A REVIEW PAPER ON DIFFERENT TEXTURE FEATURES AND THEIR APPLICATION IN OBJECT TRACKING

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ABSTRACT

Human perceives most of the information by seeing something. And texture is easily perceived by humans and is a rich source of visual information. So texture is in trend in the field of computer vision. It is used for object recognition, identification, classification and tracking. In this paper we present review on the texture features their extraction and their application in tracking.

Index Terms: Texture, transform, co-occurrence matrix, model based

Introduction

Texture of an image gives us information about the spatial array of color pixels in an image or selected region of an image. Texture pattern is a repeated element which have small amount of variation in element appearance on a surface. A sub image have constant, slowly varying and approximately periodic texture pattern for no change or very slow variation in image intensities. So texture is an important parameter in many computer vision areas, such as image recognition, identification, classification, segmentation and tracking etc. effortless texture analysis of an image can provide useful information of rapid scene identification. Texture analysis plays an important role in medical image analysis (such as distinguishing normal tissue from abnormal tissue, X-ray images, normal), remote sensing, surface inspection, document Processing, object recognition, classification and tracking etc. Different texture feature methods such as Gray Level Co-Occurrence Matrix, Run Length and Gabor filter, wavelet transform, law's Texture energy measure features methods used for texture feature extraction. Texture features are classified in basically three regions. Statistical based, structural based and syntactic features.

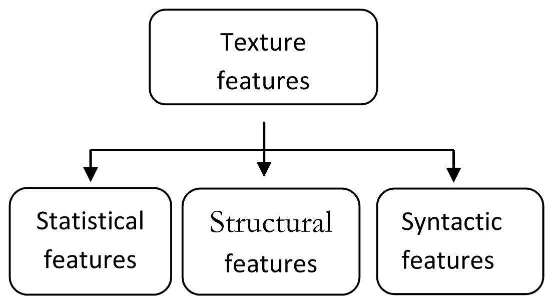


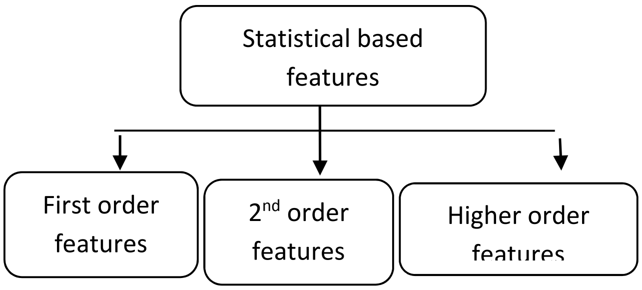
Figure 1:- classification of texture features in two areas

The paper is organized as follows: Section 2 presents statistical methods of features; Section 3 presents filter-based features. Section 4, presents some model-based methods. Finally, we conclude the paper in Section 5.

2. Statistical features

A statistical based feature analyzes quantitative measure of the collection of intensities in a region. This approach is suitable when texture key sizes are comparable with pixel sizes. One of the significant qualities of texture is its grey level spatial distribution. So this method is used to calculate local features at each pixel in the image and measure their spatial arrangement of grey values from its local features, and presents a set of statistics from the distributions of the local features. This is easier to calculate and is more commonly used, since normal textures are made of patterns of unbalanced sub elements.

Statistical based features are further classified on the basis of no. of pixels in first order, second order and higher order based features.



2.1First order based features

It is based on intensity histogram of an image. These are measured by original pixel intensity of an image. These features don't depend upon correlation with neighborhood pixels. Four statistical moments are derived from this method such as mean, standard deviation, entropy, average energy, skewness and kurtosis.

$$mean(\mu_i) = \frac{\sum_{x=1}^{P}\sum_{y=1}^{Q} I_i(x,y)}{P*Q} \quad (1)$$

$$standard\ deviation(\sigma_i) = \sqrt{\frac{\sum_{x=1}^{P}\sum_{y=1}^{Q}(I_i(x,y)-\mu)^2}{P*Q}} \quad (2)$$

$$Energy(e_i) = \frac{1}{P*Q}\sum_{x=1}^{P}\sum_{y=1}^{Q} I_i^2(x,y) \quad (3)$$

$$Entropy(H_i) = \frac{1}{P*Q}\sum_{x=1}^{P}\sum_{y=1}^{Q} I_i(x,y)\,(-\ln\ I_i(x,y)) \quad (4)$$

$$skewness = \frac{\sum_{x=1}^{P}\sum_{y=1}^{Q}(I_i(x,y)-\mu)^3}{P*Q*\sigma^2} \quad (5)$$

$$Kurtosis(k) = \frac{\sum_{x=1}^{P}\sum_{y=1}^{Q}(I_i(x,y)-\mu)^4}{P*Q*\sigma^4} - 3 \quad (6)$$

2.2 Second Order features

Grey Level Co-occurrence Matrix

The gray-level co-occurrence matrix (GLCM) has information about position of pixel intensities having similar grey level values. It is also known as grey-level spatial dependence matrix. Haralick et. al. [5] suggested a set of 14 textual features which can be extracted from the co-occurrence matrix, G_d and it is two-dimensional array, in which both row and column represent a set of possible values. Which contain information about image textural characteristics such as homogeneity, contrast and entropy. It is m*m matrix, where m represent no. of grey levels in an image. Its matrix show frequency of one grey level occurs in a specified spatial linear relation with another grey level in the image sub region. GLCM shows how often different combination of grey level co-occur in an image region. In general, the GLCM matrix is computed based on two parameters, their relative orientation θ. normally, θ is quantized in four directions (e.g., 0º, 45 º, 90 º and 135 º). And G_d [i, j] is defined by first calculating a displacement vector d = (dx, dy) and counting all pairs of pixels separated by d having gray levels i and j.

$G_d\,(i,j) = m_{ij}$, where m_{ij} is the number of occurrences of the pixel values (i, j) lying at distance d in the image. Out of 14 important statistics are as following: angular second moment (ASM), contrast, correlation, homogeneity, inverse difference moment, dissimilarity, sum entropy and information measures of correlation such as GLCM mean, GLCM standard deviation.

$$ASM(Energy) = \sum_{i,j=1}^{m} G_d^2 \quad (7)$$

It return sum of squared elements.

$$contrast = \sum_{i,j=1}^{m} G_d(i-j)^2 \quad (8)$$

Contrast gives the intensity contrast between two adjacent pixels over whole image.

$$Dissimilarity = \sum_{i,j=1}^{m} G_d|i-j| \quad (9)$$

$$homogeneity = \sum_{i,j=1}^{n}\frac{G_d}{1+|i-j|} \quad (10)$$

It calculates closeness of distribution of elements.

$$Entropy = \sum_{i,j=1}^{n} G_d(-\ln G_d) \quad (11)$$

It is a measure of information content. It calculates randomness of intensities.

$$GLCM\ mean = \begin{cases} \mu_i = \sum_{i,j=1}^{m} i(G_d) \\ \mu_j = \sum_{i,j=1}^{m} j(G_d) \end{cases} \quad (12)$$

$$IDM = \sum_{i,j=1}^{m}\frac{G_d}{|i-j|^2} \quad i \neq j \quad (13)$$

GLCM correlation matrix can have value between 1 or -1.

Autocorrelation matrix

An important property of texture is repetitive nature of position of texture element in the image. It measures linear spatial relationships between spatial sizes of texture primitives. It involves individual pixel. The set of autocorrelation coefficient is as following.

$$c(p,q) = \frac{MN\sum_{i=1}^{M-p}\sum_{j=1}^{N-q} f(i,j)f(i+p,j+q)}{(M-p)(N-q)\sum_{i=1}^{M}\sum_{j=1}^{N} f^2(i,j)} \quad (14)$$

Where p and q are positional pixel value difference in i^{th} j^{th} direction, and M and N are image dimensions.

2.3 Higher order statistic features

Gray Level Run Length Matrix Features

It is a higher order statistic features which captures the coarseness of texture images based on run-lengths of image's grey levels in a particular direction. A coarse texture, often have long grey-level runs, than that a fine texture, which contain primarily short runs. It finds strings of successive pixels that have the same gray level intensity along a specific linear orientation. For a 3D image I, a run-length matrix P (i, j) is defined as the number of pixels of gray level i and run-length j along a particular direction. Consecutive pixels with the same gray level are called a gray level run. The number of pixels in a run is the run-length. To make it rotation invariant mean of four different matrixes in direction of 0, 45, 90, and 135 degrees is taken place. Let M be the number of gray levels and N be the maximum run length. Various texture features are there to define run length matrix. Grey level run length pixel number matrix

$$P_p\,(i,j) = p(i,j).\,j \qquad (15)$$

Each element of the matrix gives the number of pixels of run length j and gray-level i. As Compared to the original matrix, it gives equal emphasis to all length of runs in an image.

Grey level run number vector

$$P_g(i) = \sum_{j=1}^{N} p(i,j) \qquad (16)$$

This vector shows the sum distribution of the number of runs with gray level i.

Run length run number vector

$$P_r(j) = \sum_{i=1}^{M} p(i,j) \qquad (17)$$

This vector gives the sum distribution of the number of runs with run length j.

Galloway [6] introduced five original features of run-length statistics as defined as follows. Short run emphasis (SRE), long run emphasis (LRE), grey level non uniformity (GLN), run length non uniformity (RLN), run percentage (RP)

$$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{j^2} = \frac{1}{n_r}\sum_{j=1}^{N}\frac{p_r(j)}{j^2} \qquad (18)$$

$$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j).\,j^2 = \frac{1}{n_r}\sum_{j=1}^{N} p_r\,(j).\,j^2 \qquad (19)$$

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N} p(i,j)\right)^2 = \frac{1}{n_r}\sum_{i=1}^{M} p_g(i)^2 \qquad (20)$$

$$RLN = \frac{1}{n_r}\sum_{j=1}^{N}\left(\sum_{i=1}^{M} p(i,j)\right)^2 = \frac{1}{n_r}\sum_{j=1}^{N} p_r(i)^2 \qquad (21)$$

$$RP = \frac{n_r}{n_p} \qquad (22)$$

Where n_r is total number runs and n_p is the number of pixels in the image. On the basis of surveillance that most of the features are functions of only p_r (j), without taking the gray level information p_g (i) into account, Chu et al. [7] proposed two new features, to extract gray level information in the matrix. Long grey-level run emphasis (LGRE), high grey-level run emphasis (HGRE).

$$LGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2} = \frac{1}{n_r}\sum_{i=1}^{M}\frac{p_{g(i)}}{i^2} \qquad (23)$$

$$HGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j).\,i^2 = \frac{1}{n_r}\sum_{j=1}^{M} p_r\,(j).\,i^2 \qquad (24)$$

In a more recent study, Dasarathy and Holder [8] described another four feature extraction functions by the idea of joint statistical measure of gray level and run length, as follows. Short run low grey-level emphasis (SRLGE), Short run high grey-level emphasis (SRHGE), long run low grey-level emphasis (LRLGE), long run high grey-level emphasis (LRHGE).

$$SRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2.j^2} \qquad (25)$$

$$SRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j).i^2}{j^2} \qquad (26)$$

$$LRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j).j^2}{i^2} \qquad (27)$$

$$LRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N} p(i,j).\,i^2 j^2 \qquad (28)$$

Dasarathy and Holder [8] tested all eleven features on the classification of a set of cell images and showed that the last four features gave better performance. This approach has two drawbacks i.e. there is no conjectural proof that, maximum texture information can be extracted from the run-length matrix, and many of these features are highly correlated with each other.

2.4 Local Binary Pattern (LBP) Features

Local binary pattern (LBP) operator is introduced as a complementary measure for local image contrast [9-10]. The LBP operator associate statistical and structural texture analysis. LBP describes the texture with smallest primitives called *textons* (or, histograms of texture elements). Local binary pattern (LBP), proposed by Ojala [10,11] as local texture operator. Its computational complexities are less, and it is easy to satisfy real-time in moving objects tracking. It is a non-parametric kernel. It is invariant to monotonic grey- scale transformations and rotation invariant which is very important for texture analysis. LBP operative represents the pixels of an image with their respective decimal weight that is known as

LBP codes that encode the local structure around each pixel. Each pixel is compared with its eight neighbors in a 3 × 3 neighborhood by subtracting the center pixel value; the resulting strictly negative values are encoded with 0, and the others with 1. For each given pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left neighbor. The corresponding decimal value of the generated binary number is then used for labeling the given pixel. The derived binary numbers are referred to be the LBPs or LBP codes.

$$\mathrm{LBP}_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} k(i_P - i_c)\, 2^P \qquad (29)$$

Where i_c corresponds to the grey value of the center pixel (x_c,y_c), in to the grey values of the 8 nearby pixels, and function k(x) is defined as:

$$k(x) = \begin{Bmatrix} 1 \text{ if } x \geq 0 \\ 0 \text{ if } x < 0 \end{Bmatrix} \qquad (30)$$

The LBP method can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. The LBP operator considers only the eight nearest neighbors of each pixel and it is rotation variant, but invariant to monotonic changes in gray-scale can be applied. The dimensionality of the LBP feature distribution can be calculated according to the number of neighbors used. LBP is one of the most used approaches in practical applications, as it has the advantage of simple implementation and fast performance. LTP, LPQ (Local Phase Quantization) operators are also their.

3. Filter based method

These methods come under structural methods. Filter based methods are classified in three groups: Gabor filter based texture features, wavelet based features and law's texture energy features.

3.1 Gabor Filter-based Texture Features

Gabor Transform

Gabor filter is consisting of a sinusoidal plane wave of some frequency and orientation modulated by Gaussian envelope. A

Specific band of frequency can be extracted by gabor filter as it act as a band pass filter. The Gabor function has good local ability in both frequency and spatial domain at the same time. It is similar to receptive field of the mammal's retina neuron, so it is applied in the region of image processing, comprehending, identifying [4] [8]. Gabor wavelet filter can distils information of the frequency domain and spatial domain, which cannot be realized by the global Fourier analysis . Gabor function is composed by the product of the elliptic Gauss function and the complex plane wave. Bank of Gabor filters are used to extract local image features. An image is convolved with a 2D Gabor function to obtain a Gabor feature image, and by varying spatial frequency and orientations, a bank of different Gabor filters can be produced. There are various Gabor features that can be exploited for feature analysis, e.g., linear Gabor features (symmetric, anti-symmetric), threshold Gabor features (symmetric, anti-symmetric), Gabor-energy features, etc.

Gabor filters are a group of wavelets. For a given image I(x, y) with size M×N, its discrete Gabor wavelet transform is given by the following formula.

$$g_{\sigma,w_0}(x) = \frac{1}{\sqrt{2\pi\sigma}} exp^{\left(-\frac{1x^2}{2\sigma^2}\right)} exp(jw_0 x) \qquad (31)$$

And 2D gabor function is given as following

$$g_{\sigma,w_0}(x,y) = \frac{1}{\sqrt{2\pi\sigma_x\sigma_y}} \exp[-\frac{1}{2}\left(\frac{x^2}{\sigma_x{}^2} + \frac{y^2}{\sigma_y{}^2}\right)] \qquad (32)$$

In the above equation σ is gauss function's standard difference, and w_0 is spatial frequency of complex plane wave. The result from gabor filter can be used directly as texture feature.

3.2 Law's texture energy feature

Another approach for generating texture feature is to use local masks to detect various types of texture. Laws develop a texture energy approach that measures the amount of variation within a fixed size window. Some operators such as sobel and laplacian are used to generate mask. Law's mask are constructed by convolving together just 3 basic 1*3 masks:

L3 = [1 2 1]
E3 = [1 -2 1]
S3 = [-1 -2 -1]

The initial of these masks indicate Local averaging, Edge detection, and Spot detection. These basic masks span the entire 1x3 subspace and form a complete set. Similarly, the 1x5 masks obtained by convolving pairs of these 1x3 masks together from a complete set:

L5 (level) = [1 4 6 4 1]
E5 (edge) = [-1 -2 0 2 1]
S5 (spot) = [-1 0 2 0 -1]
R5 (ripple) = [1 -4 6 -4 1]
W5 (wave) = [-1 2 0 -2 1]

In principle, nine masks can be formed in this way, but only five of them are distinct. Here the initial letters are as before with the addition of Ripple detection and Wave detection. These masks are subsequently convolved with a texture field to highlight its microstructure giving an image from which the energy of the microstructure arrays is measured together with other statistics.

3.3 Wavelet-based Feature

Wavelet based features are trendy in Region-based images content based images. [2, 3] So it is helpful in the cases in where users want to retrieve images based on information about their regions. Wavelet transforms are developed to characterize localized frequencies specific to each pixel location based on various wavelet transform methods. Wavelet transform characterizes multiscale frequency content, called, wavelet coefficients; an image is divided into some regions by clustering pixels in segmented regions. Wavelet coefficients provide us texture features for all regions. The segmented regions are indexed by the averaged features in the regions. Mean and standard deviation are calculated of decomposed image which are non overlapping regions. These mean and standard deviation are used as the texture features for image Multi resolution properties of wavelet help in calculating texture features. A simple Discrete Wavelet Transform representation can capture small differences in rotation or scale. Some other representations on Wavelet transform can be Discrete Wavelet Frame Transform (DWFT), Discrete Wavelet Packet Transform (DWPT), and Modulus Maxima of a Continuous Wavelet Transform (MMWT), Multi-Orientation Wavelet Pyramid, Dual-Tree Complex Wavelet Transform, or scale, rotation, and translation invariant wavelets.

4. MODEL-BASED MATHODS

They are divided in two classes: fractal feature, random field feature.

4.1 Fractal Feature

These features are discriminative and invariant in case of scale. As variation in scale are very prominent. So what needed is local interest points and characteristics of scales. These problems are easily sort out by fractal feature. This calculates densely local fractal features. Local fractal features. Local fractal dimension is invariant to local bi-Lipschitz transformations whereas its extension is able to correctly distinguish between fundamental textures primitives [2][3]. Fractal models can classify irregular textures too. A multi-fractal analysis is also proposed for texture descriptor.

4.2 Random Field Feature

Markov model and hidden markov model of grey level pixels are calculated. In these approaches relationships between the gray level of neighboring pixels are statistically characterized [21]. For example, a Gauss-Markov random field-based probabilistic texture model is developed to characterize hyperspectral textures. Another similar model is proposed for texture classification and texture segmentation. For Markov random field (MRF) models, the sufficient statistics of each sub-window can be considered as the feature vector. However, usually it is noticed that feature-based approaches are less computationally-expensive as well as more effective than Markov random field-based approaches.

5. Application of different texture features

Yu Zhao, Hanqing Lu in 2004 [20] proposed a tracking method based on Local Position Color Information (LPC) is a sub-region model matching approach. They proposed a new color representation approach to eliminate illumination efficiently. They divide the target region in similar color sub-regions, and synthesizes the sub-regions histograms into one histogram including the position information, thus the same color in the different place has the different weight. And then they applied Minimum Cross Entropy method is used as the similarity function between the target model and the target candidates. This algorithm show better result in illumination changes and same background and fore ground colors. But it cannot apply where rotation and scaling of image takes place.

Like Zhang Dong Qin in 2006 [4] uses Gabor wavelet characters to track the object. They distils characters using Gabor wavelet, choose and optimize the position and direction with the edge detection method, and find the wavelet subspace composed by the wavelet of different scale and direction, count the wavelet parameter. These wavelet parameters are then used to represent the object's edge characters. New character template is created by these character points by greedy algorithm through all the course of moving track. And then match the new character points. In abnormal conditions like light variation, scale changes, rotation etc. it can still track the object.

Wing-Pong Choi, Kin-Man Lam in 2008 [19] proposed an effective face tracking algorithm based on the combination of shape and texture information is proposed. Shape of a face, and the texture information is characterized by edge map and local binary pattern respectively. They applied their algorithm on adaboost algorithm to form a multi-view face-tracking system. They track a face region by searching for the shortest weighted feature distance between the face pattern and the possible face candidates. Experimental results show that our algorithm can track faces in varying poses (tilted or rotated) with 17 fps on average. But this method fails in occlusion and when foreground and background have same color.

Huchuan Lu1 , Ruijuan Zhang1, and Yen-Wei Chen in 2008 [26] proposed an enhanced kernel based algorithm for visual tracking based on the video sequences captured from a fixed camera on the top of the scene. They first use the LBP to detect the object, then they predict the object using kalman filter. And new search window is generated using mean shift iteration. Experiments on video sequences in different scenes have demonstrated its accuracy and robustness. Object model and matched target model and target candidate have maximum Bhattacharyya coefficient. Due to fusing multiple features, our enhanced kernel-based tracking method is robust to noise, image corruption and perturbation. Furthermore, it can largely reduce computational complexity.

Wang Chuan-xu Li Zuo-yong in 2008 [29] proposed a new algorithm for face tracking in which Color cue fuses with LBP cue under the framework of particle filter. The tracking results show a more robust face tracking performance compared with the method based on single cue. Particle filter is a practical, powerful and promising estimation method. It provides an open framework for tracking problem. This paper describes the target face more accurately by the combination of the color cue and LBP texture cue and gets a more robust tracking result than the methods based on any single cue.

Majid Asadi, Carlo S. Regazzoni in 2008 [30] presents a probabilistic Bayesian framework approach for object tracking using a combination of a corner-based model and coefficients of Undecimated Wavelet Packet Transform (UWPT) inside a patch around each corner. This algorithm unifies global descriptors with local descriptors. This maximizes the posterior of global position. Coherency is checked by Euclidian distance. Local descriptor i.e. wavelet filter out unwanted values before coherency voting. This approach indicates good performances of the algorithm in crowd scenes and partial occlusions. They use a Bayesian framework for object tracking Future works will be devoted to include online feature adaptation strategies and a multi-cue object tracking algorithm.

Zhixu Zhao, Shiqi Yu, Xinyu Wu, Congling Wang, Yangsheng Xu in 2009 [18] multitarget tracking algorithm based on local binary patterns (LBP), which is a kind of discriminative texture descriptor and Kalman filter is used to predict the blob's new position and size. They detected Blobs in the neighborhood of the Kalman predictions. More than one blob are found, by LBP distance, which is applied to locate the tracking target. They performs efficient in dealing with collisions with the LBP distance and the Kalman filter.on PC and DSP platform this algorithm have low computational complexity, have gives good result with slow illumination changes and slight leaf-shaking. But the disadvantage of this method is sudden illumination change that cannot be handled using single Gaussian model.

Amir Babaeian, Saeed Rastegar, Mojtaba Bandarabadi, Maziar Rezaei in 2009 [23] presents visual features for tracking of moving object in video sequences using Mean Shift algorithm. They used color, edge and discrete wavelet transform is used as texture feature for tracking. They extracted all features from first frame and the histogram of each feature is computed then the mean shift algorithm is run for each feature independently and the output of the mean shift algorithm for each feature is weighted based on the Bhattacharya coefficient. And the new center is calculated on the basis of integration of all feature's mean shift value. They show that tracking with multiple weighted features provides more reliable performance than single features tracking. This method cannot be used in occlusion.

Hongwei Ying, Xuena Qiu, Jiatao Song, Xiaobo Ren in 2010 [28] proposed particle filtering object tracking approach with local binary pattern and color feature. They used concept of merging global and local features to sort out problem of complex background. The experimental results show that the proposed method effectively improves the accuracy and robustness of tracking. But the tracking performance degraded for the object poses with a great change.

Chengbin Zeng, Huadong Ma in 2010 [15] proposed a method to count no. of peoples by unifying HOG (Histograms of Oriented Gradients) and multilevel LBP (Local Binary Pattern) as feature set. They detect head-shoulder of a person in partial occlusion. Further they use PCA (Principal Components Analysis) with multilevel HOG-LBP to reduce the dimension so time complexity is reduced. Their proposed algorithm PCA based multilevel HOG-LBP performs robustly. For the real time application tracking particle filter is used with above algorithm. We also incorporate the detector into the particle filter tracking to count the pedestrian flow and achieve convincing accuracy.

Parisa Pouladzadeh, Mehdi Semsarzadeh, Behnoosh Hariri and Shervin Shirmohammadi in 2011 [24] proposed a face tracking algorithm. They used meanshift for color and Local Binary Pattern (LBP) histogram as texture feature for tracking. LBP is a structural and statistical texture feature. By joining these two methods they have a more powerful face detection algorithm with a higher success rate in face tracking.
The disadvantage of this method is time complexity i.e. it can’t track face with sudden changes.

Jiu XU, Axel BEAUGENDRE and Satoshi GOTO in 2011 [17] proposed, a novel approach to achieve the multi-human tracking in video surveillance system using a HOG (histograms of oriented gradients) and particle filter. HOG is used to detect foreground objects and to extract the foreground blobs to achieve the regions of interest. They used HOG features and searching strategies to initialize the trackers of humans and track the human using particle filter tracking. They further used a color-edge texture histogram by calculating the local binary pattern of the edge of the foreground objects to show better performance in describing the shape and texture of the objects to handle occlusion. Experimental results on different data sets have proved that our method has better performance and good real-time ability. But this is non-suitable in case of illumination changes.

O. Zoidi, A. Tefas and I. Pitas in 2012 [13] proposed appearance-based method for visual object tracking of rigid objects with pose variations and small scale and 2-dimensional rotation changes. Object model is representing by salient features, which are chosen by bank of gabor filter. They choose randomly candidate objects of a search region, following by a 2-dimensional Gaussian distribution. They compare Candidate object’s cosine similarity to the detected object in the first frame and the object instance in a previous frame and a significant change in the object appearance are considered as maximal. This tracking scheme in tracking successfully any rigid object under pose variations and small changes in scale and 2-d angle and its superiority against a state-of-the-art method.

Guoyun Lian, *IEEE*, Jian-Huang Lai, Ching Y. Suen in 2012[12] they used distance based local binary pattern to describe spatial structure information in color space. CI-LBP is used to unify DLBP and color. They encode 2-D histograms into 1-d histogram. CI-LBP is occur different for both upper body part (up to back) and lower body part. Further correct detection and segmentation of objects can be improved in complex environment.

Eunsoo Choi, Seong-Whan Lee, and Christian Wallraven in 2012[14] they proposed local gabor binary pattern to recognition of face under variation in lighting conditions. They used 6 gallery and 108 probe images. They assign different weights to each facial part. For deriving the weights, they analyzed data from human face recognition by eye tracking. They pre-processed face images using a weight mask based on the salient regions from the eye-tracking data in recognition step. They have 9 kinds of illuminations for each face. They employed the ROC (Receiver operating Characteristic) curve to evaluate the Area under Curve (AUC) which is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. Their result show good performance in light variation.

But not proven as completely illumination invariant.

Lu Tian, Shengjin Wang, Xiaoqing Ding in 2012 [16] proposed a human detection and tracking system under multi-cameras with non-overlapping views using apparent features only. They first detect people and then perform object matching. They combine Histograms of Oriented Gradients (HOG) and Local Binary Pattern (LBP) to detect human and segment human body from the background using GrabCut algorithm. They also used matching of pedestrian feature extraction and object using appearance. They applied above algorithm in series over three cameras with non-overlapping views to prove the effectiveness. They implement a public security system composed of four parts including human detection, pedestrian segmentation, apparent features extraction and object matching. The results of experiments are very effective. But their algorithm disadvantage is that it can't be used in overlapping views.

Chunzhao Guo, Seiichi Mita, *Member*,and David McAllester, in 2012 [21] presents a robust stereo-vision-based drivable road detection and tracking system to navigate an intelligent vehicle through challenging traffic scenarios and increment road safety in such scenarios with advanced driver-assistance systems (ADAS). Their algorithm based on maximum a posteriori (MAP) problem in a Markov random field (MRF). They used energy function that incorporates geometry information, image evidence, and temporal support to develop an alternating optimization algorithm. And unsupervised learning of the parameters from the stereo pair using a hard conditional EM algorithm. Their algorithm results show effective and the results with respect to various challenging road scenarios such as heterogeneous. Limitation of this method is it can't detect non-flat roads in challenging environments and the segmentation based MRF model.

Wenhua Guo, Zuren Feng, Shuai Wang, Qin Nie in 2012 [22] proposed an algorithm which combines local binary pattern and color information to form a new feature CL, which is a 4-d feature. Target is tracked on the basis of centroid iteration calculated by maximum posterior probability. Selecting the texture features by boundary and angular point as the base of statistics. The CL has higher differentiation ability and lower computational complexity. In complex background, the algorithm can track the target robustly. But this method fails when foreground and background have same colors.

Fouad Bousetouane · Lynda Dib · Hichem Snoussi in 2012 [25] In this paper, they proposed a modified adaptive mean shift tracking algorithm integrating a combination of texture and color features. To be consistent to the scale change and complex non-rigid motions of the tracked target, they suggest to adapt the tracking window of the proposed algorithm with the real moving target mask at tracking over time. They used mean shift and grey level co-occurrence matrix as texture feature for tracking. Results in complex non-rigid motions and scale change at tracking over time, are very spectacular.
However, this algorithm doesn't work when the moving object is too small to be detected and when a very low resolution image is there.

Yunji ZHAO, Hailong PEI **in 2013 [27]**
Proposed a visual tracking method with online feature selection mechanism using particle filter and HOG (histogram of oriented gradient). In their proposed visual tracking method, the Bhattacharyya distance and the local discrimination between the object and background are used to define the weights of the particles, to optimize local convergence problem. They discriminate object and background by introduced weight to the particles. Experiments testified that the improved CHOG-based particle filter tracking algorithm could work well in multiple objects tracking. But they are all based on CH. This method fail if the color of object is similar to the background, this algorithm cannot work well. It is also subject to the illumination changes.

Conclusion

Texture is broadly classified into 2 categories statistical and structural. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Structural methods describe texture by identifying structural primitives and their repeated nature.
Statistical methods are better texture where database is homogeneous and structural methods

are better where repeated texture is there. So, along with tracking approaches if we integrate the Local Binary Pattern (LBP) and histogram of oriented gradients (HOG) approach then the tracking efficiency can be increased in the video because of their unifying nature with color.

Summary

Various texture descriptors and their application in the field of object tracking are discussed in this paper. This paper summarizes different methods of object tracking with their advantages and limitations. This paper also gives a description of the most favorable field of implementing for the given approach e.g. mean-shift approach with LBP and particle filter with HOG is good for tracking.

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