Moving Object Tracking using Color Feature in a Video

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Abstract

Video processing is one of the most challenging areas in image processing. It deals with identifying an object of interest. Motion detection has been used in many fields either directly or indirectly. In this paper an efficient approach to motion detection in video sequence using color feature extraction operator. Using this approach we improve the background subtraction and detecting the moving object with greater accuracy. In this paper, background modeling is done in order to make the update of background due to light illumination and change in the weather condition. Foreground detection is done before updating the background model. Color feature extraction is done in order to avoid the dynamic background such as moving leaves, rain, snow, rippling water.

Index terms— motion detection, background subtraction, color feature extraction, background modeling, dynamic background.

1 Introduction

ideo sequence can be analysis manual, semiautonomous or fully-autonomous. Manual video sequence involves analysis of the video content by a human. Such systems are currently in widespread use. Semi-autonomous video analysis involves some form of video processing but with significant human intervention. Typical examples are systems that perform simple motion detection. Only in the presence of significant motion the video is recorded and sent for analysis by a human expert. In fully-autonomous system, there is no human intervention and the system does both the low-level tasks, like motion detection and tracking, and also high-level decision making tasks like abnormal event detection and recognition. The design of an advanced automatic video system requires the application of many important functions including, but not limited to, motion detection, classification, tracking, behavior, activity analysis, and identification. Motion detection is one of the greatest problem areas in video as it is not only responsible for the extraction of moving objects but also critical to many computer vision applications.

Motion detection has been used directly in control application like object avoidance and automatic guidance system. Most of the surveillance based application like security camera, traffic monitoring, people counting use the motion detection technique. Motion detection has been used indirectly in various fields such as Human machine interaction, face recognition, remote image processing, detection for foreign bodies in human, event recognition of human action. Many intelligent video analysis system uses motion detection technique.

In this paper, we aimed to design an efficient algorithm to extract moving objects in videos. The key of background subtraction is to build and maintain an adaptive background model to represent the background of a video, which is a challenging task owing to that backgrounds of scenes in real-life are usually dynamic, including noise, illumination changes, swaying trees, rippling water and so on.

2 II.

3 Related Work

Background subtraction is a crucial step in many automatic video content analysis applications. Numerous methods for background subtraction techniques have been proposed over the past years. Codebook model (Kim,

2005) [1] is a method for real time foreground-background segmentation. Sample background values are quantized into codebooks which represent a compressed form of background model for a long image sequence. This method is able to model multi modal background pixels and also is applicable to compressed video such as MPEG. Jain et. al. [2] used simple intensity differencing followed by thresholding. Significant differences in intensity from the reference image were attributed to motion of objects. Greiffenhagen et. al. [3] proposes the fusion of color and normalized color information to achieve shadow invariant change detection. All these algorithms don't use regional information to validate local results. In [4], a frame level component is added to the pixel-level operations. Its purpose is to detect sudden and global changes in the image and to adapt the background frame accordingly. Median and Gaussian models can be combined to allow inliers (with respect to the median) to have more weight than outliers during the Gaussian modeling, Horprasert et. al. [7] use brightness distortion and color distortion measures to develop an algorithm invariant to illumination changes. Li and maylor [8] use the fusion of texture and color to perform background subtraction. The texture based decision is taken over a small neighborhood. A texture based model proposed by M. Heikkil¨a [10] [9] was popular in recent years. The authors used Local binary patterns (LBP) [10] to describe textures, and built a model based on LBP histograms over circular regions for a given pixel. The LBP based model is robust to backgrounds made of animated textures. Two extended texture-based models were proposed to improve the performance; S. Zhang et al. extended this model to temporal and proposed Spatiotemporal LBP based background model [13], and G. Xue et al. used spatial extended center-symmetric LBP (SCSLBP) [12] to build background model.

4 III.

5 Proposed Method

In proposed system, the video sequence first converted into frames as a preprocessing technique. In traditional way there will be need of standard background as a reference frame. With this approach, it is possible to detect new objects in the scene even if they suddenly stop moving. It is also possible to detect objects that have removed from the scene. However, the fixed reference background may be not applicable to the scene along with the illumination variation. Therefore, the accurate background image and a highquality and illumination tolerance background updating mechanism becomes necessary for moving object detection. After that update the background for each subtraction made for the frames.

6 a) Color Feature Extraction Operator

In real world videos, the color of foreground objects is usually different from the color of background, thus besides the intensity, color information is another important factor to distinguish foreground and background. Rc, Gc and Bc are the three color channels for each pixel (xc, yc). By adding color information, the length of binary bits grows which will lead to exponential growth of patterns, i.e. the dimension of histograms, and will seriously affect the efficiency of algorithm. So we cut down patterns by using centersymmetric Local binary patterns CS-LBP [11], choosing a small number N and dropping one of the three color bits. In fact, the three color bits are highly correlative, dropping one of them is not critical. The final spatialcolor binary patterns (SCBP) we used in this paper are defined as: If we set N = 4, the total number of SCBP patterns is 64, which is just appropriate. The SCBP histogram computed over a circular region of radius R region around the pixel is used as the feature vector to represent a pixel, and background model is built based on these feature vectors, here R region is a parameter set by the user.

7 b) Background Modelling

In background modeling, moving average is calculated for all N frames in order to estimate the background. By using the formula Where B t?1 (x, y) is the previous background model, It(x, y)is the current incoming video frame, t is the frame number in the video sequence. This initial computation is done in order to reduce the frame storage computation.

8 c) Rapid Matching

This rapid matching is done in order to determining whether the pixel values for the incoming video frame It(x, y) are equal to the corresponding pixel values of the previous video frame It?1(x, y).

9 d) Background Updating

Background pixel of B t (x, y)will then be supplied to every frame of the background model B t (x, y). Based on the best possible background pixels are then updated for the background model.

10 e) Background Subtraction

First computes the feature vector, i.e. the SCBP histogram, and then calculates the similarities between the feature vector and the pixel's model. Similarities larger than the threshold T p indicate match, and finally both the histograms and weights are updated differently according to the matching status. In the foreground detection module, a pixel is classified into foreground if there is no match occurs between feature vector and the background histograms, otherwise the pixel is labeled as background. The output of the detection module is a binary image showing foreground pixels.

Threshold T p (x, y), which is initialized as global value Tp. At each time, after updating the background model, the threshold is updated similarly:T p (x, y) = (1 ? ?) T p (x, y) + ?(s(x, y) ? 0.05) ,

where s(x, y) is the largest similarity between feature vector and background histograms, and ? is a learning rate close to one. In this way, the thresholds for static pixels will increase and decrease for dynamic Moving Object Tracking using Color Feature in a VideoSCBP 2N,R (xc, yc) = CS-LBP 2N,R (xc, yc) + 2 N+1f (Rc,Gc | ?) + 2 N+2f (Gc,Bc | ?),

pixels. Thus our background subtraction method is more sensitive in static region and more tolerant in dynamic region.

11 f) Foreground Detection

Foreground detection is done before updating the background model. Let us denote the local binary pattern (LBP) histogram of the given pixel computed from the new video frame by ~h. At the first stage of processing, ~h is compared to the current K model histograms using a proximity measure. The histogram is compared against the current B background histograms using the same proximity measure as in the update algorithm. If the proximity is higher than the threshold T for at least one background histogram, the pixel is classified as background. Otherwise, the pixel is marked as foreground.

12 g) Refinement

Histograms are computed based on the texture over surrounding regions, though that each pixel is modeled identically, it's still block-wise. On one hand, it's robust to dynamic background such as waving trees and rippling water; on the other hand it has common drawbacks of block-wise models. A major problem is that the contour of detected object is illegible. Because of using histogram over regions, not only the real foreground, but also the background pixels near the edges of foreground will be classified into foreground, and thus the contour of foreground objects is obscured. To reduce the false detection, pixel wise masking ?i is applied to the output of the background modeling.

According to the above modeling, color and intensity of each pixel is considered and find the mean and standard deviation are calculated for masking. We calculate the mask ?i for ith pixel by the following formulation: The chromaticity coordinates (ri, gi, bi) are updated the same as gi.?i = 1, if [di ? ?stdi]&[di/ gi ? ?1], 1, if ||(ri, gi, bi) ? (ri, gi, bi)||2 ? ?2,

IV.

13 Conclusion

In this paper, we aimed at subtracting background and detecting moving objects from videos. A novel motion detection method is proposed based on color and texture information. In this paper background modeling is done as first step in order to overcome the light illumination and change in the weather condition. This will help to detect the moving object with greater accuracy. Color extractor operator is used to avoid the unwanted dynamic background in the video. [1]

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Figure 1: Figure 1 :

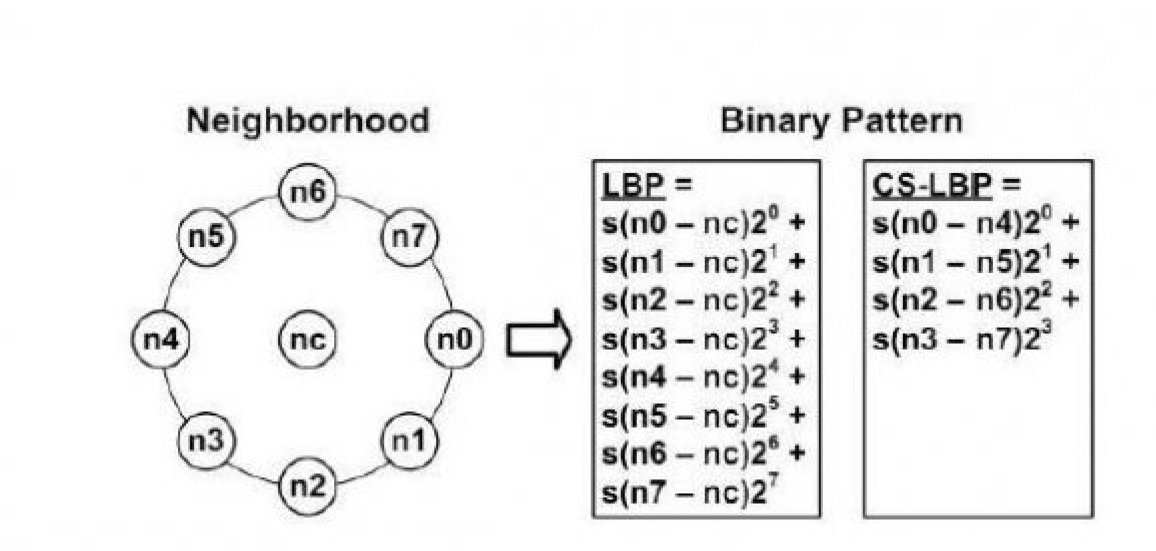

Figure 2:

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