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Crowd Density Estimation Using Local Binary Pattern Based on an Image

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Abstract—This paper presents a novel approach for texture classification, generalizing the well-known local binary patterns (LBP). In the proposed approach, a local binary pattern (LBP) operator offers a systematic way of analyzing textures. It has a simple theory and combines properties of structural and statistical texture analysis methods. LBP approach is used to find crowd density. This approach estimate the number of person in that image. Firstly system will capture a normal input image then it will be converted it into grey scale image. Following to that LBP feature will be deployed to estimate the number of people and the crowd density. This Local binary pattern has proven and depicted very promising results.

Keywords—Local binary pattern(LBP), Crowd density, Thresholding, Foreground, Neighbors

I. INTRODUCTION

The growth of population and the worldwide urbanization has becoming more and more dense. Crowd control and management is considered to be severe issue in public places. People safety and their security is major concern in public places such as market, subways etc. Crowd density is one of the important aspect which signify essential description of entire status of crowd. Surveillance in public places is necessary in order to guard people from any threat. There is lot of cost cutting in cameras and communication bandwidth which attracted many researchers towards the crowd density estimation. Video surveillance applications are becoming more popular for creating temporal profile and counting people.

Face detection can be achieved using simple features based on Haar-wavelets [1]. To detect abnormal crowd density there exists an automatic method which makes use of texture analysis and learning. This plays a key role for the intelligent surveillance system in public places [2]. (HoG) Histogram of Oriented Gradients descriptors are effectively designed for the fulfilling task of pedestrian detection [3]. Counts the number of persons in the image and also detect them on the scene[4]. By capturing head count system can evaluate the number of people present in that crowd [5].

Face is very unique part of our body which helps to identify person in the crowd as well as used for accurate detection. Face detection technique is also deployed to estimate crowd in public place. Similarly head of person can also be used into count to predict crowd density.

Automatic technique to detect abnormal crowd density by using texture analysis and learning, which is important for the intelligent surveillance system in public places. By using the perspective prediction model. Detecting abandoned objects and tracking people have already been successfully developed. Tracking people is relatively easy than counting people in groups is much more challenging. The mutual blocks between people in a group make it difficult to provide an exact count.

. This has been shown that using locally normalized histogram of gradient orientations (HOG) features in a heavy overlapping grid gives very good results for person detection. In that fine-scale gradients, good orientation binning, spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all important for good performance.

In the next section, to detect foreground of image, a introduction and basic concepts of Local Binary Pattern (LBP) is discussed. Then we proposed method for counting a people in that image .

II. FOREGROUND DETECTION

In this system, the concept of background subtraction is to subtract or difference the current image from a reference background model. That concept is use to find out crowd density from the particular image. Our application could extract an image and in that image remove background and foreground. The system has been developed in outdoor public spaces, whereby light condition varies a lot and image may be non-human objects.

It is a foundation for object tracking, recognition, counting, and so on. Generally, there are two types of foreground detection methods. One is adaptive, the other is non-adaptive. Adaptive methods usually keep a background model fixedness and the parameters of the background model evolve with time. Non-adaptive methods depend on certain numbers of video frames and do not need a background model fixedness in the algorithm.[6]

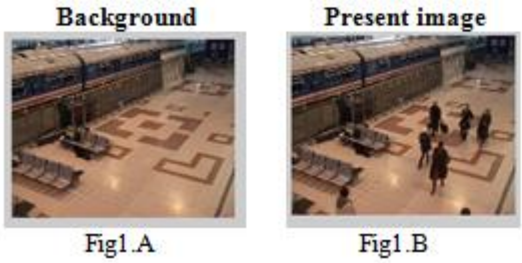


Figure 1 original image

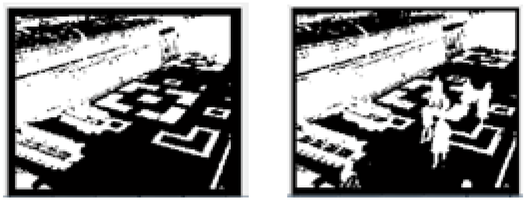


Figure 2. Foreground image

Above fig 1.a show that the background image of a particular location. Next fig 1. b is shown the current image, that particular image some person presented. fig 2 shows the foreground image of fig 1. that foreground image we can find out number of person in that image

III. FEATURE EXTRACTION

The original Local Binary Pattern(LBP) operator, LBP operator is based on labeling the pixels of an image by thresholding the 3 x 3-neighborhood of each pixel with the center value and the result as a binary number by using (1).

$$LBP_{p,r} = \sum_{n=0}^{p=1} s\left(g_p - g_c\right)2^n, \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (1)$$

where the gray value of the central pixel, is the value of its neighbors, P is the total number of involved neighbors and R is the radius of the neighborhood.

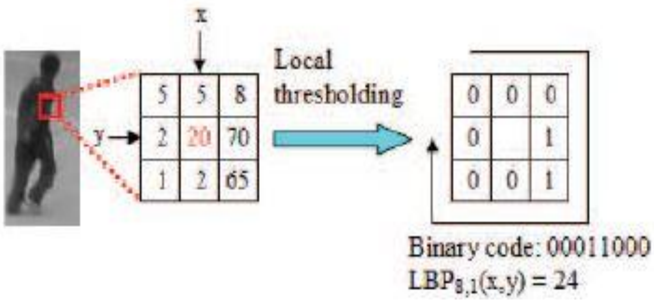


Fig 3. Example of original LBP descriptor.

Above fig. 3 shown an example of the original LBP in which the LBP code of the center pixel is obtained by comparing with neighboring pixels intensities. Example represent center pixel red in color and its value 20. The neighbor pixels intensities is equal or higher than the center pixels are labeled "1", otherwise "0".

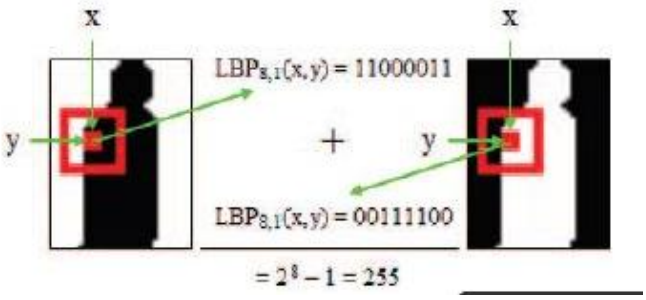


fig 4. Both left and right image repersent background and foreground

Above fig 4 show the left and right image repersents the invert into background and foreground. The LBP code in the left and right image is complementary each other, i.e. the sum of these codes is $2^P - 1$.

Suppose the coordinate of is (0, 0), then the coordinates of are (Rcos(2πp / P), Rsin(2πp / P)) . The gray values of neighbours that are not in the image grids can be estimated by interpolation. Suppose the image is of size I*J. figure 5 show Central pixel and its *P* circularly and uniformly spaced neighbours with radius *R*.

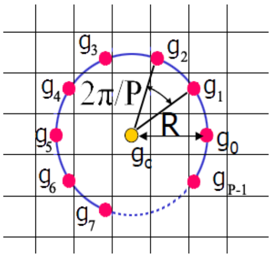


Fig 5. Central pixel and its P circularly and radius R

After the LBP pattern of each pixel is identified, a histogram is built to represent the texture image:

$$H(k) = \sum_{i=0}^{I}\sum_{j=0}^{J} f\left(LBP_{P,R}(i,j), k\right), k \in [0, K] \quad (2)$$

$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}$$

where K is the maximal LBP pattern value. The U value of an LBP pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern.

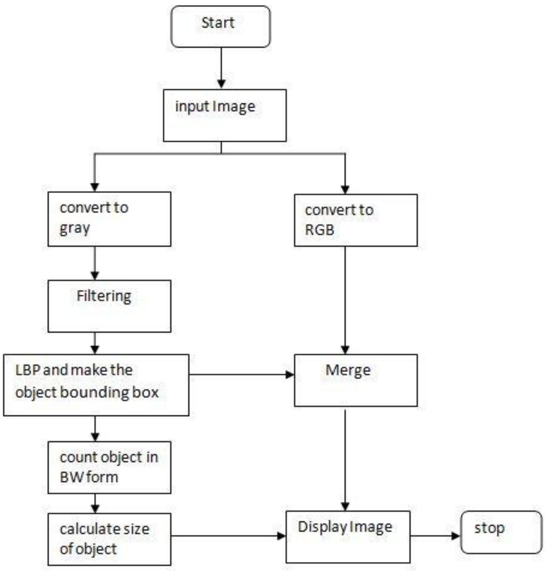
$$U\left(LBP_{P,R}\right) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \quad (3)$$

The uniform LBP patterns refer to the patterns which have limited transition or is continuities ($U \leq 2$) in the circular binary presentation. In practice, the mapping from $LBP_{P,R}$ to $LBP_{P,R}^{u2}$ (superscript "*u2*" means uniform patterns with $U \leq 2$),which has $P*(P-1)+3$ distinct output values, is implemented with a lookup table of 2^P elements.[7]

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center).
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives the feature vector for the window. The feature vector can now be processed using the support vector machine or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.[8]

IV. PROPOSED APPROACH



The above flow chart depicts estimation of number of people in the crowd. At first it captures the input image and convert it into grey scale image, then that image is used to for further removal of background. After performing this step foreground of that image is received. In that foreground system will remove noisy point and filtered image seeks appropriate foreground. In order to detected persons in the crowd use of bounding box. which helps to calculate people in that image, and later display the estimated size of crowd in that image.

V. CONCLUSIONS

A local binary pattern (LBP) operator offers a systematic way of analyzing textures. I have proposed a crowd estimation and detection for images, based on image segmentation and evaluation number of the crowd in the images. Further this crowd estimation could also be used for prediction using video based for random movement of crowd. Using video the system could track the crowd individually and estimate them using proper algorithm.

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