, but there exists a huge scope for future work in this area especially regarding issues of real-world implementation. The progress of future work is to use a hybrid combination of statistical depth features with artificial intelligence based convolutional neural networks, which are at the heart of deep learning's in computer vision, in the gait identifications problem. Also, the combination of more than one biometrics (multimodal biometrics) such as gait, face and foot pressure could be one of next intentions as non contact biometric approaches are in demand in post COVID-19 pandemic era. The complete comparison and analysis of the system on recognition on basis of ANN training done at different gait angles shows that the when trained at gait angle of 0°, the GA-NN performs with 100% accuracy for Dataset 80. When trained at gait angle 45°, the GA-NN performance starts de-generating a little with accuracy of 86.25% and GA-NN gives an erroneous performance for Dataset 160. When trained at gait angle 90°, the GA-NN performance degenerates completely and ANN doesn’t perform at all for Dataset 240. On the other hand the complete comparison and analysis of GA-NN for recognition speed shows that the system performs with great efficiency on this front with recognition times ranging from 0.05 seconds to 0.16 seconds.

VII. REFERENCES


