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Gait Recognition Based on Human Leg Gesture Classification

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Abstract: This paper presents a human gait recognition system based on a leg gesture separation. Main innovation in this paper includes gait recognition using leg gesture classification which gives a high precision recognition system. Five state of leg in human gait are extracted after background estimation and human detection in the scene. Leg gestures are classified over directional chain code of bottom part of silhouette contour. A spatio-temporal data base namely Energy Halation Image (EHI) is constructed over bottom part of human silhouette from train film sequence for five leg gestures separately. Eigen space of energy halation is applied to multilayer perceptron neural network. Five neural network system recognize people but with medium recognition rate. A neuro-fuzzy fusion technique is used for obtaining high recognition rate. Experimental results is performed over a suitable data base include 20 samples for eight person which each sample have 100 frames approximately. 99% recognition rate of the proposed system is obtained over 10 samples test patterns.

Keywords: Human leg gesture separation; Gait recognition; Background estimation; Spatio-temporal data base; Neural network classifier; Neuro-fuzzy based classifier fusion.

1. Introduction

HUMAN GAIT is an important subject in various researches. Some of them attend to gait as a biometric feature in human identification problem [1]. Human gait recognition has attracted growing attention in video-based applications [2, 3]. Recent research has shown that individuals have distinctive and special ways of walking and that human gait recognition has many advantages as human gait is a biometric feature that may be captured from a great distance and gait has the advantage of being unobtrusive. Various applications exist for gait analysis as designing of suitable recessed tactile surface [4].

Tactile ground surface indicators installed on sidewalks help visually impaired people walk safely. The visually impaired distinguish the indicators by stepping into its convexities and following them. However, these indicators sometimes cause the nonvisually impaired to stumble. In [4] have been studied effects of these indicators by comparing the kinematics and kinetic variables of walking on paths with and without indicators.

Another interest for gait identification is that of reflect gait degeneration due to ageing that might have closer linkage to the causes of falls. This would help to undertake appropriate measures to prevent falls. Like in many other developed countries, falls in older population has been identified as a major health issue in Australia [5]. In [6] automatic recognition of young-old gait types from their respective gait-patterns has been studied using support vector machine. Ageing influences gait patterns causing constant threats to control of locomotors balance.

Biomechanical analysis of gait has been successfully applied in human clinical gait analysis [7]. With regards to gait recognition, a major early result from Psychology is by Johansson [8], who used point light displays to demonstrate the ability of humans to rapidly distinguish human locomotion from other motion patterns. Cutting and Kozlowski [9] showed that this ability also extends to recognition of friends.

Identification of people by analysis of gait patterns extracted from video has recently become a popular research problem. However, the conditions under which the problem is "solvable" are not understood or characterized as are mentioned in [3]. The biggest limitation in human motion analysis is the underlying difficulty of tracking the human body for subsequent interpretation [10, and 11].

So, we propose new approach without body parts tracking which fall into motion-based category. Main innovation of the proposed method includes gait recognition based of leg gesture classification. Leg gesture studies have various applications. In this among, some interest work indicates importance of leg gesture classification as [4, 5, and 6]. In [12], matching between stored prototypes and silhouette images helps for state classification. View point of this paper [12] is based on pattern matching and recognition of state using hidden Markov model which it helps to insert the priori knowledge of gait in state recognition.

1.1. Contributions and motivation

Gesture classification can be used in human gait recognition which is main contribution of this paper. But some new notes can be found in this paper as follows,

a) A new spatio-temporal data base namely energy halation
b) Five feature space generation using leg gesture concept
c) Human gait recognition based on leg gesture classification
d) Neuro-fuzzy based combining classifiers
e) Presentation of complete system in gait recognition

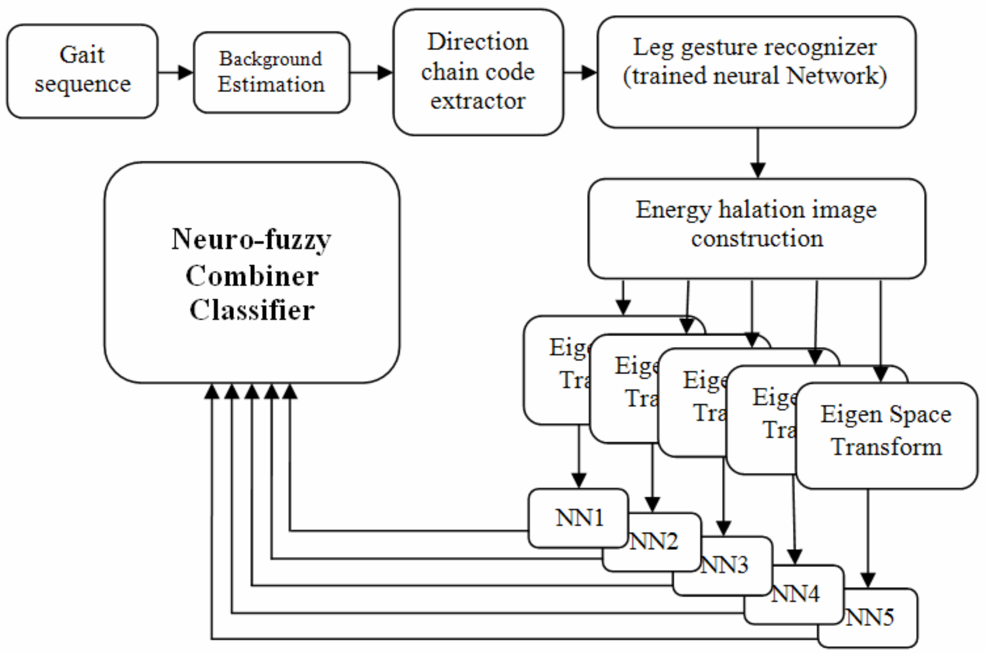

Fig.1: Block diagram of the proposed gait recognition system

Low performance in human gait recognition systems is one of motivation of the proposed method. Human detection in the scene, object tracking, and classifiers capability over time dependent features are some of problems in obtaining of low recognition rate. So, we try presenting a complete system in human gait recognition which includes many features as five above notes.

2. The proposed method

Block diagram of the proposed method can be abstracted in Fig 1. Five parts of this system are as follows and are explained in the next sub-sections.

- Background Estimation
- Leg gesture recognizer
- Energy halation image construction (spatio-temporal data base)
- Gait recognition in eigen space
- Neuro-fuzzy based combiner classifier

2.1. Background Estimation

Several approaches are known to separate foreground from background. If the background is known a simple thresholding yields to the foreground. One suitable way in object detection is background estimation. This paper use probability density function (PDF) estimation of each pixel[13]. Gaussian PDF can model variation of scene because of flicker, CCD noise, and shadow approximately. For obtaining mean and variance of

Gaussian PDF, equation (1), (2) is used which can accept scene variations. Results of human detection in the scene are shown in Fig 2.

$$\mu_t(x,y) = (1-\alpha)\mu_{t-1}(x,y) + \alpha I_t(x,y) \quad (1)$$

$$\sigma_t^2(x,y) = (1-\alpha)\sigma_t^2(x,y) + \alpha\left(I_t(x,y) - \mu_t(x,y)\right)^T\left(I_t(x,y) - \mu_t(x,y)\right) \quad (2)$$

Where $I(x,y)$, is the pixel's current value in location (x,y) and, μ_{t-1} the previous average, σ_{t-1} the previous variance; T is transpose; α is an empirical weight often chosen as a tradeoff between stability and quick update. At each *t* frame time, the *I*, pixel's value can then be classified as a foreground pixel if the inequality:

$$|I_t - \mu_t| > k\sigma_t \quad (3)$$

Where *k*, is threshold value.

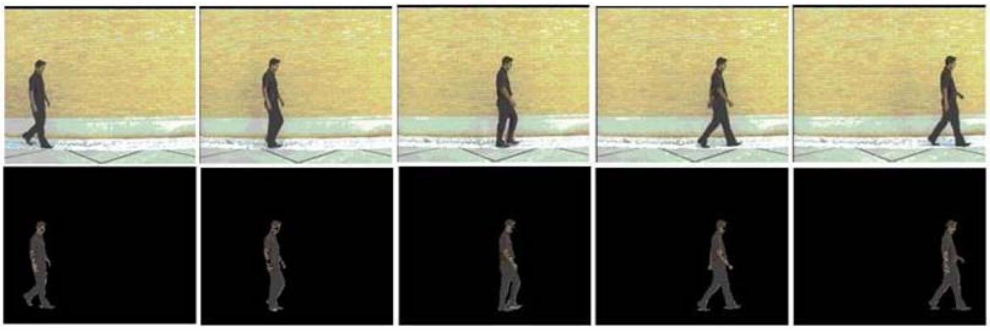

Fig. 2: Human detection in the scene using Gaussian PDF model.

2.2. Leg gesture recognizer

After background estimation and human detection in the scene, binary human image (blob) is obtained. After cutting a bottom of blob image (waist to sole), distribution function of directional chain code are extracted from blob contour. After normalizing the chain code to it's maximum a multi-layer perceptron neural network (MLP-NN) is used for leg gesture recognizing with this feature. Block diagram of leg gesture classifier is shown in Fig 3.

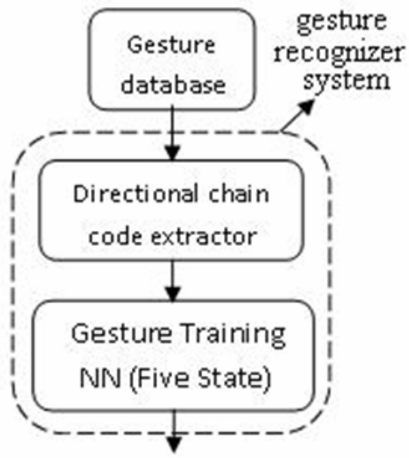

Fig. 3: Block diagram of gesture recognizer

One of leg gesture classifier parts is gesture data base which is necessary for training of MLP-NN using back-propagation algorithm. Five states are determined for leg gesture which depends on frame rate and type of application. Fig 4 shows these five states for number of people. Gesture data base is collected from a set of film includes 160 sequences of eight people. Obtained manually gesture data base includes five leg states and for each state 100 images have been collected. Extracted distribution directional chain code is shown in Fig 5-a and Fig 5-b show directional chain codes histogram for difference state.

However, trained neural network can not classify leg gestures perfectly but this problem compensate in creation of spatio-temporal data base and using classifier.

2.3. Energy halation image construction (spatio-temporal data base)

Spatio-temporal data base use for compact presentation of film sequence and use in many applications as image retrieval, gesture analysis, action recognition, and behavioral recognition in the scene.

Fig. 4: Some images for five states in gesture database
(Rows shows state type and columns shows number of people)

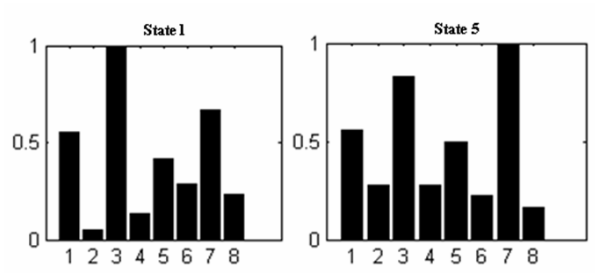

Fig. 5-a **Fig. 5-b**

Fig.5: Normalized histogram for state 1 and 2

In this sub-section we propose a spatio-temporal like motion history image (MHI) in [14] which pseudo code is as follow (Fig 6) and results is named energy halation images (EHI).

Each input frame is belonged to one of five leg gesture and use for generation of five energy halation images according to Fig 6. Obtained results include five

1. $Initializing:$
   $Let\ \ EH_i\ \ ,i=1,2,..,5\ \ forced\ to\ zeros\ with\ dimention\ 220\times 90;$
   $Let\ \ j=0\ \ ;\ \ j\ is\ frame's\ index$
2. $j=j+1;$
3. $I_i \leftarrow\ \ blob\ matrix\ of\ j-th\ frame\ with\ size\ x\times y\ ;\ \ i\ is\ state\ of\ leg\ (1\ to\ 5);$
   $note:(x,y) is\ less\ than\ (220,90)\ for\ each\ blob\ size$
4. $Adding\ zero\ rows\ and\ columns\ bilateral\ of\ I(x,y)\ that\ become\ I(220,90)\ matrix\ ;$
5. $EH_i = EH_i + I_i\ ;\ \ i\ is\ state\ of\ leg\ gesture$
6. $if\ isn't\ end\ of\ sequence\ \ goto\ step\ 2\ ;$
7. end

Fig. 6: pseudo code for generation EHI

images of energy halation for each input sequence. As an example, Fig 7 shows five images of energy halation for three people.

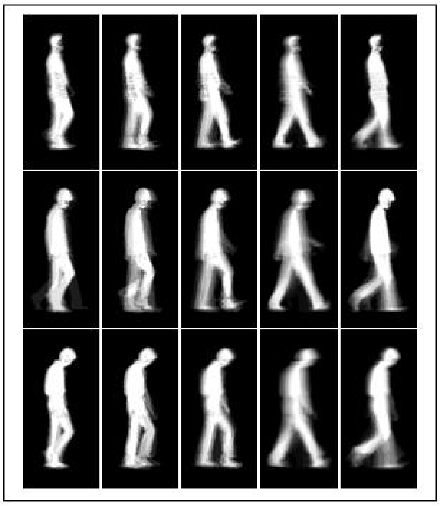

Fig. 7: Five images of energy halation (columns) for three people (rows)

2.4. Gait recognition in eigen space

As face recognition and similar applications, we use of eigen space transform for reducing the dimensions of the energy halation images before apply to MLP- neural network. Training MLP-NN is performed over each leg gesture in order to human gait recognition. So five trained MLP-NN are created and use for human identification but each networks recognize people separately based on different features (these features are energy halation over each leg gesture).

Recognition rate of each network don't satisfy for using system as good human gait recognizer so we combine neural networks output using neuro-fuzzy based mixer classifiers which it is followed in the next sub-section.

2.5. Neuro-fuzzy based combiner classifier

Neuro-fuzzy system has been proved to have significant results in modeling nonlinear functions. Neuro-fuzzy system has been used frequently in the literature as fishing predictions [15], vehicular navigation [16], identify the turbine speed dynamics [17], radio frequency power amplifier linearization [18], microwave application [19], image denoising [20, 21], prediction in cleaning with high pressure water [22], sensor calibration [23], fetal electrocardiogram extraction from ECG signal captured from mother [24], identification of normal and glaucomatous eyes [25].

In a neuro-fuzzy system, the membership functions (MFs) are extracted from a data set that describes the system behavior. The neuro-fuzzy system learns features in the data set and adjusts the system parameters according to given error criterion. In a fused architecture, NN learning algorithms are used to determine the parameters of fuzzy inference system. Below, we have summarized the advantages of the neuro-fuzzy system technique. Fusion of output classifiers with linear combiner has been pointed in [26]. In this paper, we used a nonlinear mixer classifier which is based on neuro-fuzzy system for the first time in human gait recognition.

3. Experimental results

A set of film includes 160 sequences of eight people is used as data base. Frame rate per second is 25 and image size is 352×288. Some images from data base are shown in Fig 8.

Fig. 8: Some samples of people image

Leg gesture recognizer is a three layer MLP neural network with eight input neurons and five output neurons and fifteen neurons in hidden layer that can categorize input frames to 5 states. An example of this stage is shown in Fig 9.

after application of neuro-fuzzy combiner is shown table 3. Recognition rate increase to 99.8% over test pattern whereas learning of neuro-fuzzy system has been performed over learning patterns.

4. Conclusion

An interest note was found in this paper “human gait recognition based on leg gesture”. But this paper includes a new spatio-temporal gait data base (Energy Halation Image), neuro-fuzzy based combiner classifier. To overcome the limitation of recognition

Fig. 9: Result of gesture recognizer system

As it was mentioned before, each gesture help for categorization of frame sequence and five images of energy halation are performed and five MLP neural networks are trained over 10 film sequences for 8 people. Each network has 50 neurons in input layer, and three hidden layers with 100, 90, 40 neurons and eight neurons in output layer. In testing phase, captured confusion matrixes for two networks are shown in Table1, 2. This tables show that fusion of networks

performance rate, we proposed a system for gait feature fusion. We used five spatio-temporal data base and apply their features in eigen space to five neural networks separately. Performance of each NNs for test samples was low (about 70% to 80%). Then we used a Neuro-fuzzy combiner classifier for mixing the neural networks for the first time in gait recognition. Result of combination of neural network outputs was satisfiable.

Table. 1, 2: Confusion matrix of neural network 1, 2 related to first and second gesture

NN1	P1	P2	P3	P4	P5	P6	P7	P8
P1	7	0	0	0	0	0	0	0
P2	3	7	0	1	2	0	0	1
P3	0	0	9	0	0	0	0	0
P4	0	0	0	9	1	0	0	0
P5	0	2	0	0	7	0	0	0
P6	0	1	1	0	0	7	0	0
P7	0	0	0	0	0	3	10	0
P8	0	0	0	0	0	0	0	9

NN2	P1	P2	P3	P4	P5	P6	P7	P8
P1	10	0	0	0	0	0	0	0
P2	0	8	0	0	0	0	0	1
P3	0	0	10	0	0	0	0	0
P4	0	0	0	8	1	1	0	0
P5	0	2	0	2	5	1	3	0
P6	0	0	0	0	1	5	0	0
P7	0	0	0	0	2	3	7	0
P8	0	0	0	0	1	0	0	9

Table. 3: Confusion matrix of proposed system as shown in Fig 1.

NF	P1	P2	P3	P4	P5	P6	P7	P8
P	10	0	0	0	0	0	0	0
P2	0	9	1	0	0	0	0	0
P3	0	0	10	0	0	0	0	0
P4	0	0	0	10	0	0	0	0
P5	0	0	0	0	10	0	0	0
P6	0	0	0	0	0	10	0	0
P7	0	0	0	0	0	0	10	0
P8	0	0	0	0	0	0	0	10

increase performance. As an example, network 2 can recognize people 1 but network 1 can not perform recognition over this people as well. Confusion matrix

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