International Journal of Engineering Research & Management Technology
ISSN: 2348-4039
May-2017 Volume 4, Issue-3
Email: editor@ijermt.org www.ijermt.org

A NOVEL APPROACH FOR OBJECT TRACKING OF JOINT COLOR-TEXTURE HISTOGRAM USING LBP AND DWT

KARISHMA
Computer Science & Engineering
Laxmidevi Institute of Engineering & Technology
Alwar, Rajasthan, India

RESHU GROVER
Computer Science & Engineering
Laxmidevi Institute of Engineering & Technology
Alwar, Rajasthan, India

ABSTRACT:
Object tracking is a significant task inside the field of computer vision. Video analysis have three key steps: detection of interesting moving objects, tracking of these objects from frame to frame, and analysis of object tracks to recognize their behavior. For tracking of an object mainly four steps are needed firstly the given frame is segmented. After segmentation foreground and background are extracted from the frame. This step is to decide whether the pixel belong to foreground or background. Foreground contains the object of interest. Next step is for extracting useful features. These features are used for object tracking

Object tracking using mean shift algorithm based on similarity between features of target region and candidate region. Candidate region is the current frame of tracking process. For similarity calculation color histogram and texture features are used. For texture feature extraction there are two methods LBP and discrete wavelet transform. In this paper comparison between these two approaches is done. Texture feature of target and candidate frame are extracted and integrated with color histogram. These features are together used for estimating the maximum similar candidate area with target area. This paper compares two methods of texture feature extraction. One is local binary pattern (LBP) and other one is discrete wavelet transform (DWT). These methods are compared on the basis of their computing time, performance and implementation

KEYWORDS: Mean shift tracking; Local Binary Pattern; Discrete Wavelet Transform; Kernel based tracking; texture extraction methods

I. INTRODUCTION

In today's web enabled world object tracking is an important but still difficult task. Object tracking is a process of tracking an object in a video frame by frame. Object tracking in video can be defined as segmenting an object of interest from a sequence of video scenes also known as video tracking. Video tracking is the process of locating a moving object (or multiple objects) over time using a camera. It has a variety of uses, some of which are: human-computer interaction, security and surveillance, video communication and compression, augmented reality, traffic control, medical imaging and video editing. Video tracking can be a time consuming process due to the amount of data that is contained in video. Amount of data in video is the information which is used to track target in video. There are three types of methods to track object in video: feature based method, differential method and correlation method. Feature based methods extract characteristic of object from image sequence. Using these characteristics track target in video. Kernel based method is a method of video tracking which lies in feature based method category. In this paper kernel based tracking used with mean shift tracking. This paper compares two methods of texture feature extraction from image sequence.

Object tracking is a significant process inside the field of computer vision. Its aim is to locate a moving object or several ones in a video. An algorithm is used for analyzing the video frame by frame and the goal of algorithm is to determine presence of target object in each frame and returns its location. So it is the process of extract an object from a video scene and keeps track of its motion, orientation, color etc. Its main task is to find and follow a moving object or several targets in image sequences. Object tracking can be complex due to: 1)Loss of data by projection of the 3D world on a 2D image, 2) Noise in images, 3) Complex object motion, 4) Articulate or flexible nature of objects, 5) Full and partial object occlusions, 6) Complex shapes of object, 7) Scene illumination changes, 8) Real-time processing requirements.

Object tracking is used in the automated surveillance, traffic monitoring, vehicle navigation, human-computer interaction etc. Automated video surveillance is real time tracking of humans or vehicles. It aims on real time observation of people or vehicles in busy or restricted environments leading to tracking and activity analysis of the object in the field of view. There are three main steps in video surveillance: detection of moving target objects, keeps track of target objects from frame to frame, and analysis of object which is tracked to recognize their behavior.

Object tracking follows the segmentation step and is more or less equivalent to the "recognition" step in the image processing.

There are three methods in visual object tracking. Feature based methods focus at extraction of features like as points, line segments extract from the image sequences, a matching procedure ensured the tracking stage at every time instant. Differential methods are depended on the optical flow computation that is on the apparent motion in image sequences, under some regularization assumptions. For measuring inter-image displacements these methods use the correlation. Selection of a particular approach largely depends on the domain of the problem.

There are basically three methods in object tracking

A. *Feature-based methods describe the extracted properties like as points, line segments drive from image sequences, a matching procedure ensured the tracking stage at every time instant.*
B. *Differential methods are based on the optical flow computation that is on the apparent motion in image sequences, under some regularization assumptions.*
C. *Correlation to measure inter- image displacements. Selection of a particular approach largely relies on the domain of the problem.*

The central challenge is to find out the location of a target object as it moves through a camera's field of view. This is normally done by matching multiple regions or features in consecutive frames of a video stream. Location of target object is given in first frame. Using features of target object at given location, object is tracked in further frames. Challenges in tracking objects are significant loss of information the depth of a pixel can no longer be directly measured. The limited image resolution, the small number of bits used to represent each pixel. Noise introduced during image acquisition and artifacts caused by compression all serve to lower the quality of the video data.

The increments in the need for automated video analysis have generated a great deal of interest in object tracking. Many vision applications such as human computer interfaces, video communication, video compression, road traffic control, and security and surveillance systems required object tracking. In security surveillance systems object tracking is used for tracking of a human or object that is breaching security or any rule of the system. Often the goal is to obtain a record of the trajectory of the moving single or multiple targets over time and space, by processing information from distributed sensors. Information is used to track object in sequential frames of the video.

The organization our paper is, Section II shows research related to our area. In section III, we have explained our methodology and steps involved in proposed work of our paper. Section IV shows mean shift algorithm. Section V compares the LBP and DWT, and Final Section V concludes the paper with future directions.

II. LITERATURE SURVEY

Object tracking have been a dynamic field of research for some decades. Most research is focused on modeling the differences in color, intensity, and texture of adjacent pixels or areas.

“Subhash Challa, Mark R. Morelande, D. Musicki, Robin J. Evans” [1] proposed an approach that provides very complex object tracking algorithms accessible to the increasing number of users working on real-world tracking problems and supports them to design their own tracking filters under their unique application constraints.

"Alper Yilmaz, Omar Javed, Mubarak Shah" [2] presented the state-of-the-art tracking approach, assorted them into different categories, and identify new trends. in general, object tracking is a challenging problem.
"Prajna Parimita Dash, Dipti patra, Sudhansu K. Mishra, Jagannath Sethi" [3] proposed a kernel based object tracking using color histogram technique has been applied for different challenging situations.
"Dorin Comaniciu, V. Ramesh, Peter Meer" [4] proposed a method for object tracking in this method central computational module is based on the mean shift iterations and finds the most probable target position in the current frame.
"Yuri Boykov, Daniel P. Huttenlocher" [5] presented a framework base on the adaptive Bayesian recognition technique for tracking of rigid object. This framework incorporates dependence between object characteristics (features).
"Tang Sze Ling,Liang Kim Meng,Lim Mei Kuan,Zulaikha Kadim and Ahmed A. Baha'a Al-Deen" [6] proposed a method that is explain the features of the motion tracker based on color it is used as the key-feature to compare the similarity of object. At first a motion map is produced which explain the foreground and background.
"Quan Miao,Guijin Wang,Xinggang Lin,Yongming Wang,Chenbo Shi,Chao Liao" [7] proposed a robust feature-based tracking scheme by applying adaptive classifiers to match the detected key points in sequential frames .
"Mahbub Murshad, Md. Habanul Kabir, Okbam Chae" [8] presented a tracking algorithm based on, which is used for identifying the moving objects in image sequence.
"Dorin Comaniciu, Visvanathan Ramesh, Peter Meer" [9] proposed a method towards target representation and localization. The target representation based on feature histogram is regularized by spatial masking with an isotropic kernel.
"Zhiyu Zhou, Kaikai Luo,Yaming Wang, Jianxin Zhang" [10] gave an object tracking method, mixed with color histogram, scale invariant feature transform (SIFT) and the motion prediction based on α-β-Υ filter is used.
"David G. Lowe" [11] proposed an approach to extract typical uniform features from images that is used to perform reliable matching between different views of an object or scene.
"Peshala V. Pahalawatta, T. N. Pappas,and Aggelos K. Katsaggelos" [12] presented an unscented Kalman filter framework for solving the object tracking and data fusion problem with many imaging sensors in a computationally effective way, and use a look ahead algorithm for optimization of the sensor selection based on the predicted trajectory of the target. Simulation results present the effectivity of this method of sensor selection.
"Alper Yilmaz,Xin Li, and Mubarak Shah" [13] proposed a tracking approach that keep track of the complete object regions, adapts to changing visual attributes, and handles occlusions..
"Kevin Murphy,Antonio Torralba,Daniel Eaton, and William Freeman" [14] proposed a scheme for detecting objects using an object's local and global feature.
"Alper Yilmaz" [15] gave a method of object tracking for ameliorating the tracking performance by using asymmetric kernel.
"P. Perez,C. Hue, J. Vermaak, and M. Gangnet" [16] presented a new Monte Carlo tracking technique inside a probabilistic framework, depending on the principle of color histogram distance.
"Jeongho Shin,Sangjin Kim, Sangkyu Kang, Seong-Won Leec, Joonki Paik,Besma Abidi, Mongi Abidi" [17] presented a feature-based object tracking algorithm using optical flow under the non-prior training (NPT) active feature model (AFM) framework. In this tracking procedure can be split into three steps: (i) localization of an object of interest, (ii) prediction and correction of the object's position by utilizing spatio temporal information, and (iii) restoration of occlusion using NPT-AFM.
"Lixin Fan" [18] proposed a robust tracking approach this approach stores representative object appearances as candidate templates during tracking, and selects the best template to match new frames.
"Ard Oerlemans and Bart Thomee" [19] presented an object tracking system which allows interactive user feedback to increase the accuracy of the tracking process in real- time video.
"Xiuwen Liu and DeLiang Wang" [20] proposed a filter selection algorithm to maximize classification performance of a given data set.

"Derek Hoiem , Alexei A. Efros, Martial Hebert" [21] proposed a framework for placing local object detection in the context of the overall 3D scene by modeling the interdependence of objects, surface orientations, and camera viewpoint

III. METHODLOGY

This section discusses methodology with description of each step of proposed system and provides the design of the proposed system and implementation of system using different tools is also explained. Proposed method is described using mean shift object tracking algorithm and flow chart.

A. MEAN SHIFT OBJECT TRACKING

Mean shift object tracking is a non-parametric object tracking approach. It is imagined that the data in the feature space is sampled from an unknown probability density function (pdf) which is estimated.

1) PROBABILITY DENSITY FUNCTION

Application of mathematical principles and statistical analysis to digital image processing can reveal important information. The Probability Density Function (PDF) is a fundamental concept in statistical analysis which plays an important role in image processing. Given the probability density function of a random variable x, the probability that the value of x will fall within a given interval [a, b] is given as in equation (1)

$$P(a < x < b) = \int_a^b f(x)dx \qquad (1)$$

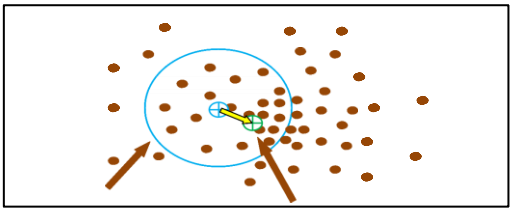
2) HISTOGRAM METHODS

PDF is estimated using histogram. In the one-dimensional case, one can divide the x-axis into successive bins and count the number of data points (observations) that belong to each bin. By dividing by the total number of data points, thereby one gets an estimation of the probability of a data point belonging in that bin. However, if the goal is to provide the estimate of the density in a particular point it is often better to place a bin so that the point was in its center. If these are n be number of data points, X={x1, x2,….xn} and defined the bins to have a width h, to find an expression for pdf at point x. Firstly the indicator function is defined, which find that the point x belongs to that particular bin or not then pdf estimation is written.

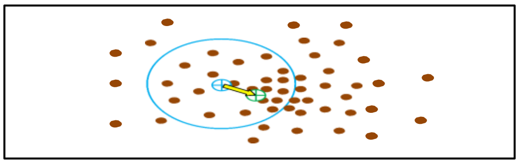
3) THEORETICAL DESCRIPTION OF MEAN SHIFT

For feature description Classic mean shift object tracking uses only color histogram. When the scale of target changes tracking of target is failed. When there is color aberration due to light changing and similar color background then there is problem of target tracking. There is another drawback of classic mean shift is due to appearance description. Color histogram and feature descriptor are complementary to each other that means when one of them is fail to track any features of the target then second one can track it.

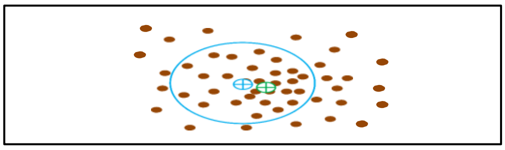
Shifting of center is displayed in Fig.1. It shows shifting of center to more dense area using mean shift approach. The mean shift window shifts to a denser region of the data set after each iteration until convergence. The meaning of convergence the distance between previous mean and present mean is smaller than a given threshold. Fig.1(a) shows the two centers, one is center of local features and other is the center of window. Fig. 1(b) shows output after some iterations in which center of window shifted towards denser region of features. Fig.1(c) shows condition of convergence.



(a)



(b)



(c)

Fig.1 Shifting of Center

B. KERNEL BASED OBJECT TRACKING

Kernel based object tracking is based on the computation of the translation of an object from one frame to another frame (next frame). In this type of approach a geometric shape is primitively chosen as kernel. Translation is computed by maximizing the likelihood between the current and the previously observed frame. Methods of object tracking based on object tracking are estimate motion of an object. Object is represented by a geometric shape. In tracking process constancy of object appearance, frame by frame is exploited. To compute motion of object, mode of the appearance distribution function is used. These methods assign weights to each pixel according to their appearance likelihood ratio between the target model and the candidate distribution.[1] To locate the new position of object these pixel weights are used. Using these pixel weights density gradient are calculated in the image coordinates. In this approach mean shift iterations are used for tracking.

C. MEAN SHIFT TRACKER

Mean shift is a non-parameter density estimation method. By iterative searching it finds the maximum similar distribution pattern with sample pattern. Mean shift is applied for target tracking by calculating similarity between features of target model and candidate model.[2] Mean shift algorithm has two parts. In one part it prepares a target appearance descriptor and in second part it tracks the target object using mean shift tracking. In classic mean shift similarity between target color histogram and candidate color histogram is calculated. In this at first frame target color histogram is prepared. After this the candidate area which has maximum similarity with target area is found. To calculate maximum similarity mean shift is used. Steps of mean shift tracking are: extract the candidate region which is most similar to target region, extract color histogram of candidate region calculate similarity measure function, calculate shift vector. Using non-parameter density estimation shift vector maximize the similarity between target histogram and candidate histogram. Mean shift algorithm is iteratively converge to the maximum similar candidate area with target.
Classic mean shift has some advantages as it gives good real time performance, good search efficiency; it is insensitive to non-rigid deformation, partial occlusion and overlap. It uses color histogram for feature representation which is invariant to rotation. Color histogram is also robust to partial occlusion. Classic mean shift also has advantage of color histogram. It has some drawbacks due to fixed kernel bandwidth. When the target scale changes tracking of target is failed. When there is color aberration due to light changing and similar color background then there is problem of target tracking. Some improved methods are introduced in reference [22-24]. There is another drawback of classic mean shift is due to appearance description. It uses color histogram as appearance descriptor; color features cannot provide enough information about the target. To fix this problem for appearance description with color histogram another feature descriptor is used. In an improved version of mean shift texture features are also used with color histogram for appearance description. Color histogram and feature descriptor are complementary to each other means when one is fail to track some features of the target then other one can track it.

IV. MEAN SHIFT ALGORITHM

Mean shift algorithm is performed mainly in two parts. In one part target appearance model is prepared and in another part tracking is take place.

A. TARGET APPEARANCE

Firstly target appearance model is prepared. This model is further used for target tracking by estimating maximum similarity between target model and candidate model.
Target representation in classical mean shift is done using color histogram, but in advanced mean shift target is represented using texture features and color histogram.

1) COLOR FEATURE DESCRIPTOR

Color features of target are described using color histogram. In color histogram each sub-space of RGB spaces is divided into k-intervals known as bins. Each interval consists of feature space. On the basis of data of pixels in target area probability of each bin is calculated. This probability is integrated into color histogram. After integration each pixel in target region are given a weight value. Inner pixels are more distinguishable than outer because of interference created by background. So inner pixels have given higher weight than outers.

Total number bins in feature space are m_c=k^3.

The probability density of color feature space values u=1…….m_c is calculated as follows:

$$\hat{q}_{c_u} = C\sum_{i=1}^{n} k\left(\left\|\frac{x_0-x_i}{h}\right\|^2\right)\delta[c(x_i)-u] \qquad (1)$$

"Eq. (1)" is kernel density estimation expression. x_0 is the center of target area.

x_i =1………n are n pixels of the region.

k() is the monotone decreasing profile function. $\delta(x)$ is the delta function.

Role of $\delta[c(x_i)-u]$ is to find whether color value of x_i belongs to u-th bin or not. It returns value 1 if it belongs to u^{th} bin otherwise 0.

C is the normalization constant.

It is calculated as

$$C=\frac{1}{\sum_{i=1}^{n} k\left(\left\|\frac{x_0-x_i}{h}\right\|^2\right)} \text{ to ensure} \sum_{u=1}^{m} q_{c_u} = 1.$$

After calculating target appearance model, in later frames candidate appearance model is calculated.

$$\hat{p}_{c_u}(y) = C_h\sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta[c(x_i)-u] \qquad (2)$$

Where y is center of candidate region

$$C_h = \frac{1}{\sum_{i=1}^{n} k(\|\frac{y-x_i}{h}\|^2)} \text{ is normalization constant.}$$

2) *Texture Feature Description*

Texture feature description gives texture features of the target appearance and candidate appearance which is used in calculating similarity between target model and candidate model. These features are used with color histogram.
In this paper two approaches for texture feature description are compared:

a) **DISCRETE WAVELET TRANSFORM**

Discrete wavelet transform is used to extract texture feature of image. Using extracted wavelet coefficient histogram is calculated to adapt the mean shift framework.

It is an effective way in multi-resolution image processing. In this method first the image is decomposed into sub-image with different multi-resolution space and independent frequency band. Further processing is done on sub-image coefficient. In four sub-image of an image three are high-frequency sub-image and one is low frequency sub-image. For further processing low-frequency sub-image is used to produce four sub-images.

Statistical characteristic of low-frequency sub-image are similar to original image. High frequency sub-images represent the edges and texture of image.

Discrete wavelet coefficient of an image is calculated using following equation:

$$W_{sd}(x,y) = \frac{1}{\sqrt{M}} \sum_{y \in ROI} I(y) V_{sd}(y) \qquad (3)$$

Where V_{sd} the wavelet function, s is the scale, d is the direction number.

First obtain s*d sub-spaces of wavelet coefficient. After this divide each sub-space into j-intervals and calculate the probability of $m_t = s * d$ bins.

After this probability density of texture feature space values u=1…m_t is estimated as follows:

$$\hat{q}_{t_u} = C \sum_{i=1}^{n} k\left(\left\|\frac{x_0 - x_i}{h}\right\|^2\right) \delta[t(x_i) - u] \qquad (4)$$

Candidate region's probability density of texture feature space values u=1…m_t is estimated as follows:

$$\hat{p}_{t_u}(y) = C_h \sum_{i=1}^{n_h} k\left(\left\|\frac{y - x_i}{h}\right\|^2\right) \delta[t(x_i) - u] \qquad (5)$$

b) Local Binary Pattern

The LBP operator labels the pixel in an image by thresholding its neighbor-hood with the center value and considering the result as a binary number (binary pattern). The general version of the LBP operator is defined as follows:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \qquad (6)$$

g_c corresponds to the gray value of the center pixel, (x_c, y_c) is center pixel of a local neighborhood.

g_p is the gray values of P equally spaced pixels on a circle with radius R.

Function s(x) is defined as:

$$S(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

The gray-scale and rotation invariant LBP texture model is obtained by

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & if\ U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \qquad (7)$$

Where

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

"*riu2*" means that the rotation invariant "uniform" patterns have a U value of at most 2. By definition, the P +1 "uniform" binary pattern occur in a circularly symmetric neighbor set of P pixels. Above equation assigns a unique label to each of them corresponding to the number of "1" bits in the pattern (0 to P), while the "non uniform" patterns are grouped under the "miscellaneous" label (P + 1).

In order to make LBP more robust against subtle changes in pixel values, the thresholding strategy in the LBP operator is modified by replacing the term $s(g_p - g_c)$ with $s(g_p - g_c + a)$. The greater the value of $|a|$ is, the higher fluctuations in pixel values are allowed without affecting much the thresholding result. The LBP feature of each point in the image region, whose value is between 0 and 9 is calculated. Thus an appearance model combining the color and texture is constructed and it consists of color channel and LBP texture pattern. The $LBP^{riu}_{8,1}$ model has nine uniform texture patterns. Each of the $LBP^{riu}_{8,1}$ uniform patterns is regarded as a micro-texton. The local primitives detected by the $LBP^{riu}_{8,1}$ model include spots, flat areas, edges, line ends and corners, etc. In target representation, the micro-textons such as edges, line ends and corners, by name of "major uniform patterns", represent the main features of target, while spots and flat areas, called "minor uniform patterns", are minor textures. The main uniform patterns of the target are extracted by the following equation:

$$LBP_{8,1}^{riu\,2} = \begin{cases} \sum_{p=0}^{7} s(g_p - g_c + a)\; U(LBP_{8,1}) \le 2 \; and \\ \sum_{p=0}^{7} s(g_p - g_c + a) \in \{2,3,4,5,6\} \\ 0 \qquad\qquad otherwise \end{cases} \tag{8}$$

In LBP$^{riu}{}_{8,1}$, the labels corresponding to minor uniform patterns are 0, 1, 7 and 8 respectively, and the label of non uniform patterns is 9. The labels corresponding to main uniform patterns are 2–6, which have five patterns. This equation groups the minor uniform patterns as non uniform patterns. Generally, the main LBP features of a target are more important than its minor features to represent the target. First this equation is used to form a mask and then the color and LBP features within this mask are used to model the target appearance model.

B. TARGET TRACKING

With the descriptions of target and candidate, the similarity between them can be calculated using similarity measure function. The tracking process is achieved by the search in the current frame to maximize the similarity function to obtain the location of target. The color texture integrated similarity is defined as:

$$\hat{\rho}_{com}(y) \equiv \sum_{u=1}^{m_c} \sqrt{\hat{p}_{c_u}(y)\hat{q}_{c_u}} \sum_{u=1}^{m_t} \sqrt{\hat{p}_{t_u}(y)\hat{q}_{t_u}} \tag{9}$$

To maximize $\hat{\rho}_{com}$, the target central position in last frame y_0 is taken as initial candidate center in current frame, then searching the best match of the target from this initial center. Then based on Taylor series expansion of the integrated formula $\hat{\rho}_{com}$ can be approximated as:

$$\hat{\rho}_{com} = \frac{C_h}{2} \sum_{i=1}^{n_h} w_i k\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \tag{10}$$

Where

$$w_i = \sum_{u=1}^{m_t} \sqrt{\hat{p}_{t_u}(y)\hat{q}_{t_u}} * \sum_{u=1}^{m_c} \sqrt{\frac{\hat{q}_{c_u}}{\hat{p}_{c_u}(y_0)}}\,\delta[c(x_i)\; u] + \sum_{u=1}^{m_c} \sqrt{\hat{p}_{c_u}(y)\hat{q}_{c_u}} * \sum_{u=1}^{m_c} \sqrt{\frac{\hat{q}_{t_u}}{\hat{p}_{t_u}(y_0)}}\,\delta[t(x_i) - u$$

Using mean shift algorithm, the candidate center y_1 re-positioned in each iteration is calculated as follow:

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i w_i g\left(\left\|\frac{y_0-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} w_i g\left(\left\|\frac{y_0-x_i}{h}\right\|^2\right)} \tag{11}$$

V. COMPARISON OF LBP AND DWT

Anyone of the LBP and DWT can be used for texture feature extraction in video tracking. Features extracted using one of these methods is are used with color histogram for target tracking. Texture features are integrated with color histogram; integrated features are used for feature description of target region and candidate region.

In this paper LBP and DWT are compared. This paper concludes which one is better for texture feature extraction in video tracking.

A. OUTPUTS SHOWING THE DIFFERENCE BETWEEN TWO METHOD

Figure 2 shows output using LBP and Figure 3 shows output using DWT of same image.

Figure 2 Output of LBP method

Figure 3 Output of DWT methods

As it can be seen from the Figure 1, and Figure 2, DWT gives better output in comparison of LBP. Computing time taken by LBP is 0.102669 seconds and time taken by DWT is 0.225109 seconds

.

Table 1 Comparison of LBP and DWT

Features	LBP	DWT
Output	goo d	Better than LBP
Implementation	Difficult in comparison	Easy
Computing Time	Less time consuming	More time consuming

VI. Conclusion

Video tracking using features of target, need more information other than provided by color histogram for better output. Color histogram has some limitation such as similar background, to overcome these limitations texture features are too used for the feature description. This paper compares two approaches of texture feature extraction one is LBP (Local Binary Pattern) and other is DWT (Discrete Wavelet Transform). It concludes that DWT is better than LBP as it gives better output.

VII. References

1. Subhash Challa,M. R. Morelande,D. Musicki,Robin J. Evans, "FUNDAMETALS OF OBJECT TRACKING", Edition Ist ISBN-13: 978-0521876285 (31 july,2011).
2. A. Yilmaz, Omar Javed, Mubarak Shah," Object Tracking: A survey", ACM Comput. Surve. 38, 4, Article 13(Dec. 2006).
3. Prajna P. Dash,Dipti patra, Sudhansu Kumar Mishra, Jagannath Sethi," Kernel base Object Tracking use Color Histogram Technique", International Journal of Electronics and Electrical Engineering ISSN : 2277-7040Volume2 Issue 4(Apr 2012).
4. D. Comaniciu, V. Ramesh and P. Meer, "Kernel-based object tracking", IEEE Trans Pattern Analysis and MachineIntelligence 25(5) (2003) 564–575.
5. Yuri Boykov, Daniel P. Huttenlocher," Adaptive Bayesian Recognition in Tracking Rigid Objects", 2000 IEEE.

6. Tang Sze Ling,Liang Kim Meng,Lim Mei Kuan,Zulaikha Kadim and Ahmed A.Bahaa Al-Deen," Color based Object Tracking in Surveillance Applications", Proceedings of the International MultiConference of Engineers and ComputerScientists 2009 Vol I, Mar.18 - 20, 2009,Hong Kong
7. Quan Miao,Guijin Wang,Xinggang Lin,Yongming Wang,Chenbo Shi,Chao Liao," Scale and Rotation Invariant Feature-Based Object Tracking via Modified On-line Boosting", Proceedings of 2010 IEEE 17th International Conference on Image Processing, September 26-29, 2010, Hong Kong.
8. Mahbub Murshad, Md. Habanul Kabir, Okbam Chae," Moving Object Tracking –An edge segment based approach", International Journal of Innovative Computing, Information and Control, Volume 7, Number 7(A), July 2011
9. D. Comaniciu, V. Ramesh, P. Meer, "Real-Time Tracking of Non-Rigid Objects using Mean Shift", IEEE, 2000.
10. Zhiyu Zhou,Kaikai Luo,YamingWang,Jianxin Zhang," Object Tracking based on Multi-feature Fusion and Motion Prediction", Journal of Computational Information Systems 7: 16 (2011) 5940-5947
11. David G.Lowe," Distinctive Image Features from Scale-Invariant Keypoints", International Journal of ComputerVision 60(2), 91–110, 2004.
12. Peshala V. Pahalawatta, Thrasyvoulos N. Pappas, and Aggelos K. Katsaggelos, "Optimal Sensor Selection for Video-Based Target Tracking in a Wireless Sensor Network", IEEE 2004
13. Alper Yilmaz,Xin Li, and Mubarak Shah," Contour-Based Object Tracking with Occlusion Handling in Video Acquired Using Mobile Cameras", IEEE Transactions on pattern analysis and machine intelligence,volume 26, No. 11, NOV 2004
14. Kevin Murphy,Antonio Torralba,Daniel Eaton, and William Freeman," Object detection and localization using local and global Features", Category-Level Object Recognition, Vol. 1 (2005).
15. Alper Yilmaz," Kernel-based object tracking using asymmetric kernels with adaptive scale and orientation selection", Machine Vision and Applications (2011) 22: 255 –268.
16. P. Perez,C. Hue,J. Vermaak, and M. Gangnet," Color-Based Probabilistic Tracking", Springer-Verlag Berlin Heidelberg, 2002, pp. 661–675.
17. Jeongho Shin,Sangjin Kim, Sangkyu Kang, Seong-Won Leec, Joonki Paik,Besma Abidi, Mongi Abidi," Optical flow-based real-time object tracking using non-prior training active feature model", Real-Time Imaging 11 (2005), PP. 204 – 218.
18. Lixin Fan, "A Feature-based Object Tracking Method Using Online Template Switching and Feature Adaptation", Sixth International Conference on Image and Graphics, 2011.
19. Ard Oerlemans and Bart Thomee," Interactive Feedback for Video Tracking Using a Hybrid Maximum Likelihood Similarity Measure", Springer-Verlag Berlin Heidelberg 2007.
20. Xiuwen Liu, DeLiang Wang," Texture Classification Using Spectral Histograms", IEEE Ttansactions on image, volume. 12, No. 6, JUNE 2003
21. Pandey A.,Bansal K.K.(2014): "Performance Evaluation of TORA Protocol Using Random Waypoint Mobility Model" *International Journal of Education and Science Research Review* Vol.1(2)
22. Tiwari S.P.,Kumar S.,Bansal K.K.(2014): "A Survey of Metaheuristic Algorithms for Travelling Salesman Problem " *International Journal Of Engineering Research & Management Technology* Vol.1(5)
23. Derek Hoiem, Alexei A. Efros, Martial Hebert," Putting Objects in Perspective", Springer Science Business Media, LLC 2008.
24. T.L.Liu, and H.T. Chen, Real-time tracking using trust-region methods (IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, No. 3,pp. 397-402,2004)
25. R.T. Collins, Mean-shift Blob Tracking through Scale Space, (IEEE Conference on Computer Vision and Pattern Recognition, Vol. 2,pp. 234-240,2003)
26. Z. Zivkovic and B. Krose, An EM-like algorithm for color-histogram-based target tracking (IEEE Conference on Computer Vision and Pattern Recognition, pp.789-803,2004)