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A novel object detection technique for videos with homogeneous background

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***Abstract*---**Object detection and tracking in video frames play a major role in all the computer vision systems. Several computer vision systems use background subtraction method for detecting the objects. However, Background subtraction method often results in lack of accuracy during frame comparison. Also, it leads to increase in memory requirements and computational complexity while setting threshold. The new Local Mean Diamond Pattern (LMDP) is introduced here to overcome the existing issues by extracting the objects directly from the frames. The extracted objects are tracked using mean shift tracking algorithm. The experimental result shows that the LMDP outperforms the existing methods viz., Local Binary Pattern (LBP), Local Extrema Pattern (LEP) and Local Rhombus Pattern (LRP) in terms of accuracy.

***Keywords*---**Local Binary Pattern (LBP), Local Extrema Pattern (LEP), Local Rhombus Pattern (LRP), Local Mean Diamond Pattern (LMDP).

Introduction

In the recent days, the video analytics become an essential feature of several video applications such as Intelligent Scene Monitoring (ISM), Automatic Number Plate Recognition (ANPR), etc., [10]. Tracking the object in video frames is necessary to analyze the video contents and to characterize the objects. As an advancement of object tracking, a system has been designed by Sachin Sharma et al to detect the animals within 30 meters ahead of the vehicle and thereby avoid the accident in highways [10]. In supermarkets, the application extends the possibility of counting the products automatically along with the existing video based

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monitoring system [2]. The steps involved for tracking the objects include pre-processing, feature extraction and Object identification [1]. The pre-processing includes image resizing, image formatting and background modeling. Background model is created for detecting the objects from the imagery sequences. Most of the background based objects detection algorithm uses the background models. Background model is used to analyze the difference between the incoming frames of the video stream and the scene background. The extracted foreground objects can be classified into any one of the categories such as human, animal, vehicle, etc., based on the shapes, colors and features [9][11][6]. Feature extraction and identification are carried out by several existing patterning techniques. The Local Binary Pattern (LBP), k-Means Clustering LBP, Block Based LBP (BLK-LBP), Centre Symmetric LBP (CS-LBP), Directional Local Extrema Pattern (DLEP) and Local Rhombus Pattern (LRP) are the familiar techniques that are useful in extracting the features. These patterning techniques are suitable for all the colour models such as RGB, HSV and HSL [14][13][7][9][15]. However, the background subtraction method often leads to lack of accuracy in frame comparison, increase in memory requirements and complexity while setting threshold.

In this paper, a novel Local Mean Diamond Pattern (LMDP) is introduced to overcome the existing issues on model based object detection. The LMDP algorithm extracts the objects directly from the video frames. The experiment results reveal that the proposed LMDP outperforms the existing Local Binary Pattern (LBP), Local Extrema Pattern (LEP) and Local Rhombus Pattern (LRP). The related works such as LBP, LEP and LRP are explained in second section. The proposed LMDP is explained with its algorithm, flow chart and process in third section. The well known mean shift keying algorithm along with the LMDP is used for tracking the extracted objects. The experimental results are compared with existing algorithms in fourth section of this paper. The final Section concludes the work.

Related Works

In the video processing field, the Local Binary Pattern (LBP) was initially used to identify the facial expressions because of its ability to recognize the dynamic texture in the images [4]. The LBP became the familiar tool for other purposes such as boundary detection, objects comparison, foreground mask creation, selected objects tracking, etc,. Further, the Local Extrema Pattern (LEP) and Local Rhombus Pattern (LRP) were introduced based on this LBP. The Directional Local Extrema Pattern was introduced by Subrahmanyam Murala et al in 2012 for extracting the features in four directions (0^0,45^0,90^0 & 135^0) of centre pixel with respect to its neighbors [14]. In 2013,[13] the combined LEP and RGB Colour model for feature extraction was proposed and this was also compared with LBP to prove its efficiency. Online video object tracking with the new integrated technique was carried out by Mallikarjuna Rao et al in 2014. In which, the LBP was used along with colour RGB model and Sobel Edge Detector [7]. The joint colour - texture and joint colour –Local Rhombus Pattern (LRP) were proposed for patterning the futures by Pallavi et al in the year of 2015. The object identification without computational complexity was done by using joint colour – texture model. The accuracy in avoiding the false detection and avoiding the duplication was increased by using joint colour – LRP model [9][15]. Recently, k-Means Clustering

LBP was proposed by Shanmugapriya in 2017, in which the shape feature extraction was done by k-means clustering algorithm and the LBP was applied to extract the text features from the video frames [5].

The tracking is done by mapping the histograms of objects in subsequent video frames. There are several methods that are used for mapping the histograms in frame sequences. Amidst Kalman filer estimation with template matching [8], Bayesian tracking method [2], Particle Filtering [7] and Mean Shift keying technique [14][13][7][9][15] the Mean shift Tracking algorithm is often used due to its efficiency. Several algorithms used this mean shift key algorithm for tracking the objects in video frames. Here, the familiar LBP, LEP (0^0) and LRP are taken and explained conceptually and their performances are computed for object extraction in homogeneous Background. The mean shift tracking algorithm is used to track the extracted objects.

Local Binary Pattern

The LBP was introduced by Ojala et al for local information of pixels in an image. In LBP, every pixel of the image is treated as the center pixel, one at a time, and local information is acquired for each pixel that depends on neighboring pixels. Each center pixel is subtracted from all neighboring pixels and a binary number is assigned to each neighboring pixel. These binary numbers construct the local binary pattern for the center pixel. Consequently, eight bit binary code is formed in clockwise direction right from right middle of threshold as shown in below equation. The decimal value for the corresponding binary code is computed and substituted in the place of centre pixel as shown in Fig.1. The eq.1 is used for computing the LBP.

$\boldsymbol{T_n}$ is the difference between the centre pixel and neighbor pixels.

$$\boldsymbol{T_n = I_n - I_c \qquad n = 0, 1, 2 \dots 7}$$

For a center pixel $\boldsymbol{I_c}$ and neighbouring pixels $\boldsymbol{I_n}$, LBP can be obtained as follows

$$f(x) = \begin{cases} \mathbf{0}\ if\ \boldsymbol{T_n} < 0 \\ \mathbf{1}\ if\ \boldsymbol{T_n} \geq \mathbf{0} \end{cases}$$

The LBP is defined as follows

$$\boldsymbol{LBP} = \sum_{i=1}^{7} \mathbf{2}^{(i-1)} \times \boldsymbol{f}(\mathbf{I_n} - \mathbf{I_c}) \qquad \mathbf{(1)}$$

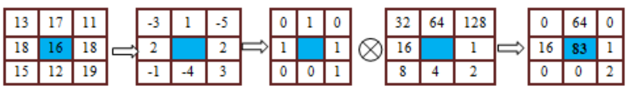

Fig. 1. Local Binary Pattern

Local Extrema Pattern

In LEP, all pixels are being considered as centre such as LBP. It uses eight neighborhood pixels for patterning the centre pixel which considers as a threshold pixel. Local Extrema Pattern in 0◦ direction is calculated for all neighbors by computing local differences between the pixel concerned and its neighbors in 0^0 directions. If the differences are equal or higher than the pixel, which accepts as binary value '1', else accepts as binary value '0' (if less than the value of pixel). After calculated the neighbors binary values such as 0's and 1's, eight bit binary code is formed in clockwise direction right from right middle of threshold. The decimal value for the corresponding binary code is calculated and substituted in the place of centre pixel as shown in fig.2. LEP is obtained by using the eq.2.

$$\boldsymbol{I'(g_i) = I(g_c) - I(g_i)\ where\ i = 1, 2, 3, 4, 5, 6, 7\ \&\ 8}$$

The local extrema patterns are obtained by using the following equation:

$$\hat{\mathrm{I}}_{\alpha}(\mathbf{g_c}) = \mathbf{f}(I'(g_j), I'(g_{j+4}))$$
$$j = \left(1 + \frac{\alpha}{45}\right)\ \forall\ \alpha = 0^0, 45^0, 90^0, 135^0$$
$$\mathbf{f}\left(I'(g_j), I'(g_{j+4})\right) = \begin{cases} 1 & I'(g_j) \times I'(g_{j+4}) \geq 0 \\ 0 & \text{else} \end{cases}$$

The LEP is defined as follows

$$LEP\left(I(g_c)\right) = \sum_{\alpha} 2^{\left(\left(\frac{\alpha}{45}\right)-1\right)} \times \hat{\mathrm{I}}_{\alpha}(\mathbf{g_c});$$

$\forall \alpha = 0^0, 45^0, 90^0, 135^0$ **(2)**

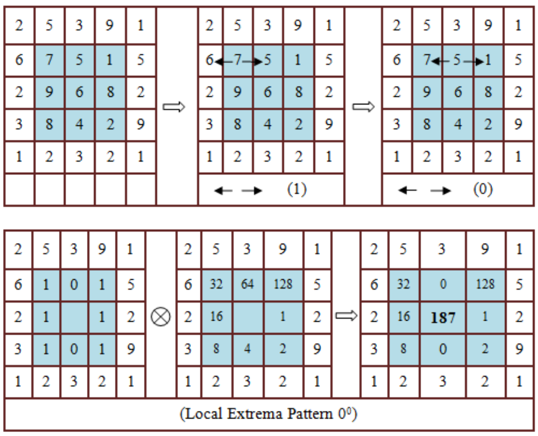

Fig. 2. Local Extrema Pattern

Local Rhombus Pattern

In Every pixel of the image is treated as the center pixel. Four neighborhood pixels, two each in the vertical and horizontal directions have been used for pattern formation. For each of the four pixels, two neighboring pixels of them are considered, and relationships based on their comparison are extracted. Signs of both relationships are compared; binary value 1 is substituted if both signs are same and 0 if they differ. Local rhombus patterns are multiplied by some weights (2^n) with four rhombus pixels alone and summed up to a pattern value. LRP is obtained by using the eq.3.

$$F(T_1^n, T_2^n) = \begin{cases} 0 \text{ if } T_1^n \geq 0 \text{ and } T_2^n < 0 \\ 0 \text{ if } T_1^n < 0 \text{ and } T_2^n \geq 0 \\ 1 \text{ if } T_1^n \geq 0 \text{ and } T_2^n \geq 0 \\ 1 \text{ if } T_1^n < 0 \text{ and } T_2^n < 0 \end{cases}$$

$$T_1^n = I_{n-1} - I_n,\ T_2^n = I_{n+1} - I_n,\ \forall\ n = 3, 5, 7$$
$$T_1^n = I_8 - I_n,\quad T_2^n = I_{n+1} - I_n,\ \text{for n=1}$$

The LRP is defined as follows

$$LRP(x, y) = \sum_{i=0}^{3} 2^i \times F(T_1^{2i+1}, T_2^{2i+1}) \qquad \textbf{(3)}$$

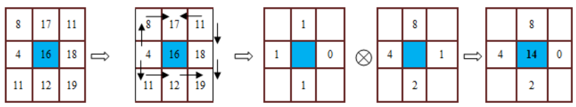

Fig. 3. Local Rhombus Pattern

The objects aren't extracted by using these existing LBP, LEP and LRP as shown in fig.6 due to their ways of computations. The proposed LMDP can extract the objects because of its calculation that computes the mean value of the neighbors in all four directions individually. The LMDP ignores the homogeneous background as much as possible. The differences between objects and background are depicted clearly by LMDP.

Proposed work and Discussion

Local Mean Diamond Pattern

Unlike the Local Rhombus Pattern, the name diamond pattern means the four pixels used for computing the mean and further patterning that will be taken from the diamond direction of every pixel. Initially, every pixel of the image is treated as a center pixel. The mean values of four sides are calculated and the values are substituted in the corresponding side's centre pixel (Diamond Pixel). The difference between centre and its diamond shape neighbor pixels are computed and the values are replaced by the diamond pixels. Comparisons are made between centre pixel and the centre pixels of all four sides. Value 1 is substituted if both signs are same and 0 if they differ. The four sides' binary values are multiplied by some weights (2^n) in order (clock wise or counter clock wise) and the summed up value is replaced in the centre pixel. For a center pixel $\mathbf{I_c}$and neighboring pixels$\mathbf{I_n}$, LMDP can be obtained as follows.

The mean values of all four sides are computed and stored individually in $\boldsymbol{T_n}$ as shown below.

$$\boldsymbol{T_n} = \frac{1}{3}(\boldsymbol{I_{n-1}} + \boldsymbol{I_n} + \boldsymbol{I_{n+1}})\ for\ \boldsymbol{n} = \mathbf{1,3,5,7}\ where\ \boldsymbol{I_8} = \boldsymbol{I_0}$$

$\boldsymbol{T_n}$ is replaced by the difference value between the centre pixel and neighbor pixels.

$$\boldsymbol{T_n} = \boldsymbol{T_n} - \boldsymbol{I_c} \qquad for\ \boldsymbol{n} = \mathbf{1,3,5,7}$$

$$\boldsymbol{f}(\boldsymbol{x}) = \begin{cases} \mathbf{0}\ if\ \boldsymbol{T_n} < 0 \\ \mathbf{1}\ if\ \boldsymbol{T_n} \geq 0 \end{cases}$$

The LMDP is defined as follows

$$\boldsymbol{LMDP} = \sum_{i=1}^{4} \mathbf{2}^{(i-1)} \times \boldsymbol{f}(\boldsymbol{T_n} - \boldsymbol{I_c}) \qquad \textbf{(4)}$$

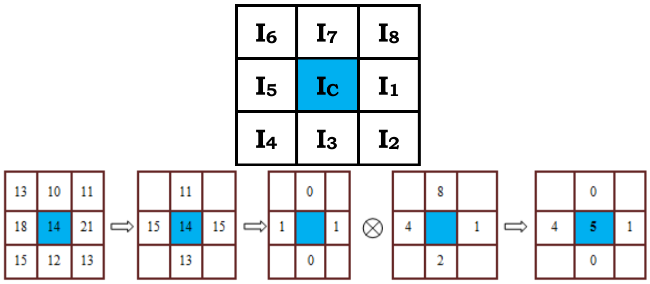

Fig. 4. Local Mean Diamond Pattern

Algorithm

Input: A video footage which contains homogeneous background.
Output: Extract the objects directly from the video frames

Steps

- Convert the video into image frames
- Consider every pixel of all frames as a centre pixel and the surrounding pixels are its neighbors
- Compute the mean values for neighbors in four sides (Right, Bottom, Left and Top) and replace the centre of neighbors with their corresponding mean values
- Compute the difference between centre and its diamond shape neighbor pixels and put it in the place of diamond pixels.
- Replace the Diamond pixels as follows:
  - Put 1 if it is greater than or equal to 0
  - Put 0 if it is less than 0
- Four bit binary code is formed in clockwise direction right from right middle of centre. The decimal value for the corresponding binary code is computed and substituted in the place of centre pixel
- Repeat the process from step2 to step6 till the end frame
- The objects are extracted after applied the LMDP on all frames

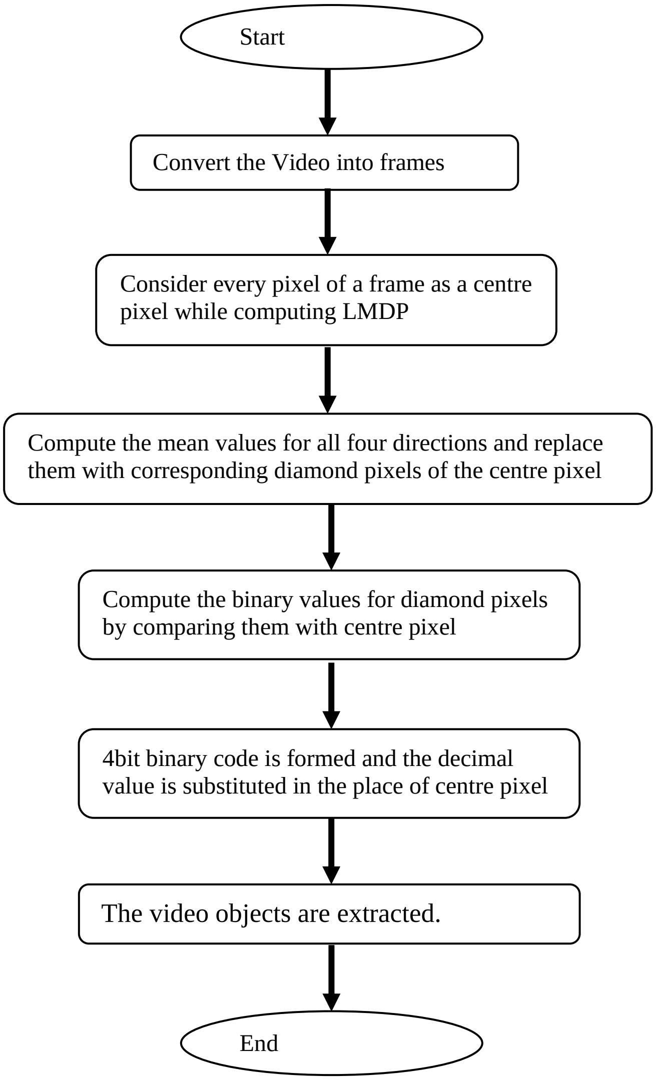

Fig. 5.Flow Chart of Object Detection by LMDP

In the LMDP based tracking algorithm, as shown in the flow chart fig.5, initially the homogeneous based background video is converted into frames. The objects are extracted from the frames by using LMDP. The extracted objects can be tracked by familiar mean shift tracking algorithm.

Experimental Results

The aircrafts video data set is used for proving efficiency in experimental result since the proposed algorithm has been working with homogeneous Background video data sets alone. Initially the aircraft video was converted into frames. A sample converted original image and the patterned images are given in fig.6. True and false pixel counts are measured from the patterned images. The accuracy has been measured in percentage as given in table1 and column chart fig.7.

Table 1: Accuracy of Objects Detection among LBP LEP, LRP & LMDP

Methods	Total no of Pixels: 49868		Accuracy of Objects detection in percentage	
	Total no of True Pixels: 4118	*Total no of False Pixels: 45750*	*True Pixels*	*False Pixels*
LBP	2982	28460	72.4%	62.2%
LEP	2923	8328	70.9%	18.2%
LRP	2875	5906	69.8%	12.9%
LMDP	2832	179	68.8%	.003%

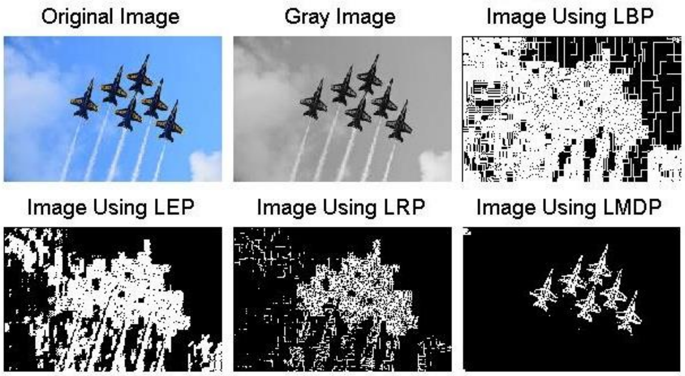

Fig. 6. Output Comparison among LBP, LEP, LRP & LMDP

The experimental result shows that the proposed patterning algorithm produces accuracy in detection of objects from homogeneous background based videos. In the table, the true and false pixels detection rate are clearly tabulates as follows, the LBP detects 72.4% true pixels and 62.2% false pixels, the LEP detects 70.9% true pixels and 18.2% false pixels, the LRP detects 69.8% true pixels and 12.9% false pixels, and the new LMDP detects the 68.8% true pixels and 0003% false pixels. Though the true pixels extract by existing LBP, LEP and LRP are greater than new LMDP, the LMDP ignores false pixels as well. The new LMDP detects very few 0.003% false pixels as noticed in the table and column chart. The accuracy is measured by the scale of ignoring the false pixels because the objects can only be extracted if the false pixels are being ignored. Otherwise, it is not easy to separate the objects from the background. Henceforth the new LMDP can extract the objects from homogeneous background videos whereas the existing LBP, LEP and LRP are unable to extract the objects because of their higher false pixels detecting rate.

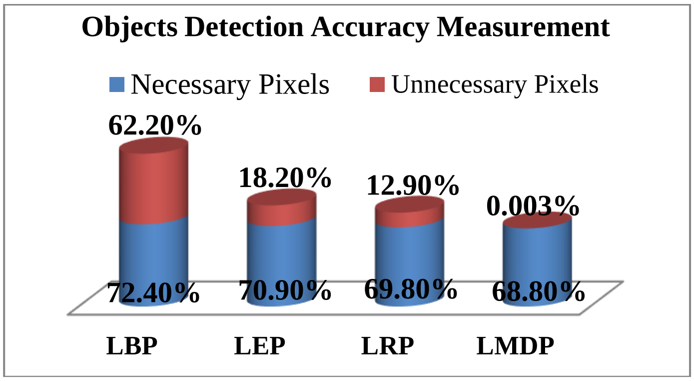

Fig. 7. Objects Detection Accuracy Measurement among LBP, LEP, LRP & LMDP

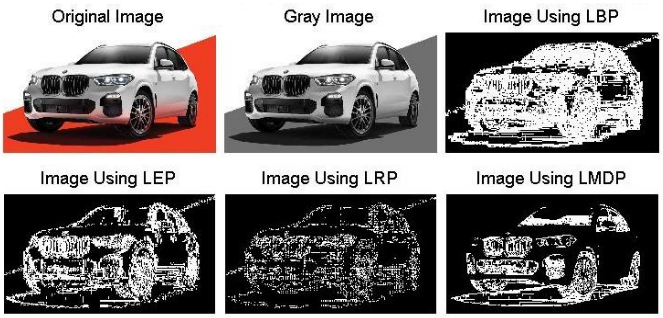

Fig. 8. Homogeneous background elimination

The LMDP has an additional advantage of eliminating homogeneous background which may have more than one colour. A car video is taken for experimental test. The video contains a car object and homogeneous background with two colours such as red and white. The resultant patterned image proves the differences between two existing patterns (LBP & LRP) and two new patterns (LMDP & EMDP). Here the existing LBP and LRP could not ignore the homogeneous background. But, the new LMDP and EMDP are able to ignore the homogeneous background even in more than two colours ie., shown in the fig.8. The car object can be extracted without any occlusion.

Conclusion

In this paper a new Local Mean Diamond Pattern is presented for homogeneous background based videos. The LMDP is used for extracting the objects from video frames. It is introduced to overcome the short fallings of model based object detection method such as lack of accuracy in frame comparison, increase in memory requirements and complexity while setting threshold. Air Craft video dataset is used as a homogeneous background dataset. The air craft objects are detected accurately by the proposed LMDP algorithm and the extracted objects are tracked by mean shift tracking algorithm. The LMDP is compared with the existing Local Binary Pattern (LBP), Local Extrema Pattern (LEP) and Local Rhombus Pattern (LRP). Unlike LBP, LEP and LRP, the new LMDP detects the objects accurately. The experimental result shows that the proposed algorithm stands in high accuracy of detection than the existing LBP, LEP and LRP. In addition, it is proved with car data set that the LMDP ignores the multicolor homogeneous background and the object is extracted without occlusion.

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