Background Subtraction and Target Classification for Gait Recognition

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***Abstract:*-This paper deals with background modeling and moving object classification for gait recognition. Current image-based human recognition methods such as fingerprints, face, iris biometric modalities, generally require a cooperative subject views. These methods cannot reliably recognize non cooperating individuals at a distance in the real world under changing environmental conditions. In such conditions, recognition of a person using gait has good advantage. First step in gait recognition is the background subtraction/modeling. This is the crucial step in gait recognition. By using this, identification of moving objects from background scene has to be done. Perfect background subtraction is essential to get a high recognition rate. Next step is the separation of human beings from other moving objects (*viz;* car, tree etc.). In this paper, we have used a modified background subtraction algorithm and subsequently used feature-based classification of pedestrian from other moving objects. Experimental results demonstrated the effectiveness of the proposed method.**

***Keywords* - Gaussian Mixture Model, Temporal consistency, Classification metric operator.**

I. Introduction

Generally used biometric recognition techniques have some disadvantages. They require co-operation of the individual that is to be identified. Gait, which concerns recognizing individuals by the way they walk, is a relatively new biometric without these disadvantages. Background subtraction/modeling is the first and crucial step in gait recognition. Fig. 1. Shows the general block diagram of gait recognition system. The main challenge involved in gait recognition is imperfect foreground segmentation and changes in clothing of the object. So, background subtraction plays a vital role in gait recognition. Background subtraction identifies the moving objects from background scene. Generally two types of background subtraction techniques are there. They are recursive and non-recursive. Background subtraction using frame difference method is simple one. In this method, previous frame acts as a background model for current frame. By calculating difference between these two frames moving objects are estimated. But it fails in uncontrolled environments. This method comes under no recursive type. One more existing method is single Gaussian model. It comes into recursive type. In this, each pixel is modeled by single and separate Gaussian.

In this paper, Gaussian Mixture Model (GMM) is used for Background subtraction in which we have incorporated an additional step of image filtering by median filter. This is to remove some noises appeared due to the bad background subtraction. Next step is the classification of human beings from other moving objects. Some classification metrics are used for this classification.

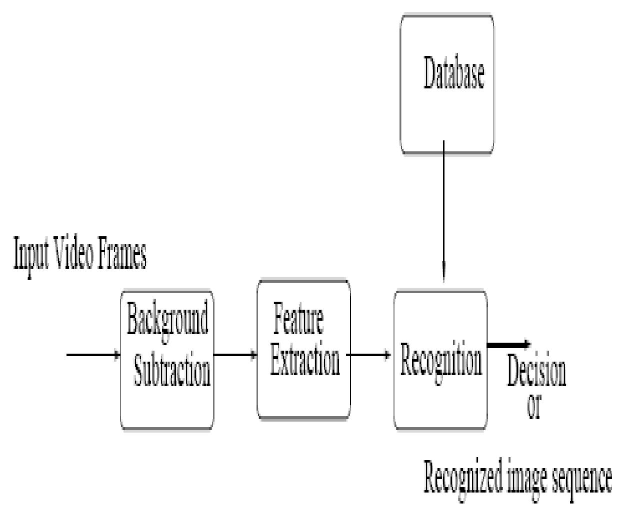

Fig. 1. Block diagram of gait recognition system

This classification metric is calculated by considering shape and boundary information of the objects.

II. Gaussian Mixture Model

In Gaussian Mixture Model each pixel is modeled by mixture of Gaussians (states). Each pixel (corresponding to objects) comes into the view represented by any one of a set of states k € {1, 2…K}. In these *K* states some states correspond to background rest of the states represents foreground. Each state modeled by set of *K* parameters $_k$= p (k).p (k) is the probability of the surface *k* appearing the pixel view. By observing the pixel values we are estimating the states. Pixel values are samples of random variable *X*. So, it can be modeled by *K* Gaussians as

$$f_{X/k}(X/k,\theta_k)=\frac{1}{(2\pi)^{\frac{n}{2}}\left|\sum_k\right|^{\frac{1}{2}}}e^{-\frac{1}{2}(X-\mu_k)^T\sum_k^{-1}(X-\mu_k)} \quad (1)$$

θ_k is the Gaussian density parameter set give by $\theta_k=\{\mu_k,\sigma_k\}$. μ_k and σ_k are mean and standard deviation of K^{th} density. The total parameter set used in this is given by $\Phi=\{\omega_1,.,.,\omega_k,\theta_1,.,.,\theta_k\}$.All these *K* densities are disjoint. So, the distribution of *X* can be modeled as

$$f_X(X/\phi)=\sum_{k=1}^{K}p(k)f_{X/k}(X/k,\theta_k) \quad (2)$$

First step in this GMM is estimating the current state. Among all *K* states most likely state is estimated for given sample *X* = *x*. This can be done by finding posterior probability for each of *k* distributions. This is given by Bayes'stheorem.

$$p(k/X,\phi)=\frac{p(k)f_{X/k}(X/k,\theta_k)}{f_X(X/\phi)} \quad (3)$$

The *k* which gives the maximum posterior probability is deemed to be current state. The maximum posterior estimate is given by,

$$\begin{aligned}\hat{k}&=\arg\max_k p(k/X,\phi)\\&=\arg\max_k w_k f_{X/k}(X/k,\theta_k)\end{aligned} \quad (4)$$

Next step is to find whether that current state is foreground or background. First arrange (rank) the states according to the value ω_k/σ_k. Generally background surfaces have more probability and less variance. To estimate foreground objects, we first provide prior probability *T*. The first *B* of the ranked states whose accumulated probability accounts for *T* are deemed to be background. Rests of the states are foreground.

$$B=\arg\min_b\left(\sum_{k=1}^{b}w_k>T\right) \quad (5)$$

If the estimated current state is in those first *B* states then it is background otherwise it should be foreground. The recursive relations used to update the Gaussian parameters are given by

$$\hat{\omega}_{k,t}=(1-\alpha_t)\omega_{k,t}+\alpha_t \quad (6)$$

$$\rho=\frac{\alpha_t}{\omega_{k,t}} \quad (7)$$

$$\hat{\mu}_{k,t}=(1-\rho)\mu_{k,t}+\rho X_t \quad (8)$$

$$\hat{\sigma}^2_{k,t}=(1-\rho)\sigma^2_{k,t}+\rho(X_t-\mu_t)^2 \quad (9)$$

Calculation of posterior probability is time taking process. So, instead of calculating posterior probability, the value falling within λ =2.5 standard deviations of the mean of one of the Gaussian densities is calculated. The Gaussian density which satisfies above relation is taken as the current state. Any previously unseen foreground object comes in to the view can be accommodating by assigning a small prior probability.

After background subtraction, along with foreground objects some noise also present due to the bad background subtraction. This can be eliminated by using some image filtering techniques. In this, median filter is used to remove those noises.

III. Moving Target Classification

Next step in gait recognition is moving object (target classification). Moving objects obtained from background subtractions are classified in to human, vehicle, background clutter. Human, with its more complex shape, will have more dispersions than vehicle. A classification metric operator *ID*(*x*) and the notion of temporal consistency are used for classification. The metric is based on the knowledge that humans are in general smaller than vehicles. In this dispersedness is taken as classification metric and is given by,

$$Dispersedness=\frac{Perimeter^2}{Area} \quad (10)$$

Fig. 2. Shows the typical dispersedness values for a human and a vehicle. The first step in this is to record all N_n potential targets $P_n(i) = R_n(i)$. These regions are classified

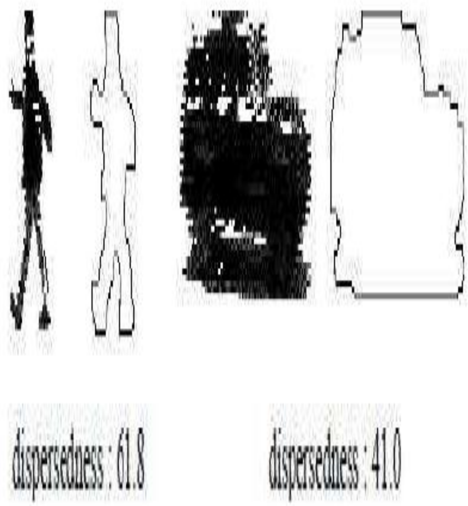

Fig. 2. Typical dispersedness values for a human and a vehicle [5].

according to the classification metric and the result is recorded as classification hypothesis $\hat{A}(i)$ for each one.

$$\chi(i) = \{ID(P_n(i))\} \qquad (11)$$

Each one of these potential targets must be observed in subsequent frames. Each previous motion region $P_n(i)$ is matched to the spatially closest current motion region $R_n(j)$.Any previous potential targets have not been matched to current regions removed from the list, and any current motion regions R_n which have not been matched are added to the list. At each frame, their new classifications are used to update the classification hypothesis. After this a simple application of MLE is employed for classification.

IV. Expermental Results

In this, Gaussian Mixture Model is implemented to get background subtraction results. The performance of this has been evaluated based on PETS'2001 data set [6] and a surveillance video collected in brisbane railway station. PETS'2001 data set contains more complex scenes with clouds motion, shadows and small illumination changes. It has the frame rate of 30 frames per second and with a frame size of 768 x 576. The surveillance video has frame rate of 18 frames for second and frame size of 704 x 576. In this video more illumination changes are there. After background subtraction some noises may present. Median filter is used to remove these noises. Following Figs. 3-4. shows the obtained experimental results for background subtraction. Second row in these Figs shows background subtraction result without median filter. It is seen that some noises are present. Third row shows the result after applying median filter. Next step is the classification of human beings (pedestrian) from other moving objects. In this, one classification metric (dispersedness) and temporal consistency is used for this classification. Figs. 5-8. Shows classification results.

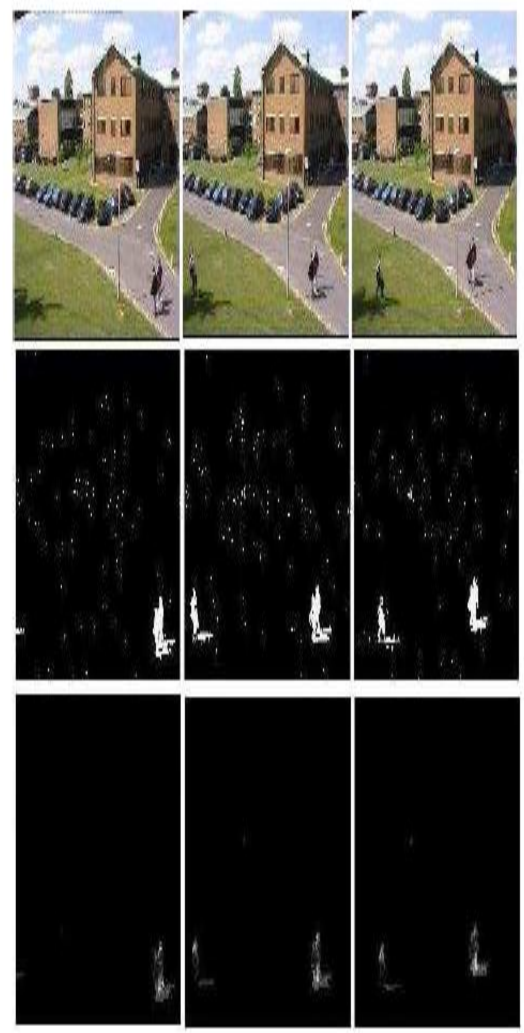

Fig. 3. Background subtraction results. The first row shows input video frames (Pets2001: *http://www.cvg.cs.rdg.ac.uk/PETS2001/pets2001-dataset.html*). Second row shows background subtracted frames. Third row shows the background subtraction result after median filter.

Fig. 4. Background subtraction results. The first row shows input video frames. Second row shows background subtracted frames. Third row shows the background subtraction result after median filter.

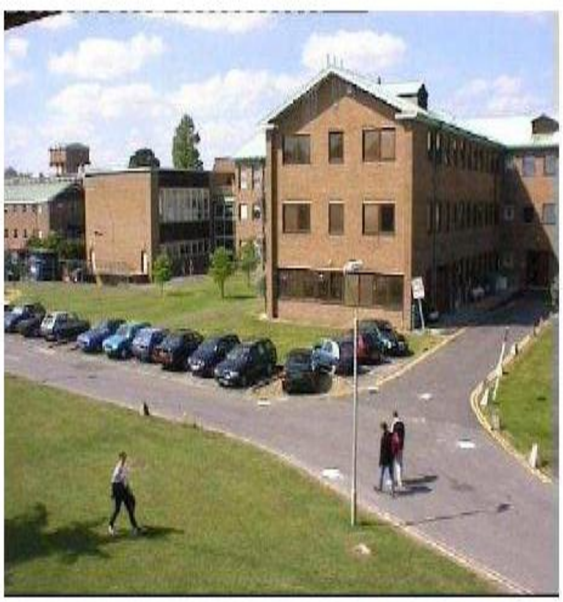

Fig. 5. Input video frame.

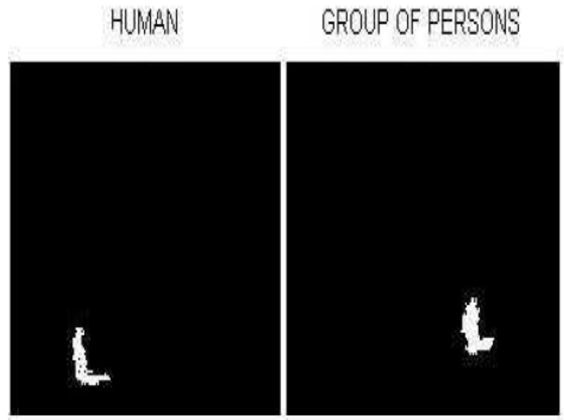

Fig. 6. classification result.

Fig. 7. Input video frame.

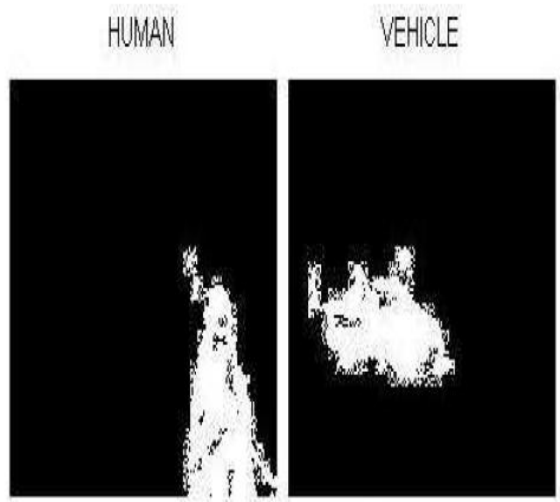

Fig. 8. Classification results.

V. Conclusion

In this paper, Background subtraction and moving target classification is presented. Background subtraction identifies the moving objects from background in a scene. Gaussian Mixture Model in addition with median filter is used for background subtraction. Compared to previous methods we got some good results by using this method. Next step of gait recognition system, the classification of moving objects has done. Shape and boundary information of the objects is used for classification. In this, one classification metric (dispersedness) and temporal consistency is used for this classification. Next step in gait recognition is recognition/ classification. Hidden Markov Model is proposed for recognition by considering the key frames as the states of the model. The results of the proposed background modeling and object classification are quite visually convincing to apply them in HMM framework.

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