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A Gait Recognition System using GA-based C-SVC and Plantar Pressure

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Abstract

In order to conduct the gait recognition system, a wireless in-shoe wearable plantar pressure acquisition system based on ATmega16 and 8 FSR sensors was applied to data acquisition for the gaits which consist of standing, walking, jumping and going upstairs. And four volunteers (2 females and 2 males) were invited in this research to collect the pressure information. MATLAB and LIBSVM were applied to conduct all algorithms proposed by this study. Genetic Algorithm (GA) was used to set the best tuning (penalty) parameter and the best (gamma) of Gauss radial basis kernel (RBF) for C-support vector classification (C-SVC) model and the GA-based C-SVC was obtained. A dataset named 'train-data', containing 800 sets of pressure data was used to train the GA-based C-SVC as the algorithm of gait recognition. Finally a testing dataset containing 400 sets of pressure data was applied to test the algorithm of gait recognition called GA-based C-SVC. The accuracy of this GA-based C-SVC was 98% for standing, 91% for walking, 82% for going-upstairs and 97% for jumping. In generally speaking, a better GA-based C-SVC was obtained in this research.

Keywords: *C-SVC; GA; Plantar pressure; Gait recognition*

1. Introduction

In recent years, a growing need for a full range of visual surveillance and monitoring systems in security-sensitive environments such as banks, airports and human identification at a distance has gained increasing interest from computer researchers. Gait recognition is only a recognizing technology which can be detected and measured at a distance. It overcomes the challenges when using physical or close contact such as finger print recognition, face recognition by its inherent biological characteristics such as; non-invasive, non-contact, hiding and disguising difference, far-distance recognition and so on.

1.1. Previous Approaches to Gait Recognition

Although gait recognition is a new research field, there have been some studies and researches. Currently, gait recognition approaches can be mainly classified into two classes: motion-based methods and model-based methods.

Model-based methods aim to model human body by analyzing the parts of body such as hands, torso, thighs, legs, and feet and perform model matching in each frame of a walking sequence to measure these parameters.

As a typical example of model-based approaches of gait recognition, Cunado et al. [1] considered legs as an interlinked pendulum, and gait signatures were derived from the frequency components of the variations in the inclination of human thighs. These features were analyzed using the phase-weighted Fourier Magnitude Spectrum for gait recognition. Johnson and Bobick [2] used activity-specific static body parameters for gait recognition without directly analyzing the dynamics of gait patterns. Yam et al. [3] first used running and walking to recognize people. They then explored the relationship between walking and running that was expressed as a mapping based on phase modulation. In addition, Cunado et al. [4] used thigh joint trajectories as features.

Recently, in literature [5], a simple but efficient gait recognition algorithm using spatial-temporal silhouette analysis was proposed by Wang and Tan. This can be considered "not rocket science" as it may be very easy to understand the technology in it.

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The advantages of model-based approaches are that they offer the ability to derive gait signatures directly from model parameters.

As for the motion-based approaches of gait recognition, Jiwen Lu and Erhu Zhang [21] proposed a gait recognition method using multiple gait features representation based on Independent Component Analysis (ICA) and genetic fuzzy support vector machine (GFSVM) for the purpose of gait recognition at a distance. Hayfron-Acquah et al. [22] described an automatic gait recognition method using the generalized symmetry operator, and Phillips et al. [23] applied a baseline algorithm based on spatial-temporal silhouette correlation to the gait identification problem. These authors should basically be on "the same wavelength" in the understanding of gait recognition, as they are able to approach it from different points of view.

1.2. Plantar Pressure Acquisition System

Plantar pressure acquisition system is one of the most important application techniques in gait recognition, clinical foot-pain treatment and footwear design fields and has also become a powerful tool for biomechanical research. This wide application could make a "lay man" equate it to the present day ipads. Numerous systems have been developed for Ground Reaction Force (GRF) assessment and gait-phase detection.

In-shore plantar pressure acquisition system, which is capable of simultaneously measuring GRF-induced plantar forces and detecting gait-phases of human, has emerged as an attractive alternative for ground mounted force platform due to several outstanding merits including portability, flexibility and great convenience. Therefore, researchers in this field can make more heads or tail out of it.

As for the number of force sensors to be used, many authors have proposed different numbers to recognize the gait phase; for instance, [8] used four to identify the gait phases with a classification algorithm, and has obtained good results. And in mid-2000s, according to literature [7], Faivre employed eight sensors in the in-shoe plantar pressure system and Flexiforce sensor (Tekscan Inc., USA) or FSR sensor (Interlink Electronics, USA) have been commonly used.

Different sensing principles have also been widely explored for in-shoe plantar pressure system. Spring elements with strain gauges were commonly used to measure vertical reaction and shear forces. F-scan (Tekscan Inc., USA) utilizes force sensitive resistors. A Novel pedar system (Novel USA, Inc.) that captured dynamic in-shoe temporal and spatial pressure distributions were utilized for dynamic gait stability analysis [9], gait recognition [10], and altered gait characteristics during running [11]. Both systems (F-scan and Novel pedar) used electrical wires to connect in-shoe sensors and data acquisition system around the waist, which caused inconvenience and discomfort during strenuous exercises. A wireless structure shoe-integrated sensor system was developed for gait analysis and real-time feedback [12].

2. Proposed Algorithms

The studies of gait recognition and its key technologies have an important academic significance and practical value. So in this paper, a gait recognition system using GA-based C-SVC and plantar pressure was introduced.

2.1. Genetic Algorithm

Genetic Algorithm (GA) [6], a kind of self-adapted global optimization probability searching algorithm by simulating creatures' gene and evaluation in natural environment was developed and investigated by professor Holland and his students (e.g. DeJong) in Michigan University in 1975. Recently, Genetic Algorithm has been successfully applied to various optimization problems and it contains 4 general steps; initialization, selection, recombination (crossover) and mutation.

The general algorithm of Genetic Algorithm is shown in Figure 1.

Step 1 Generate initial population randomly with a fixed number of individuals and encode each individual.

Step 2 Calculate the fitness of each individual, and then judge this population by Optimization Standard. If it is fit, the calculation is over. Or turn to step 3.

Step 3 Select the 'good parents' via fitness.

Step 4 Generate the offspring through the recombination of the parents.

Step 5 Generate the offspring through the mutation of the parents.

Step 6 Get a new population that comprises the offspring from step4 and step 5 and return to step 2.

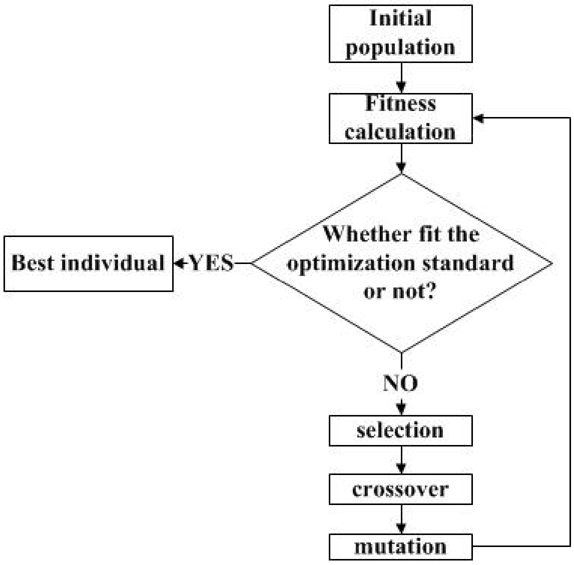

Figure 1. The general flow chart of Genetic Algorithm

2.2. C-Support Vector Classification

The Support Vector Classification (SVC), a branch of Support Vector Machine (SVM) which is based on extremely well developed machine learning theory named Statistical Learning Theory (SLT), is a prominent classifier that has been proposed by Vapnik and his co-workers (Corte and Vapnik, 1995; Vapnik, 1995,1998) [19].

C-Support Vector Classification (C-SVC) [20], a part of SVC, can be characterized as a supervised learning algorithm capable of solving nonlinear classification problems.

Generally speaking, according to the Lagrange function, Karush–Kuhn–Tucker (KTT) conditions, strong duality theorem and Slater conditions [20], given a training dataset with instance-label pairs $\{(x_i, y_i)\}_{i=1}^{m}$, where $x_i \in X \subseteq \Re^n$ is an input vector and $y_i \in \{-1,1\}$, the initial algorithm model of C-support Vector Classification (C-SVC) is:

$$\min_{\alpha} \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} y_i y_j K(x_i, x_j)\alpha_i \alpha_j - \sum_{j=1}^{m}\alpha_j \text{ s.t. } \sum_{i=1}^{m} y_i \alpha_i = 0, 0 \le \alpha_i \le C, i = 1,...,m \quad (1)$$

In Eq. (1) α_i denotes Lagrange multipliers, $K(x_i, x_j)$ that can expand the linear problems to the non-linear problems is called kernel function, and C represents the tuning (penalty) parameter. Thus the algorithm of C-SVC is:

Step 1 Given a training dataset with instance-label pairs $\{(x_i, y_i)\}_{i=1}^{m}$ where $x_i \in X \subseteq \Re^n$ is an input vector and $y_i \in \{-1,1\}$.

Step 2 Chose a proper tuning parameter $C > 0$ and a kernel function $K(x_i, x_j)$.

Step 3 Obtain $\alpha^* = (\alpha_1^*, ..., \alpha_m^*)^T$ via Eq. (1).

Step 4 Select a vector of α^* from 0 to C, and then calculate $b^* = y_j - \sum \alpha_i^* y_i K(x_i \cdot x_j)$.

Step 5 Construct the decision function $f(x)=\mathrm{sgn}(g(x))$ where $g(x)=\sum_{i=1}^{m} y_i\alpha_i^* K(x_i \cdot x)+b^*$.

3. Materials and Methods

3.1. In-Shoe Wearable Plantar Pressure Acquisition System

In order to effectively obtain the different types of plantar pressure such as standing, walking, jumping and going upstairs as the training and testing data, this paper designed an in-shoe wearable plantar pressure measurement system.

According to the literatures mentioned above, this study chose FSR sensors provided by Interlink Electronics in USA as data acquisition sensors.

Force Sensing Resistors (FSR) are polymeric thick film (PTF) devices which exhibit a decrease in resistance with an increase in the force applied to the active surface. Its force sensitivity is optimized for use in human touch control of electronic devices. FSRs are not load cells or strain gauges, though they have similar properties [17].

As illustrated in Figure 2, the heel, metatarsals and hallux are the primary regions to bear the body weight [18]. Therefore, this paper was designed to have four force sensors configured at the Heel, Meta 2nd, Meta 1st, and Hallux for each foot to obtain plantar force and detect gait phase. The sensors were packaged in two pairs of insole and the insole was adhered to a pair of shoes, as shown in Figure 3 and Figure 4. A total of eight FSR sensors were applied in this experiment.

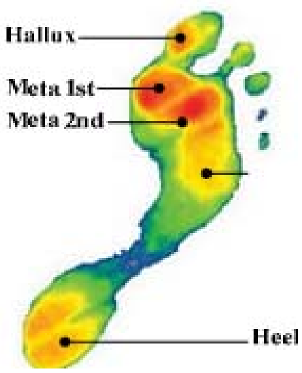

Figure 2. Plantar pressure distribution [13]

Figure 3. The package of sensors in the shoes

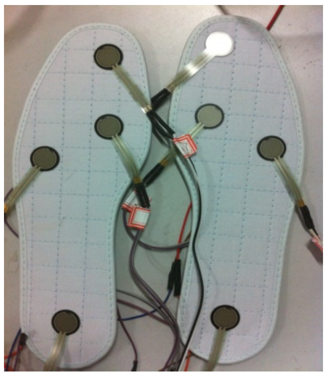

Figure 4. The position of sensors in insole

This research used a kind of microcontroller named ATmega16 that is a low-power CMOS 8-bit microcontroller based on the AVR enhanced RISC architecture as the main chip of this data acquisition system because of its 10-bit successive approximation analog to digital converter (ADC) which is connected to an 8-channel Analog Multiplexer that allows 8 single-ended voltage inputs constructed from the pins of Port A, and the single-ended voltage inputs refer to 0V (GND).

Therefore this research designed the data acquisition program using C language by CodeVision AVR to turn the analog plantar pressure information to digital information by the ADC in ATmega16.

As for the data uploading, the wireless serial module named XL105-232 was utilized to upload the data to the computer in this study.

In summary, the whole system board of data acquisition contained: a microcontroller named ATmega16, a wireless serial module named XL105-232, a linear compensation circuit for sensors with 10 $k\Omega$ resistors, and a voltage-stabilizing filter circuit.

The procedure for data acquisition was as follows; collecting analog signal via FSR sensors, then obtaining digital signal through ATmega16, and finally uploading the digital signal to the computer by wireless serial module.

3.2. Data Acquisition

In order to get more universal and efficient data of plantar pressure, this research made use of four volunteers; two females and two males to conduct the data acquisition of this experiment. The information of the volunteers is as shown in Table1.

Table 1. General information of volunteers

Gender	Age	Height	Weight	Feet size
Female	23	167 cm	55 kg	39 cm
Female	22	160 cm	48 kg	37 cm
Male	20	174 cm	60 kg	41 cm
Male	22	167 cm	65 kg	40 cm

Four kinds of general gaits; standing, walking, jumping and going upstairs were designed to be recognized by the algorithms of gait recognition introduced in this paper and it was decided to acquire 1000 groups of data for each kind of gait, namely; 250 sets of standing-data, 250 sets of walking-data, 250 sets of jumping-data and 250 sets of going-upstairs-data were obtained by each volunteer. And once the data of plantar pressure was sent to the computer, the data was saved to a text file via a control program that was designed by this study through Microsoft Vision C++ 6.0.

Therefore each dataset contains one thousand sub datasets for standing, walking, jumping, and going-upstairs was obtained from the four volunteers.

Then this research selected 200 data randomly from each dataset respectively to make a training dataset called ‘train-data’ and 100 data from each dataset to get the testing dataset named ‘test-data’.

3.3. Simulation of GA-Base C-SVC for Gait Recognition

When using the C-SVC model (Eq. (1)), two problems were confronted; how to choose the optimal penalty parameter C for C-SVC, and how to set the best kernel parameters. To implement proposed approach, this research used the RBF kernel function for the C-SVC because the RBF kernel function can analyze higher-dimensional data and requires that only two parameters, C and γ (gamma) be defined. Therefore the Genetic Algorithm was used to optimize the parameters C and gamma in this research.

MATLAB, LIBSVM [15] and LIBSVM-Faruto Ultimate Version [14] were applied to simulate the algorithm of gait recognition namely GA-base C-SVC.

According to the designed programs of algorithms, because of using GA for searching the best C and best gamma, this paper used 100 as the maximum number of generations, 20 as the size of population, 0.9 as the rate of individuals to be selected, 0.7 as the rate of recombination, and 0.025 as the rate of mutation. The search range of penalty parameter C and γ is from 1 to 100. And the selection methods of the GA are Rank-based Fitness Assignment and Stochastic Universal Sampling. The fitness function of this Genetic Algorithm is the accuracy of 5-Fold Cross Validation of C-SVC.

K-Fold Cross Validation (KCV) is one of the most popular resampling techniques, which is effective, reliable and simple [16].

This research made a numeral label to represent all the types of gait, thus ‘1’ was chosen to represent ‘standing’; ‘2’ represented ‘walking’; ‘-1’ for ‘jumping’ and ‘-2’ for ‘going-upstairs’.

So generally speaking, in order to establish a GA-based C-SVC system of gait recognition precisely, the following main steps (as shown in Figure 5) must be preceded;

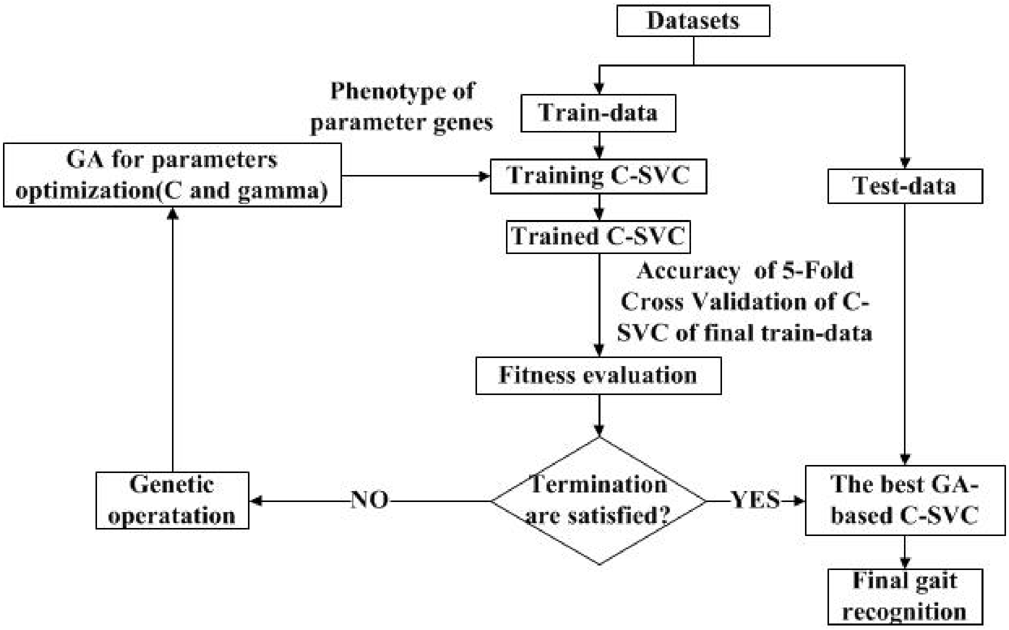

Figure 5. System architectures of GA-based C-SVC of gait recognition

Firstly obtain the data of plantar pressure and chose the ‘train-data’ and ‘test-data’. Secondly get the optimal parameters of C-SVC by the Genetic Algorithm and train it to get ‘the best GA-based C-SVC ’. Finally start the gait recognition through the ‘test-data’.

4. Experimental Results

The ‘train-data’ was an 800×8 dataset made of 800 sub datasets which contained 200 data from ‘standing’, 200 data from ‘walking’, 200 data from ‘jumping’ and 200 data from ‘going-upstairs’; and ‘test-data’ was a 400×8 dataset that comprised 100 data from ‘standing’, 100 data from ‘walking’, 100 data from ‘jumping’ and 100 data from ‘going-upstairs’ after selecting the experimental data.

The best was 13.6452 and the best gamma was 0.0029564, after utilizing the GA for optimizing as shown in Figure 6.

The final classification model based on GA-based C-SVC using the best parameters and ‘final train-data’ was done by the algorithm designed by this research through MATLAB and LIBSVM-Faruto Ultimate Version. And the result of final gait recognition based on the final GA-based C-SVC was as shown in Table 2.

From the experimental result of final gait recognition shown in Table 2, it can be concluded that this research obtains a better GA-base C-SVC for gait recognition, and the accuracy of the classifier is more than 90% except for ‘going-upstairs’ because of its complication among other three gait.

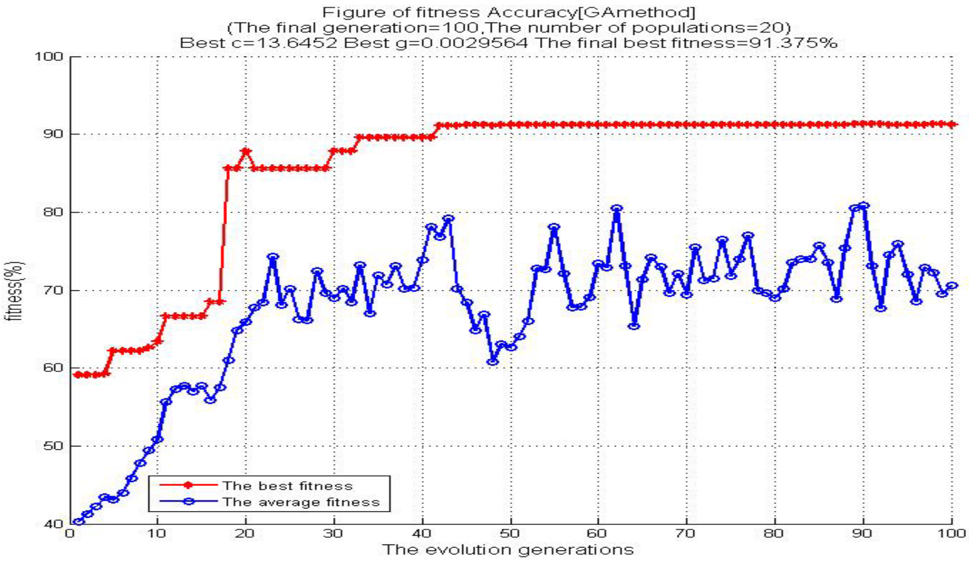

Figure 6. The result of parameters optimization of C-SVC by GA

Table 2. The result of final gait recognition

Gaits	True number of gaits	Classified number of gaits	Accuracy of the trained GA-based C-SVC
Standing	100	98	98%
Walking	100	91	91%
Jumping	100	97	97%
Going-upstairs	100	82	82%

5. Discussions and Conclusions

Using the Genetic Algorithm for parameters optimization of SVM is a great method of this study. It may not be an easy concept to understand as one will need to “beat brains out”, but one can make heads or tails out of it for future studies.

Although our recognition accuracy is comparatively high and encouraging, it still does not give much conclusion about gaits.

In order to get a better classification of ‘going-upstairs’ or more complicate gait, an improved GA or other algorithms for parameter optimization such as particle swarm optimization (PSO) or more experimental data should be applied in the SVC in future studies.

Of course other kernel functions of SVM such as Sigmoid kernel, Spline kernel, Fourier kernel also can be chosen to get the classification model if further researches will go on.

In addition, υ-support vector classification (υ-SVC) can be tried as the initial classification model in the future works and the parameter υ could be optimized by other optimization algorithm.

Besides SVM, there are many other kinds of algorithms which can be applied to gait recognition. Examples include; BP neural network, the algorithm of Locality Preserving Projections (LPP), the algorithm of Statistical Shape Analysis (SSA), and the algorithm of combining static and dynamic biometrics. The bottom line in this research is that something was realized from the concept used.

Finally, Principal Component Analysis (PCA) or Factor Analysis (FA) can be applied to pre-processing the datasets in further studies.

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