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Video Based Crowd Density Estimation For wide area Surveillance

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***Abstract*— Crowd density estimation has gained much attention from researchers recently due to availability of low cost cameras and communication bandwidth. In video surveillance applications, counting people and creating temporal profile is of high interest. Many methods based on texture features have been proposed to solve this problem. Most of the algorithm only estimate crowd density on the whole image while ignore crowd density local region. In this paper, we propose novel texture based LBPCM (Local binary pattern co-occurrence matrix) for crowd density estimation. The CSLBP (Center Symmetric local binary patterns) algorithm is used to extract the features from both Gray and Gradient images to improve the performance of crowd density estimation.**

***Keywords*— Crowd density Estimation, novel, CS (Center Symmetric) LBP**

I. INTRODUCTION

There is currently significant interest in visual surveillance systems for crowd density analysis. In particular, the estimation of crowd density is receiving much attention in security community. Its automatic monitoring could be used to detect potential risk and to prevent overcrowd (e.g. in religious and sport events). Many stadium tragedies could illustrate this problem, as well as the Love Parade stampede in Germany and the Water Festival stampede in Colombia. To prevent such mortal accidents and for safety control, crowd density estimation could be used. It is extremely important information for early detection of unusual situations in large scale crowd to ensure assistance and emergency contingency plan. Polus first introduce the level of services for a pedestrian flow, which is widely adopted. Based on this idea, crowd density can be defined as: free flow, restricted flow, dense flow and jammed flow. In real world surveillance application, different crowd density levels maybe need different attention.

In recent years many crowd density analysis methods have been proposed. Crowd density methods can be divided into 3 categories. Firstly, crowd analysis based on background removal techniques.

Secondly, crowd analysis based on image processing and pattern reorganization techniques. In this category, texture features are widely used. Thirdly crowd analysis based on information fusion.

Marana consider that high density crowd has fine patterns of texture, while images of low density have coarse patterns of texture. Based on this assumption, many image texture features have been used in crowd density estimation. Some crowd density estimation algorithms, like GLCM and GOCM, extract features from the whole image and give an overall density level estimation for the whole image. However, there are two main shortages of this kind of method. One is that pedestrian may only appear in a certain area of the image, such as pedestrian would be only in the walkway. The other is that in real-world applications the density level of a specific area is crucial. For instance, in the stadium, the density level of the exit is more important than that of the spectator seats.

In this paper, we propose a novel strategy to use CSLBP for crowd density estimation. Firstly, we present a novel LBP Co-occurrence Matrix (LBPCM) based algorithms to extract texture features. It contains the spatial information of LBP while other histogram based LBP descriptors often neglect. Moreover, overlapping cells are used to extract texture feature vector, which can code more local information. Secondly, we extract LBPCM on gray image and gradient image respectively and then concatenate them to construct one feature vector. Experimental results show the proposed method can achieve significant improvement than other existing texture features.

II. EXISISTING SYSTEM

In recent years a number of security agencies specialized in crowd management have emerged and the visual surveillance research has studied the automated monitoring crowd movements. In Foreground based method the foreground is extracted firstly by background removal using a reference image, then crowd density is computed as a function of the number of foreground pixels, the function itself is obtained by curve fitting. However, these methods may fail when the background changes gradually over time.

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Optical Flow and Background Model (OFBM), which is based on LK optical flow and GEM methods, is computed for the whole image and used for crowd density estimation. This approach overcomes the shortages of optical flow and background subtracts such as sensitiveness of light changing and producing accumulate errors. However this modelling is time-consuming.

Most of these approaches mentioned focus on single region crowd analysis, which can be divided into crowd information extraction and crowd density modelling. Texture based methods are often used to extract the crowd information, which include speed, direction and location of a crowd in a video sequence and soon. These methods cannot work for high density crowds.

III. Overview Of Our Approach

The proposed architecture is as shown in figure.1.Before carrying out crowd estimation we are training system by extracting features from some frames and these features are stored in knowledge database.

Pre-processing is done for input video data; the Video data often contains high-frequency noise information. The presence of high-frequency noises causes the low frequency motion information to be undetected. At first, the video sequence is fed to a subroutine that creates a structure video data. Each of the video frames is converted from RGB to gray scale for processing. In order to handle noise information, a 2D Gaussian filter was designed over the entire image with a standard deviation of 0.5 and a block size of 5 × 5. By this we do not loose complete edge information and at the same time keeping low-frequency information.

Motion Estimation is performed done after obtaining the gray scale images, dense optical flow between two frames are computed using Horn-Shunck. In this method irradiance of the scene is assumed to be constant while determining the optical flow. And then we propose a sliding-window based framework to classify and locate crowd area firstly we cut image blocks from the original images which varies in crowd density levels, background and illumination condition. These blocks are annotated with the corresponding crowd density level. Secondly we divide each block into several overlapping cells and then texture features are calculated from each cell. We concatenate these features to construct one feature vector, which is the texture descriptor of an image block. After calculating all the feature vectors of the image blocks we use SVM to train classification modes for each crowd density level.

IV. Problem Formulation

The problem of crowd density estimation can be defined as following. Let X = {(xi, Ci) i=1,…,N} denote the training set, where xi ∈ X is a training image block and Ci ∈ {0, 1, 2, 3} denotes the crowd density level: free flow, restricted flow, dense flow and jammed flow. The texture features are calculated for each xi ∈ X and finally we have the feature set F= {(fi,Ci)i=1,…,N}., where fi represents the texture feature for image block xi . Then the feature set F is trained by SVM to get a SVM model M. Next, each testing sample yi of the testing set Y is calculated to get its texture feature descriptor. Then model M classify yi into a density level Ci ∈ {0, 1, 2, 3}. Continuing with this procedure, each testing sample can be classified.

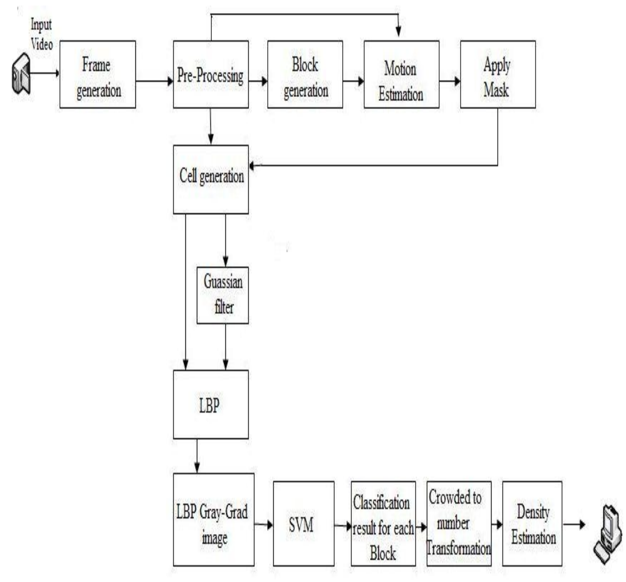

Figure 1: Block Diagram of the Crowd density estimation for wide area surveillance

V. LBP Co-Occurrence Matrix (LBPCM) Based Algorithms

This algorithm is used to extract texture features. It contains the spatial information of LBP while other histogram based LBP descriptors often neglect. Moreover overlapping cells are used to extract texture feature vector, which can code more local information. Secondly we extract LBPCM on gray image and gradient image respectively and then concatenate them to construct one feature vector. Experimental results show the LBPCM algorithm method can achieve significant improvement than other existing texture features.

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A. Local Binary Pattern Image

LBP is proposed by Ojalaet in 1994. And it has been found to be a valuable texture feature. As Fig.2 shows, LBP is calculated one pixel by another. For each pixel, it is compared to its neighbors (number of neighbors can be 8, 9 or even more). Then follow the neighbours clockwise or Counter-clockwise. If its value is bigger than the center pixel, write "1". Otherwise, write "0". When traversed all the neighbors, an 8-digit binary number can be obtained. Usually it is converted to decimal. In most cases, the histogram is calculated by LBP over the cells in the detection window and is used as classification features. In our work, LBP image is constructed for further processing. We calculate LBP for each pixel with distance as 1 pixel and consider all the 8 neighbors. Then each pixel, except the boundary of the input image block, gets a LBP value. The LBP value of a pixel is exactly an integer between 0 and 255, which makes the LBP map of the whole image block can be processed as a gray scale image. B.

4	7	8
6	5	1
9	3	2

→

0	1	1
1		0
1	0	0

→ **10110001**

Figure 2. Example of LBP algorithm

B. COMBINE GRAY AND GRADIENT FEATURES:

Combine Gray and Gradient Features: Gradient map of an image contains much information of edge features. We know that different objects have different edge distributions, which may present unique edge texture each other. Considering pedestrian, dense crowd has more edges of human, which presents fine patterns of texture while sparse crowd has fewer edges of human, which presents coarse patterns of texture. Thus also calculate LBPCM on gradient image (LBPCM-grad) for classification as gray image and gradient map can complement with each other, LBPCM gray and LBPCM-grad is concatenated to construct one texture feature vector (LBPCM-gray-grad).

C. LBP CO-OCCURRENCE MATRIX (LBPCM) BASED ALGORITHMS:

This algorithm is used to extract texture features. It contains the spatial information of LBP while other histogram based LBP descriptors often neglect. Moreover overlapping cells are used to extract texture feature vector, which can code more local information.

Secondly we extract LBPCM on gray image and gradient image respectively and then concatenate them to construct one feature vector. Experimental results show the LBPCM algorithm method can achieve significant improvement than other existing texture features.

D. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is a machine learning tool that is based on the idea of large margin data classification. The tool has strong theoretical foundation and the classification algorithms based on it give good generalization performance. Standard implementations, though provide good classification accuracy, are slow and do not scale well. Hence they cannot be applied to large-scale data mining applications. They typically need large number of support vectors. Hence the training as well as the classification times are high.

Binary pattern recognition involves constructing a decision rule to classify examples into one of two classes based on a training set of examples whose classification is known a priori. Support Vector Machines (SVMs) construct a decision surface in the feature space that bisects the two categories and maximizes the margin of separation between two classes of points. This decision surface can then be used as a basis for classifying points of unknown class.

To train the SVM, we search through the feasible region of the dual problem and maximize the objective function. The optimal solution can be checked using the KKT conditions.

Linear SVM

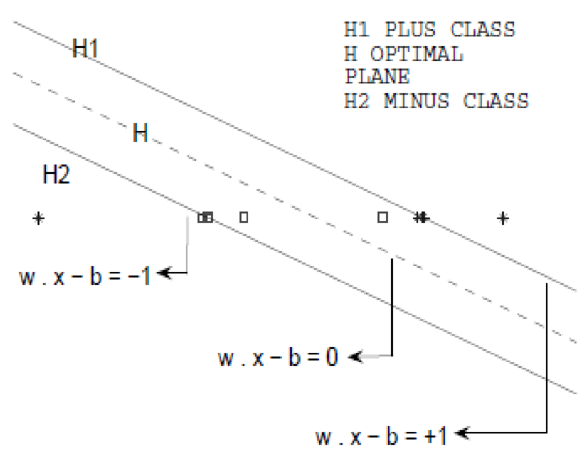

Figure: Example of supported Vector Machine

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VI. CONCLUSION

Crowd density estimation is an important issue in real world applications, especially for public security and management. The crowd usually presents some kind of texture features, so pattern recognition methods base on texture have been widely used for crowd density estimation. Among the various texture features, LBP has been found to be a very well descriptor to local texture patterns. It is widely used in computer vision technology based video surveillance applications. However, texture feature by LBP histogram loss the spatial information of LBP. In this paper, we proposed a novel strategy to use LBP features. We calculate the co-occurrence matrix on the LBP map instead of using histogram. Then the cell based method is used to construct the LBPCM feature vector. In our work, texture features on gradient images and gray images are combined together to achieve a better performance. Experimental results have proved the effectiveness of the proposed method. At last, we give a demonstration for local crowd density estimation and location using LBPCM in video surveillance applications. In future work, we are going to improve the computational efficiency of LBPCM and make it more robust to scale variance.

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