

Human Recognition based on Gait Features and Genetic Programming

Dipak Gaire Sharma, Rahadian Yusuf, Ivan Tanev, and Katsunori Shimohara
*Graduate School of Science and Engineering, Doshisha University, 1-3 Tatara Miyakodani,
Kyotanabe, Kyoto 610-0394, Japan*

*E-mail: sharma2013@sil.doshisha.ac.jp, yusuf2013@sil.doshisha.ac.jp, itanev@mail.doshisha.ac.jp,
kshimoha@mail.doshisha.ac.jp*

www.doshisha.ac.jp

Abstract

Human walking has always been the curious field of research for different disciple of social and information science. The study of human walk or human gait in association with different behaviors and emotions has not only fascinated social science researchers, but its uniqueness has also attracted many computer scientists to work in this arena for the quest of uncovering reliable mechanisms of biometric identification. In this research, we used a novel method for human identification based on inferring the relationship between the human gait features via genetic programming. Moreover, we focus on generating the unique numerical signature that is similar for different locomotion gaits of a particular individual but different across different individuals.

Keywords: Human Identification, Biometrics, Genetic Programming, Human Gaits, Nature Inspired Computing

1. Introduction

Analysis of human behavior involves different methods to identify or recognize human. It is done by the visual analysis where different characteristics are studied to authenticate people¹. This approach is gaining substantial amount of interest because it is also driven by the task of automated human identification which is very crucial in different fields that are sensitive to the issues of security. There are different methods that are

implemented for this task, and among them gait recognition is a new dimension unlike gait classification. Gait is a rhythmic physical movement of body parts. As analysis of gait does not require a person to face the sensors directly, it can be done without any notice by the subject, because of this feature, it has been the important dimension of research in computer vision among different security agencies throughout the world.

Human locomotion is said to be unique. It is unique in a sense that human being holds distinctive ability to determine their close friend and family easily. It was

proven by Johansson² in 1973 by the experiment where he attached light markers to the subject, and people were asked to identify the subject based on those attached markers. It is also unique because many animal behaviors such as walking or swimming require rhythmic contraction of muscles which is generated by the signals from the neurons called Central Pattern Generator (CPG)^{3, 4}. These CPG are responsible for generating rhythm and shapes the pattern of the motor neurons. Basically each and every individual have unique walking pattern, therefore, it can be considered as one of the most reliable source of human recognition.

This paper is the finding in a research of gait feature recognition where genetic programming (GP) is used to generate unique signature among different individuals. Although there are variety of genetic programming approaches available, in this case XML-based Genetic Programming⁵ approach was deployed. The study on human gait analysis using a genetic programming approach is relatively an understudied problem. Therefore, our study will also be the milestone towards the analysis of efficiency and reliability of GP in case of human gait analysis and human recognition.

2. Previous Work

Human gaits recognition and human recognition by motion is one of the active topics in the field of Computer Research. Many existing approaches focus on analyzing human motion using video frames and applying the different processing techniques^{6,7}. We can find vast research done in this field using different dimensions. However, some are focused on limb gait features while other are based on merging the features and most use classifiers from the gait classification record such as Back Propagation Neural Network Algorithm, Fisher Distance, Support Vector Machine and K-Nearest Neighbor. If we analyze different research that has been done so far, we could find that most of the research are focused on the classification of gait features but none of these research focuses of finding the relationship between several gaits of individuals. Therefore, this research is concerned on generating a unique numerical signature which is similar for different motion gaits of a particular individual but different across different individuals which further can be used as a mechanism of human recognition.

3. Computational Approach

This study involves different computational steps and methodologies that were implemented to achieve the experimental result of this research, these steps includes;

3.1. Data Acquisition

The initial step involves the technique of identifying a person while in motion and generates the skeleton frame from the captured data. For this task, a device from the Microsoft called Kinect for Windows is used. This device has the ability to detect human motion and generate skeleton with 20 different joints. To interface this device, we developed an application that could track a person. A sample snapshot of this application is shown in Figure 1.

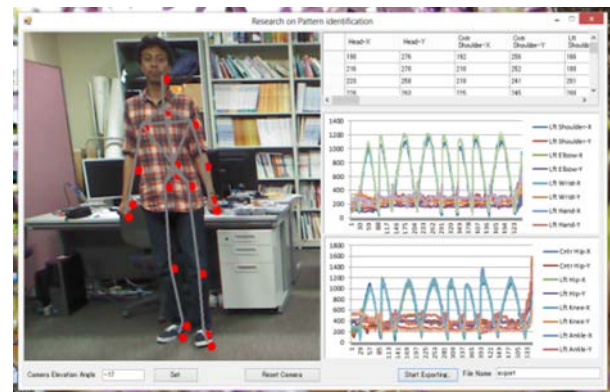


Fig.1: Application Interface for analyzing the gaits to identify the major joints that are used to determine the features.

3.2. Smoothing Parameters

The next step comprises of method to generate the numerical dataset for the skeleton previously generated where joint coordinates are accessed from the device and are stored in a data file. Since data from the Kinect are not consistent for our work, the task of smoothing those dataset are required, which is done using the mathematical model known as sliding window average method, as shown in Equations 1, 2, 3 and 4. This method is important because it help to exclude the extreme parameters and helps to increase the probability of minimizing noise level in our dataset.

$$y_1 = \frac{1}{k}(x_1 + x_2 + \dots + x_k) \quad (1)$$

$$y_2 = \frac{1}{k}(x_2 + x_3 + \dots + x_{k+1}) \quad (2)$$

$$y_3 = \frac{1}{k}(x_3 + x_4 + \dots + x_{k+2}) \quad (3)$$

...

$$y_{n-k+1} = \frac{1}{k}(x_{n-k+1} + x_{n-k+2} + \dots + x_n) \quad (4)$$

3.3. Feature Extraction

The third step is basically concerned with feature finding. These features are calculated from the dataset which are previously obtained after noise reduction. For this task we made some basic calculation and extracted the values of major features of human gaits. These include the angle between joints, the angular displacement, velocity, distance between joints and rate of change in distance. These features are calculated for few selected joints from arms, legs, hip and shoulder. As the features are calculated frame by frame, they were reduced to a single value by considering the average of each feature. As a whole, total of 30 features of dataset were evaluated and stored in database to use as an offline source. We used these features as the terminal set in our genetic programming framework.

3.4. Genetic Programming

The fourth step involves implementation of genetic programming framework. Since our problem is concerned with finding relationship between human gaits which is not known in advance as well as does not possess any predefined method of performing the operation, the use of genetic programming is the best technique to implement for this task. For the purpose of evolving an association between gaits feature, we used our XML-based Genetic Programming framework⁵ (XGP). Beside this, the communication with different sub-systems and calculation of fitness value from fitness evaluator is also performed in this phase. A sample snapshot of the XGP applied for the recognition of human gaits is shown in Figure 2. The main parameters of XGP are show in Table 1.

4. Experimental Results

We implemented the system with Intel Core 2 Quad processors each with 2.5GHz speed, and 2GByte of physical memory. We acquired the initial data i.e. the feature of human gaits in the Socio Informatics Laboratory of Doshisha University. Data were collected for one individual at the initial experimental test, where the individual was asked to make three different gait movements starting from (i) normal walk, (ii) slow walk and (iii) fast walk, respectively. The motion detection sensor was placed perpendicular to the walking direction at the distance of 3 to 4 meters.

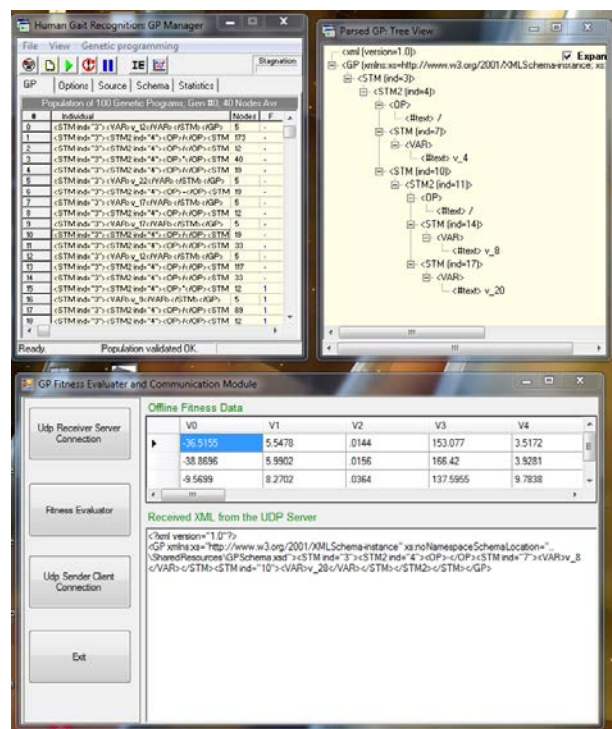


Fig.2: XGP applied for recognition of human gaits: GP Manager (top) manages the population of genetic programs, and the fitness evaluation subsystem (bottom), which calculates the signatures for three gaits of the same person, and measures the quadratic deviation of these three signatures.

The experimental results of the fitness convergence of 20 independent runs of XGP are shown in Figure 3. Table 2 shows the values of signatures of three human gaits, obtained from a sample best-of-run genetic program. Notice that despite the fact that these three gaits have different values of their respective features; the values of the three signatures are very close. The

obtained fitness value is very small too, and it is equal to 2.

Table 1: Main Parameters of XGP

Parameters	Values
Terminal Set	(i) Variable v_0, v_1, \dots, v_{29} (feature of human gaits) (ii) Random Integer constants [0,10]
Function Set	{+, -, *, /}
Population Size	100 genetic programs
Selection Ratio	10%
Mutation Rate	2%
Selection Method	Binary Tournament Selection
Fitness Value	Quadratic Deviation of 3 gaits scaled up to 1000 times. Lower fitness value correspond to better solutions
Termination Criteria	Fitness value ≤ 2 or # Generations = 100

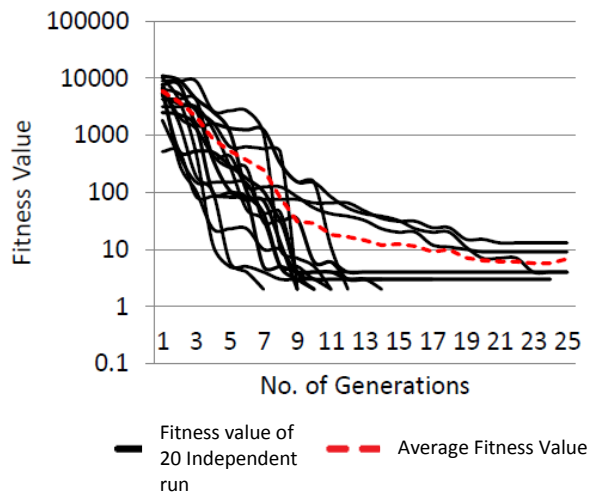


Fig.3: Fitness convergence characteristics of 20 independent runs of XGP. The dashed line represents the convergence of the average fitness value.

Table 2: The values of signatures of three human gaits of a same person, obtained from sample best of run genetic program (fitness value=2).

Gaits	Values
Normal Walk	17.0000869346814
Slow Walk	17.000062104833
Fast Walk	16.9998314813823

5. Conclusion

The characteristics shown in Fig.3 illustrate how the fitness improves as the evolution progresses; the improvement is dramatic and the average fitness decreases from the initial value of around 7000 to around 8, which is almost 1000 times. The result is obtained relatively quickly, within about 20 generations, which correspond to about 4 hours of runtime. Such an impressive performance of XGP could be explained by the fact that so far we tried to evolve very close signatures of three different gaits of a single person, and we have yet to evolve similarly close to each other three signatures of the gait of another person. Moreover, the signatures of the gait of both persons should be distinguishably different. We anticipate that the addition of additional person(s) in the gait identification and classification task would significantly increase the computational effort of XGP.

The future work includes experiments with multiple individuals and researching on the methods to evolve the distinguishable signatures of their respective gaits.

References

1. L.Wang, W.M. Hu, and T.N. Tan, *Recent Developments in Human Motion Analysis*, (Pattern Recognition, Vol. 36, Issue 3, 2003), pp.585-601.
2. G.Johansson, *Visual Perception of Biological Motion and a Model for its Analysis*. Perception and Psychophysics R. M. Karp, Reducibility among combinatorial problems, in *Complexity of Computer Computations* (Plenum, New York, 1972), pp. 85–104.
3. J.Duysens et al, *Neural control of locomotion; Part 1: The Central Pattern Generator from cats to humans*, (Gait & Posture, Vol. 7, Issue 2, 1998), pp. 131-141.
4. Levitan, Kaczmarek, *The Neuron Cell and Molecular Biology*, Third Edition, Oxford.
5. I.Tanev and K.Shimohara, *XML-based Genetic Programming Framework: Design Philosophy, Implementation, and Applications*, (Artificial Life and Robotics, Vol.15, No.4.).
6. Hu Ng et al. *Human Identification Based on Extracted Gait Feature*, (IJNCCA, Vol. 1, No. 2, 2011), pp. 358-370.
7. Liang Wang et al, *Silhouette Analysis-Based Gait Recognition for Human Identification*,(PAMI, Vol. 25, Issue 12, 2003), pp.1505-1518