DETECTION AND TRACKING OF MULTIPLE MOVING OBJECTS IN VIDEO

Wei Huang and Jonathan Wu
Department of Electrical and Computer Engineering, University of Windsor
Windsor, Ontario, N9B 3P4, Canada

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Abstract: This paper presents a method for detecting and tracking multiple moving objects in both outdoor and indoor environments. The proposed method measures the change of a combined color-texture feature vector in each image block to detect moving objects. The texture feature is extracted from DCT frequency domain. An attributed relational graph (ARG) is used to represent each object, in which vertices are associated to an object's sub-regions and edges represent spatial relations among the sub-regions. Object tracking and identification are accomplished by matching the input graph to the model graph. The notion of inexact graph matching enables us to track partially occluded objects. The experimental results prove the efficiency of the proposed method.

1 INTRODUCTION

The efficient detection and tracking of multiple moving objects is currently one of the most active research topics in computer vision. It has many applications such as visual surveillance, human-machine interfaces, video communication, and so on.

As for motion detection, the background subtraction technique is a popular method. In (Stauffer and Grimson, 2000), the pixel value was modeled by a mixture of weighted K Gaussian distributions to support multiple backgrounds. (Elgammal et al., 2002) used a nonparametric kernel density model by estimating the probability of pixel intensity directly from a set of recent intensity values.

As to the tracking method, the most widely used cues in object tracking are color, spatial position, shape and motion. In (Xu et al., 2004), five significant features were used, including velocity, size, elliptic-fit aspect ratio, orientation, and dominant color. (Brasnett et al., 2005) demonstrated that the combined color and texture cues provided a good tracking result that was more accurate than the two cues individually.

In this paper we introduce a new motion detection method which does not compute any model of the background. We measure the change of a combined color-texture feature vector in each image block within a time window and then directly obtain moving objects by statistically analyzing the change. For effective tracking, the attributed relational graph is used to represent each moving object. A combined color-texture-position feature vector is used to describe each object's sub-regions, which are associated to the vertices of the ARG. Inexact graph matching enables us to track and identify partially occluded objects. In the discussion below, we calculate the color-texture combined feature vector for motion detection in Section 2.1, and then we explain the details of detecting moving objects using eigenspace decomposition and statistical analysis in Section 2.2. Section 2.3 describes how to construct the attributed relational graph to represent the detected object. Section 2.4 gives the details of identifying objects using inexact graph matching technique. We show experimental results for real image sequences in Section 3. Conclusions are given in Section 4.

2 PROPOSED ALGORITHM

2.1 The Color-Texture Feature Approach for Motion Detection

In (Latecki et al., 2004), an idea was introduced that the texture vectors are very likely to have a large spread when a moving object is passing through a

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fixed position. Motivated by this idea, we measure the change of a combined color-texture feature vector to detect moving objects. Combining color and texture as the feature vector can still extract foreground objects when the color distributions of the foreground and background are similar, in which case the Gaussian mixture model will fail. We assume a stationary camera.

We use some DCT coefficients as the texture feature. We partition every new frame into blocks with 8 * 8 pixels, where every two neighboring blocks overlap each other by four pixels horizontally or vertically for improving the spatial resolutions of the detection results. A feature vector is extracted for each block. Eleven features are used for detection. Two of them are the average color components (A_{Cb}, A_{Cr}) in an 8 * 8 block. The other nine features are the first nine AC coefficients inside each block along the zigzag scanning. We use the well-known YC_bC_r color space, where Y encodes luminance, C_b and C_r encode color information (chrominance). To obtain the other nine features, the DCT is applied to the Y component of the image block. One color-texture feature vector for a block u is then expressed as:

$$\mathbf{f}_{u,t} = \left(A_{Cb}, A_{Cr}, A_{1,2}, A_{2,1}, A_{1,3}, A_{2,2}, A_{3,1}, A_{1,4}, A_{2,3}, A_{3,2}, A_{4,1}\right)^T \quad (1)$$

2.2 Detection of Moving Objects by Measuring the Change of the Color-Texture Feature Vector

By measuring the change of the color-texture feature vector over time, we are able to detect whether a particular block belongs to a background or to a moving object. We compute the covariance matrix of the feature vectors in the same block location within a small number of consecutive frames. The eigenvalues of the covariance matrix refer to the variance of the data in the direction of the basis vectors. We use the largest eigenvalue as a local change measure. The larger the largest eigenvalue, the more likely is the presence of a moving object.

In practice, for each block u, we consider the color-texture feature vectors for a symmetric window with size of 2S+1 around the temporal instant τ : $\mathbf{f}_{u,\tau-S}, \mathbf{f}_{u,\tau-S+1},\ldots, \mathbf{f}_{u,\tau},\ldots, \mathbf{f}_{u,\tau+S-1}, \mathbf{f}_{u,\tau+S}$. S is set to 1 here. For these vectors, the covariance matrix $R_{u,\tau}$ is:

$$R_{u,\tau} = \frac{1}{2S+1}\sum_{t=\tau-S}^{\tau+S}\left(f_{u,t} - \bar{f}_u\right)\left(f_{u,t} - \bar{f}_u\right)^T \quad (2)$$

Then, the covariance matrix $R_{u,\tau}$ is decomposed into its eigenvectors $e_{u,\tau}(k)$ and eigenvalues $\lambda_{u,\tau}(k)$ (k =1, 2, …, 11).

$$R_{u,\tau}.e_{u,\tau}(k) = \lambda_{u,\tau}(k).e_{u,\tau}(k) \quad (3)$$

The largest eigenvalue $\lambda_{u,\tau}{}^m$ is the local change measure $C_{u,\tau}$.

$$C_{u,\tau} = \lambda_{u,\tau}{}^m \quad (4)$$

Finally, we mark each block as part of a moving object or background according as whether the change measure is larger than a predefined threshold or not. We assume that the values of the local change measure $C_{u,\tau}$ in every video frame obey the Gaussian distribution. We compute the mean μ_τ and variance $\sigma_\tau{}^2$ of all $C_{u,\tau}$ for u=1, 2,…, L. L is the total number of sub blocks of every video frame. A block will be labelled as moving if

$$\frac{\left(C_{u,\tau} - \mu_\tau\right)^2}{\sigma_\tau{}^2} > th1 \quad (5)$$

Where *th1* is a constant and is set to 0.5 here.

$$\mu_\tau = \frac{1}{L}\sum_{u=1}^{L} C_{u,\tau} \quad (6)$$

$$\sigma_\tau{}^2 = \frac{1}{L}\sum_{u=1}^{L}\left(C_{u,\tau} - \mu_\tau\right)^2 \quad (7)$$

The pixels belonging to an object are connected. A connected component analysis algorithm is used to find connected components in the binary images that we obtained at the motion detection stage. We use a size filter to remove the connected component whose area is below a threshold *th2*.

2.3 Object Representation by the Attributed Relational Graph

Currently, color histogram is widely used to represent detected objects (Comaniciu et al., 2003). However, color histograms have limited discriminative power. Two images producing identical color histograms may have totally different spatial organization of colors. In this paper, we use an attributed relational graph to represent each object, in which vertices are associated to an object's sub-regions and edges represent spatial relations among the sub-regions. Therefore, the tracking and identification of objects amounts to graph matching. Both input and model graphs are automatically extracted from video sequences. Usually, the graphs extracted in the first frame act as the model graphs.

To fragment an object into sub-regions, we first use a combined color-texture-position feature vector to describe the detected image blocks which belong to the object. The two color features are the average color components (A_{Cb}, A_{Cr}) in an 8*8 image block. The one texture feature is the average summation of the first nine squared AC coefficients along the zigzag scanning. The two position features are simply the coordinates of the image block. After obtaining the feature vectors for all the blocks, we perform normalization on the five features to eliminate the effects of different feature ranges. Then the k-means algorithm is used to cluster the feature vectors into several classes with every class in the feature space corresponding to one spatial sub-region of the detected object. The k-means algorithm does not specify the value of *k*. To compute the optimal value of *k*, we iterate it between a minimum $(k_{\min} = 2)$ and a maximum value $(k_{\max} = 5)$ until a stop constraint is satisfied.

After the segmentation, we are ready to build the ARG for each detected object. An ARG is a graph in which attribute vectors are assigned to vertices and to edges. Formally, we define an ARG as $G = (N, E, \mu, \nu)$, where *N* represents the set of vertices of *G* and $E \subseteq N \times N$ the set of edges. Two vertices *a*, *b* of *N* are said to be adjacent if $(a,b) \in E$. Furthermore, $\mu : N \rightarrow L_N$ assigns an attribute vector to each vertex of *G*, while $\nu : E \rightarrow L_E$ assigns an attribute vector to each edge in *G*.

The structure of an object can be represented as a collection of sub-regions which are related by their relative positions within the object. The sub-regions are represented by vertices in a graph, while relations between them are represented by edges. Let us consider any two vertices *a*, *b* in *N*. The vertex attribute $\mu(a)$ is defined as follows:

$$\mu(a) = \left(C_{Cb}, C_{Cr}, T_{AC}, P_x, P_y\right)^T \tag{8}$$

The five terms correspond to the color component C_{Cb}, color component C_{Cr}, texture T_{AC}, spatial coordinate P_x and spatial coordinate P_y at the centroid location of a cluster, respectively. Each cluster obtained by k-means algorithm corresponds to a sub-region within the object.

The edge attribute $\nu(a,b)$, for *a*, *b*, in *E*, is defined as the length value of the edge linking the two vertices *a* and *b*.

In practice, the object is represented by a signature, which is composed of two parts: the first one is the feature vectors of all sub-regions, which are called vertex attributes, and the second one is a representation of the topology of the sub-regions within the object. Spatial relationships between sub-regions are characterized by an adjacency matrix of sub-regions with a value of 1 if both sub-regions have at least one pixel in common, otherwise 0. For the pair of adjacent sub-regions, the length value of the corresponding edge is stored in a distance matrix.

2.4 Inexact Graph Matching for Tracking and Identification of Moving Objects

When graphs are used to represent objects, the problem of objects tracking and identification can be seen as a problem of graph matching. The notion of inexact graph matching enables us to track partially occluded objects. Two matched graphs do not have to be identical but only similar in terms of vertex number, vertex attributes or edge number. Our implementation of the matching algorithm is given below:

In the following, *a*, *b* refer to vertices in the input graph *I*, and a', b' correspond to vertices in the model graph *M*.

1) For each vertex *a* in the input graph, a search is conducted to find the best matching vertex a' in the model graph, such that the Euclidian distance of the matching vertex attributes $d(\mu(a), \mu(a'))$ is the minimum value. The vertex similarity for this pair of vertices is computed as:

$$S^{\nu}_{aa'} = e^{-\left|d(\mu(a),\mu(a'))\right|} \tag{9}$$

We have to satisfy two basic constraints during the matching process:

2) A vertex in the input graph cannot match with two different vertices in the model graph.

3) Two different vertices in the input graph cannot match with a single vertex in the model graph.
It is possible that some vertices in the input graph do not have matching vertices in the model graph because the two graphs may have different vertex number.
4) After the vertices are matched, total similarity is computed by taking into account the topology of the matched graphs.

Let the vertices a and b match a' and b' respectively. Then the topology similarity for this pair of vertices is computed as:

$$S^e_{aba'b'} = e^{-\left|v_{ab} - v_{a'b'}\right|} \quad (10)$$

Where v_{ab} and $v_{a'b'}$ are the length values of the edges ab and $a'b'$.
5) The total similarity for matching the input graph to the model graph is given by

$$S_1(I,M) = \frac{\alpha}{N_s}\sum_a S^v_{aa'} + \frac{1-\alpha}{N_e}\sum_a\sum_b S^e_{aba'b'} \quad (11)$$

Where N_s is the maximum vertex number between the two matching graphs. N_e is the maximum number of really existing edges between the two matching graphs. It is possible that edges in the input graph do not have corresponding edges in the model graph and vice-versa. α is a scaling parameter which controls the relative importance of the two similarity functions. α is set to 0.6 here.
6) The total similarity is then scaled to reflect the difference in the size and position of the input and model objects.

$$S(I,M) = m * p * S_1(I,M) \quad (12)$$

If m^i and m^m denote the sizes of the input object and model object respectively, then:

$$m = \min\left\{\frac{m^i}{m^m}, \frac{m^m}{m^i}\right\} \quad (13)$$

$$p = \begin{cases} e^{-d/d_0} & d < d_0 \\ e^{-1} & \text{otherwise} \end{cases} \quad 14)$$

where d is the Euclidian distance between the centroids of the input and model objects. d_0 is a constant and set to 20 here. The motivation of adding the position scaling factor p into the similarity fuction is that an object will not move far from its last position. Therefore, the centroid presents us with a useful feature for tracking objects. To let this factor work properly, we update the model's position once we get an input object matched to that model.
7) The best candidate match M^* satisfies

$$S(I,M^*) = \max_M S(I,M) \quad (15)$$

When the value of $S(I,M^*)$ is more than a predefined threshold, we say the input graph/object is identified with the model graph/object. Otherwise, we assume a new object enters the scene, it will be tracked and labelled, and the corresponding ARG of that object is constructed and stored in the model graph/object list.

3 EXPERIMENTAL RESULTS

Our proposed method is tested on both outdoor and indoor image sequences: PETS 2001 dataset 2 and PETS 2006 S3-T7-A dataset. The image sizes of the PETS 2001 and PETS 2006 datasets are 768*576 and 720*576, respectively. The PETS 2001 dataset involves swaying trees. The PETS 2006 dataset involves cast shadows. Results are shown in Fig. 1-Fig. 4.

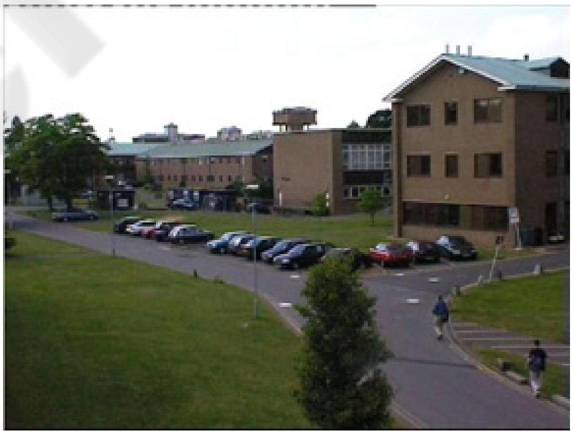


Figure 1: (a) Original image from PETS 2001 dataset 2.

Figure 1: (b) Motion detection result.

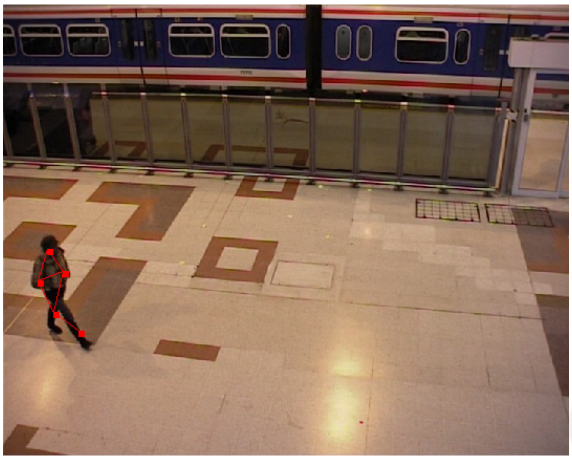


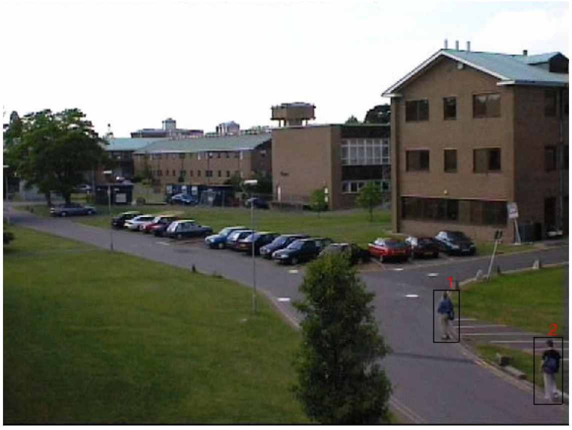
Figure 2: Original image from PETS 2006 S3-T7-A dataset with the attributed relational graph.

(a)

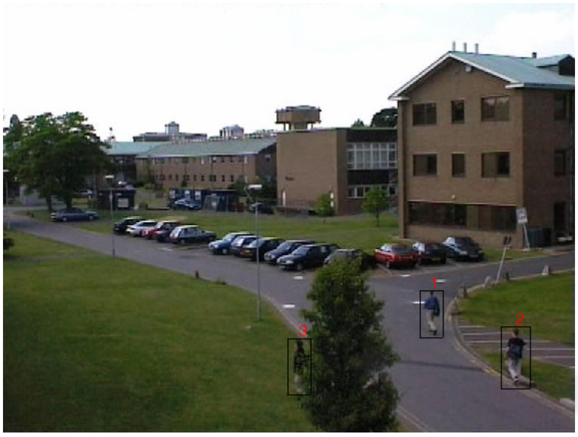
(b)

(c)

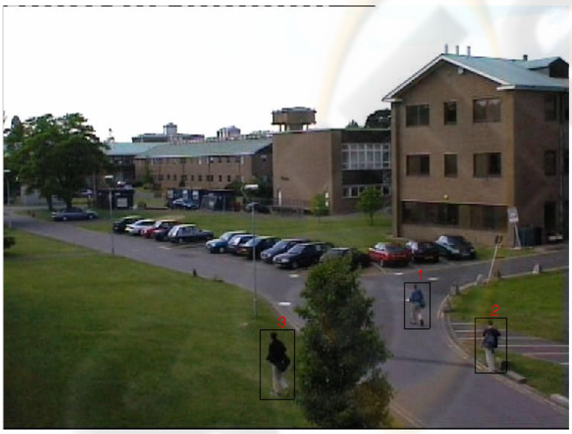
Figure 3: Tracking a single object in indoor environment.



(a)



(b)



(c)

Figure 4: Tracking multiple moving objects in outdoor environment with dynamic background.

4 CONCLUSIONS

In this paper, we propose a novel method for detection and tracking multiple moving objects in both outdoor and indoor environments. To detect the moving objects, we compute a combined color-texture feature vector for each image block and measure the change of the color-texture feature vector of the image block within a certain time interval. For tracking and identification of the detected multiple moving objects, we represent each object by an ARG, in which vertices are associated to an object's sub-regions and edges represent spatial relations among the sub-regions. The notion of inexact graph matching enables us to track partially occluded objects. The future work is to solve the case when an object is totally occluded.

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