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Fast Human Detection in Surveillance Video

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Abstract : *In this paper we are proposing a fast and efficient algorithm to track humans in a indoor surveillance video. Here we have used hog features and correlation based method to track humans in a surveillance video. Strips on the borders of a frame is analyzed to know the entry of new objects in to the frame. This algorithm can applied to real time systems due to the low time complexity of the system.*
Keywords – *Image correlation, human tracking, hog features.*

I. INTRODUCTION

In video surveillance systems one of the main steps is human detection and tracking. Surveillance systems should able to detect and track humans in the video. In order to implement human detection and tracking in real time systems it should be fast and accurate. The human detection algorithms should be invariant to illumination changes, pose, viewpoint and partial occlusion. More sophisticated algorithms are required for tracking if humans are partially occluded and there are illumination changes. Human activity recognition systems and driving assistance systems requires accurate and fast human detection algorithms.

Since human detection using direct feature extraction from every frame is time consuming, we have used correlation based method along with HoG features in order to improve the fastness of the system. Strip selection from the video frames again increases the fastness of the system. Strips from frames are selected in order to select the candidate frames.

II. PREVIOUS WORK

Human detection using window scanning method is one of the basic methods to track human objects in a video, which scans all possible windows in a frame to track the objects [1]. To reduce the time complexity of window scanning method particle swarm algorithm is used [2]. Disadvantage of particle swarm optimization algorithm is the low accuracy. Many supervised learning algorithms have proposed for detecting human object from an image [3, 4, 5, 6]. Tuzel et al. [7] used covariance matrices as object descriptors.

In [8], optical flow patterns were used which is trained using SVM. In [9], moving pixels are grouped in to blobs and using shape features these blobs are classified in to human or non human objects. Gavrila and philomin compared edge images using chamfer distance for human detection [10]. Mikolajczyk et al [11] parts based human detection method containing detectors for front and side profiles of upper and lower body parts, heads and faces. There are existing systems which uses filters such as particle filters [12], Kalman filters [13] and HMM (Hidden Markov Model) filters [14] to track humans in video.

III. PROPOSED METHOD

Here we are used HoG features [15] and correlation based method to detect humans in video frame. For human detection in surveillance video, HoG features are extracted only to some candidate frames from the video. This reduces time required to detect and track the human objects in the video frames. In general case the candidate frames are selected in frequent intervals. For our experiment we have selected the interval as N, where N=number of frames per second. If we have the information about the surveillance area in prior, strip based method for candidate frame selection can be used. The architecture of the proposed work is given in figure 1.

1.1 HoG feature extraction

Here we used Histograms of Oriented Gradients (HoG) features to achieve a fast and accurate human detection system. The features used in our system are HoGs of variable-size blocks that extracts orientation of edges in human images automatically. Using AdaBoost classifier, the appropriate block is identified from the set of variable size boxes as the detectection window.

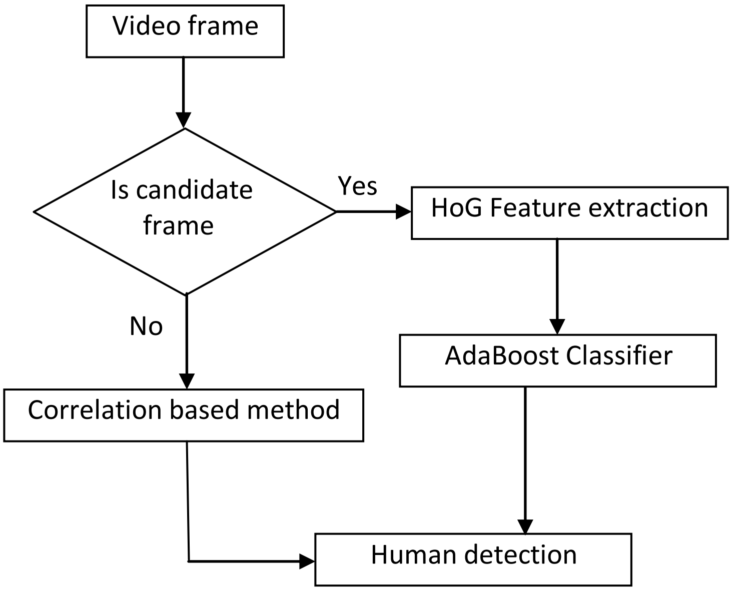

Fig. 1: Proposed architecture

1.2 Candidate frame selection

Strips are selected at the entry and exit of the human object in video frame as shown in figure 2. In general case the strips are selected from the borders of the video frame as shown in figure 3. After the selection of strips from the video frames histogram of the strips are calculated. The position and number of strips in the frame is determined by the entry and exit of the object in the surveillance area. If histogram of strips in the current frame matches with histogram of the strips in the previous video frame, then no object has entered into the current video frame. If histogram of the strips in the current frame doesn't match with histogram of the strips in the previous video frame, it indicates that new object has entered into the surveillance area. In this case current frame is selected as the candidate frame for the HoG feature extraction and human detection and tracking is done using HoG features. In some cases, due to the structure of surveillance environment, strip selection will not give exact results, in such case candidate frames are selected in frequent intervals. Example for this type of video frame is shown in figure 4. HoG feature vectors extracted classified using adaboost classifier [16]. Figure 5 shows human detected using HoG features.

Fig. 2: Video frame with strips

Fig. 3: General strip selection

If histogram of the strips in the current frame matches with the histogram of the strips in the previous frame and previous frame does not have any human then no tracking algorithms are applied in the current frame. If histogram of the strip in the current frame matches with the histogram of the strip in the previous frame and previous frame contains human object then correlation based method is applied for human detection.

Fig.4: Frame in which strip selection not possible

Fig. 5:Human detected using HoG features

1.3 Correlation based method

If there is human in Nth frame and to detect and track the human in (N+1)th frame we need to select sample windows from (N+1)th frame as shown in figure 6. After selecting sample windows from (N+1)th frame, the correlation between tracked window in the Nth frame and sample windows in (N+1)th frame is calculated using the equation (1). The sample window that having highest correlation is selected as the track window for the (N+1)th frame. Sample windows are selected such that some are near and some are away from the present human window. If the frame contains multiple humans window selection and correlation evaluation is done separately to each human object. Correlation based method can detect partially occluded humans from image.

$$\rho = cor[X,Y] = \frac{\operatorname{cov}[X,Y]}{\sqrt{\operatorname{var}[X]\operatorname{var}[Y]}} \qquad (1)$$

$$\operatorname{var}(X) = E[(X-\mu)^2], \quad \operatorname{var}(Y) = E[(Y-\mu)^2], \ \operatorname{cov}[X,Y] = E[(x-E[x])(y-E[y])]$$

Fig. 6: Sample window selection

IV. Conclusion

Experimental results show that our system is fast and have high success rate in human tracking. From the experiments conducted we have achieved more than 86% of detection rate. Twenty videos from the campus are taken for the experiment. Total length of the videos is more than 6 hours. Correlation based method can also detect partially occluded human objects. Results of detection for some videos are given in figure 7. In figure 7 X-axis represents total number of frames in a video and Y-axis represents correctly detected frames.

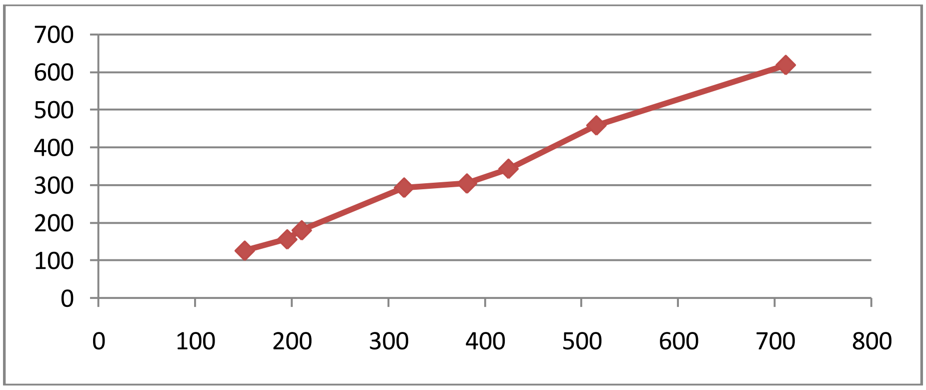

Fig. 7: Result

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