1. Introduction

Visual object tracking is an important task within the field of computer vision applications such as surveillance [1],[2],[3], perceptual user interface[4], pedestrian protection systems[5], smart rooms[6] and other applications. Itaims at locating a moving object or several ones in time using a camera. An algorithmanalyses the video frames and outputs the location of moving targets within the videoframe. So it can be defined as the process of segmenting an object of interest from avideo scene and keeping track of its motion, orientation, occlusion etc. in order toextract useful information by means of some algorithms. Its main task is to find andfollow a moving object or several targets in image sequences.

Visual object tracking follows the segmentation step and is more or less equivalentto the "recognition" step in the image processing. Detection of moving objects in videostreams is the first relevant step of information extraction in many computer visionapplications. There are basically two types of approaches in visual object tracking: Deterministic methods [7] and probabilistic methods [8]. The mean shift tracking is one of the deterministic methods that has gained much our attention in past few years because its robustness and low complexity.

The Mean shift is a non-parametric density estimation method which finds the most similar distribution pattern with a simple pattern by iterative searching. Mean Shift is a powerful and versatile non parametric iterative algorithm that can be used for lot of purposes like finding modes, clustering etc. Mean Shift was introduced in Fukunaga and Hostetler [22] and has been extended to be applicable in other fields like Computer Vision.

Mean shift considers feature space as an empirical probability density function. If the input is a set of points then Mean shift considers them as sampled from the underlying probability density function. If dense regions (or clusters) are present in the feature space, then they correspond to the mode (or local maxima) of the probability density function.For each data point, Mean shift associates it with the nearby peak of the dataset’s probability

density function. For each data point, mean shift defines a window around it and computes the mean of the data point. Then it shifts the centre of the window to the mean and repeats the algorithm till it converges. After eachiteration, we can consider that the window shifts to a denser region of the dataset.

Mean shift algorithm climbs the gradient of a probability distribution to find the nearest domain mode (peak)

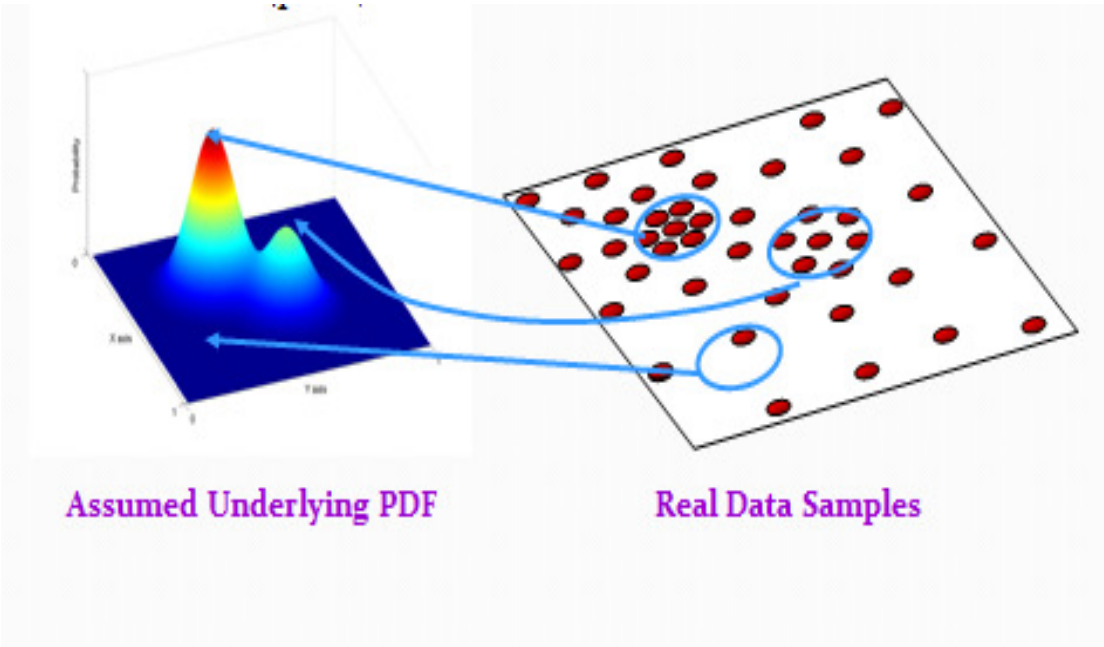


Figure 1: *Gradients of probability density function corresponding to the densities of points.*

The mean shift is applied in real-time object tracking is published in [9] namedkernel basedobject tracking or mean shift tracking. The size and shape of the interest area isusually described by kernel function. The most used kernel function is Epanechnikov kernel [23] and its kernel profile is

$$( ) = \begin{cases} \frac{1}{2} & ^{-1}(+ 2)(1 - \| \|^2) , \quad \| \| \leq 1 \\ 0 & , \quad \end{cases} \tag{1}$$

The biggest advantage of mean shift tracking is that the computational costis much cheaper than other matching method because the dense gradient climbing approachis used rather

than the brute-force searching approach. Therefore, it became one of the mostpopular object tracking algorithms for its low computational cost and robustness.

Despite the popularity of the mean shift algorithm, there are still several disadvantage ofit. First, the spatial information of the object is not strongly encoded in the representation ofthe object, thus the scale and orientation information of the object will be lost during tracking.Second, the mean shift tracking algorithm uses a static model of the objectwhich assumes that the object will not change its outlook much which is not true in the realenvironment. For example, one can easily fail a mean shift tracker by rotating the trackedobject to the other side (suppose that the two sizes of the object are different which is truefor most of the cases). The third and an important one is that itassumes that the object will not move more than its own size between 2 consecutive frames,thus searching window size is limited to the size of the object. This decreases the computationalcost and the distraction of the background, but makes it less robust for the case of abruptchange in objectmotion.

In our work, we have presented a new mean shift tracking algorithm integrating texture and color features with frame differencing. The proposed frame differencing with color and texture-based target representation based on co-occurrence distribution and discriminant Haralick texture features that are more appropriate for tracking the target in complex situations as like illumination changes, occlusion, abrupt object location changes etc.

2. Related Work

Comaniciu et al.[9]apply the mean shift method to feature space analysisfor object tracking. The feature histogram-based target representations are regularized by spatial masking with an isotropic kernel. Themasking induces spatially-smooth similarity functions suitable for gradient-based optimization.Hence, the target localization problemcan be formulated using the basin of attraction of the local maxima. They employ a metric derived from the Bhattacharyya coefficient assimilarity measure, and use the mean shift procedure to perform the optimization.Their semi-automatic method works bysearching in each frame for the location of the target region,where the color histogram is similar to the reference colorhistogram of the tracked target.

Leichter et al. [10] presentedan improved mean shift tracking algorithm based on multiplereference color histograms in which authors proposedto update the target model at tracking over time with multiplehistograms.In contexts where multiple views ofthe target are available prior to the tracking, this paper enhances the Mean Shift tracker to use multiplereference histograms obtained from these different target views. This is done while preserving both theconvergence and the speed properties of the original tracker. They first suggest a simple method to usemultiple reference histograms for producing a single histogram that is more appropriate for trackingthe target. Then, to enhance the tracking further, they propose an extension to the Mean Shift trackerwhere the convex hull of these histograms is used as the target model. Many experimental results demonstratethe successful tracking of targets whose visible colors change drastically and rapidly during thesequence, where the basic Mean Shift tracker obviously fails.This strategy still computationally expensiveand insufficient in several real world conditions, especiallyif the target color is similar to the background components' color at tracking over time.

Azghani et al. [11] suggestedan intelligent modified mean shift tracking algorithmusing a local search based on a genetic algorithm to improvethe convergence procedure. First, a background eliminationmethod is used to eliminate the effects of the background onthe target model. The mean shift procedure is applied only forone iteration to give a good

approximate region of the target. Inthe next step, the genetic algorithm is used as a local searchtool to exactly identify the target in a small window around theposition obtained from the mean shift algorithm. Thesimulation results prove that the proposed method outperformsthe traditional mean shift algorithm in finding the preciselocation of the target at the expense of slightly morecomplexity. However, their method still limitedaround the limitations of genetic algorithms and not robustin several conditions (e.g. light change etc.), because no information has been used to improve thetarget description, which is the major need of any tracker.

Ming-Yi et al. [12] presented an improved mean shift trackingalgorithm using a fuzzy color histogram. A fuzzy color histogram generated by a self-constructingfuzzy cluster is proposed to reduce the interference fromlighting changes for the mean shift tracking algorithm. Theexperimental results show that the proposed tracking approachis more robust than the conventional mean shift tackingalgorithm and the cost of increasing computation time is alsomoderate.Although it isa good idea to avoid the pre-defined color bins. The trackingtherefore may fail if the appearance of the object variessubstantially.

Peng et al. [13] proposed a target model updatingmethod in the mean shift algorithm, in which authorspropose to integrate an adaptive KALMAN filter into themean shift algorithm to update the target model and to handletemporal appearance changes. They propose a new adaptive model update mechanism for the real-time mean shift blob tracking.Kalman filter has been used for filtering object kernel histogram to obtain the optimal estimate of the object model because of its popularity in smoothing the object trajectory in the tracking system. The acceptanceof the object estimate for the next frame tracking is determined by a robust criterion, i.e. the result of hypothesis testingwith the samples from the filtering residuals. Therefore, the tracker can not only update object model in time but alsohandle severe occlusion and dramatic appearance changes to avoid over model update. They have applied the proposedmethod to track real object under the changes of scale and appearance with encouraging results.However, to update thetarget model in each frame makes the tracker computationallyexpensive and sensitive to occlusions and noise.

Jaideep et al.[14] proposed a robusttracking algorithm which overcomes the drawbacks of globalcolor histogram based tracking. They incorporate tracking based onlyon reliable colors by separating the object from its background. Afast yet robust update model is employed to overcome illuminationchanges. This algorithm is computationally simple enough to be executedreal time and was tested on several complex video sequences.

Object tracking based on Mean Shift (MS) algorithm[15] has been very successful and thus receives significantresearch interests. Unfortunately, traditional MS basedtracking only utilizes the gradient of the similarity function(SF), neglecting completely higher-order informationof SF. The paper regards MS based tracking asan optimization problem, and proposes to make use ofboth the Gradient and Hessian of SF. Specifically, They introduceNewton algorithm with constant, unit step andNewton with varying step lengths, and Trust region algorithm.The advantage of exploiting higher-order informationis that higher convergence rate and betterperformance are achieved.

The standard mean shift algorithmassumes that the representation of tracking targets is alwayssufficiently discriminative enough against background. Mosttracking algorithms developed based on the mean shift algorithmuse only one cue (such as color) throughout theirtracking process. The widely used color features are notalways discriminative enough for target localization becauseillumination and viewpoint tend to change. Moreover, thebackground may be of a color similar to that of the target. Wang et al. [16] present an adaptive tracking algorithm that integrates colorand shape features. Good features are selected and appliedto represent the target according to the descriptive ability ofthese features. The proposed method has been implementedand tested in different kinds of image sequences. The experimentalresults demonstrate that our tracking algorithm isrobust and efficient in the challenging image sequences.

[17] This paper extends the classic Mean Shift tracking algorithmby combining color and texture features. In the proposedmethod, firstly, both the color feature and the texture feature ofthe target are extracted from first frame and the histogram ofeach feature is

computed. Then the Mean Shift algorithm is runfor maximizing the similarity measure of each featureindependently. In last step, center of the target in the new frameis computed through the integration of the outputs of MeanShift. Experiments show that the proposed Mean-Shift trackingalgorithm combining color and texture features provides morereliable performance than single features tracking.

In spiteof all attempts [14–17] to improve the mean shift trackingalgorithm, the complex conditions of the real world remainthe biggest challenge, which require the use of a very powerfuland rich descriptor for better target representation. Untilnow, the proposed improvement into the mean shift trackerremains in target description by isolated pixels such as thecolor histogram and texture that lacks of spatial configurationof pixels. These features are insufficient and often invalidin practice, mainly in presence of noise, clutter, illuminationchange, and local deformation.

Contextual information playsan important role in objects description for objects recognition
[18], classification [19].Inter-frame context matching for object tracking hasbeen proposed recently by Ying and Fan [20], in which theauthors propose a new approach to extend the optical flow tocontextual flow. In their paper, the authors propose to matchnot only a brightness information but the visual context ofeach pixel, where the visual context is defined as a colorcontext and spatial relation between the interest pixel and itsneighborhood (e.g. edge direction); although that is a goodidea for matching a constant and invariant pattern especiallyin motion estimation, but still complicated and computationallyexpensive, especially in real time object tracking applications.

Bousetouane F. et al [21] believe that oneway to improve the tracking in complex conditions is notby using direct information from isolated pixels as the colorhistogram but through increasing the level of the target description.This level can be described through the exploitation of discriminating and invariant internal targets' propertiescomputed from local dependencies between a set ofpixels within the target region, such as: local variation, degreesof texture organization, rate of homogeneity, disorderdegrees, edge direction,

spatial context, color context, etc. technique is effective in real world conditions but it fails if there is a sudden change in speed of object in some frames as like in the caseof abrupt motion change.

3. The basic mean shift tracker

The mean shift algorithm is a simple iterative statistical method; firstly introduced by Fukunaga and Hostetler [22] for finding the nearest mode of a point sample distribution,

which produced good results in many applications such as segmentation and classification. Basic kernel based object tracking was presented by Comaniciu et al. [9] , they show that show that by spatially masking the target with an isotropic kernel, a spatially-smooth similarity function can be defined and the target localization problem is then reduced to a search in the basin of attraction of this function. The similarity between the target model and thetarget candidates in the next frame is measured using themetric derived from the Bhattacharyya coefficient. Here the Bhattacharya coefficient has the meaning of correlation between the reference model and target model. Authors proved that theobject center point in the mean shift algorithm could convergeto a stable solution.Method is based principally on two steps: target appearance description using color feature and the mean shift tracking procedure to estimate the new target location. The kernel profile is often used to describe the histogram which gives higher weight to pixels near the center of the tracking window. To estimate the new state of the target, we must minimize the distance between the histogram of the reference target at time*t* and the histogram of the candidate target at time*t* – 1. To compute this distance, a popular used distance is the Bhattacharyya coefficient.

3.1 Target representation using histogram:-

M-bin RGB color histogram is used to represent the appearance of the target region. The reference target model is represented by its colorprobability density function $\{[\ ]\}_{=1,2,\ldots}$ which estimates the color distribution of the target in reference frame is given by equation (2). Without the loss of generality, the target model can be considered at the spatial location 0.

$$= \sum_{=1} \left(\left| \ \right|^{2} \right) [\ (\ ) - \ ] \qquad (2)$$

Where $\{\ \}_{i = 1,2,\ldots\ldots n}$ be the normalized pixel locations in the region defined as the target model. And $(\ )$ is the epanechnikovkernel profile with property that that it is isotropic and it assigns smaller weights to pixels farther from the center and is the kronecker delta

function. The constant is the normalization constant, which is derived from the condition $\sum_{=1} = 1$ as

$$= \frac{1}{\Sigma_{=1} \left(\left| \left| \right| \right|^2 \right)} \quad (3)$$

And $( )$ denotes the index associated to the pixel location in the binned feature space.

The candidate target model is represented by the probability density function{ $_1 ( ))$,centered at y in the current frame. Using the same kernel profile and same bandwidth, the probability of the feature space is given by equation (4)

$$[\quad]_\downarrow ( ) = \quad _1 \Sigma_\downarrow (\quad = 1)^\dagger \doteq ([|| [\quad - \quad]_\downarrow / h ||]^2) \quad [(_\downarrow) - \quad] \quad (4)$$

Where the normalization constant isderived in same manner as for the $[(\quad]\}$ and is represented by equation (5) and the bandwidth h defines the scale of the target.

$$_1 h = 1/(\Sigma_1 (\quad = 1)^\uparrow \doteq ([|| [\quad - \quad]_\downarrow / h ||]^2)) \quad (5)$$

The similarity measure, Bhattacharya coefficient, is used to measure the similarity degree between reference target histogram and candidate target histogram.The Bhattacharya distance is defined as

$$( ) = \sqrt{1 - [( ), \quad]} \quad (6)$$

Where the Bhattacharya coefficient is

$$[( ), \quad] = \sum_{=1} \sqrt{ \quad ( )}$$

3.2 Target localization: tracking procedure

For finding the new location of target in current frame, the distance in (6) should be minimized and it is equivalent to maximizing the Bhattacharya coefficient. In the current

frame, the search for the new target location starts from estimated target location in the previous frame (assuming $y_{0)}$. Using Taylor series expansion of the Bhattacharya coefficient around $(\ _{0})$, the linear approximation with some manipulations is

$$[(),\ ] \approx \frac{1}{2}\sum_{=1}\sqrt{(\ _{0})} + \frac{1}{2}\sum_{=1}\ ()\sqrt{(\ _{0})} \qquad (7)$$

The approximation is satisfactory when the target does not change drastically from the initial, which is often a valid assumption between two consecutive frames. The centre of the window is recursivelymoved from the current location $_{0}$ to the new location $_{1}$ according to the equation

$$_{1} = (\Sigma_{}(\ =1)^{} \ K_{} \downarrow\ (\ \|(\ _{0} - \downarrow)/\|^{2})\ )/(\Sigma_{}(\ =1)^{} \ K_{} \ (\|(\ _{0} - \ _{}) \qquad (8)$$

Where $()= -\ '()$ and

$$= \sum_{=1}\sqrt{(\ _{0})}\ [(\ )- \ ] \qquad (9)$$

The mean shift will converge in real target location in limited iterations in the current frame.

3.3 Limitations of the basic mean shift tracker:

Despite the popularity of the mean shift algorithm and itsrobustness in some conditions, this algorithm has many limitationsthat we can mention:

1. The spatial relation between the set of pixels within interest target region is lost.
2. When the target has a similar appearance to the background, the mean shift tracker converges to a false position.

These defects are due to theuse of simple target appearance as a color histogram, whichis insufficient and very sensitive to clutter interference, illuminationchanges, abrupt change in object's location.

4. Target representation using texture

As discussed in last section that the basic mean shift tracker, that uses only color as a feature, is failed in many situations like illumination changes in background, clutter interference, occlusion and abrupt location change of object. Bousetouaneet. al [21] tried to make the basic mean shift tracking algorithm more robust by combining gray level co-occurrence based texture features to the color in complex real world conditions. They suggested a new texture based target representation for better and discriminant target description. Texture analysis is one of the most used techniques in several areas to describe the spatial context of pixels within a specific region at different levels.

4.1 Texture analysis:

Texture analysis [24] is very important for machinevision system. It has no specific definition to identify.Vision researchers define texture definition in differentway. Texture analysis makes an important role inmedical image analysis (such as distinguishing normaltissue from abnormal tissue, X-ray images, normal),remote sensing, surface inspection, documentprocessing etc.

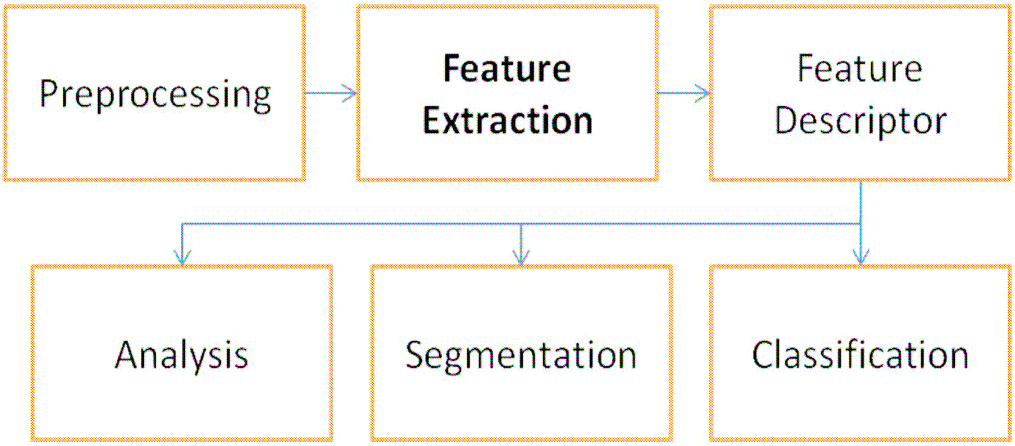


***Figure2**: A simple flow-diagram that depicts the position of feature extraction for various applications*

For texture analysis we have toconsider step by step process like feature extraction,texture discrimination, texture classification and shapefrom texture. Feature extraction is the first step of imagetexture analysis. It calculates a characteristic of a digitalimage able to

numerically explain its texture properties. This numerically obtain data are used for texturediscrimination, texture classification or object shapedetermination.

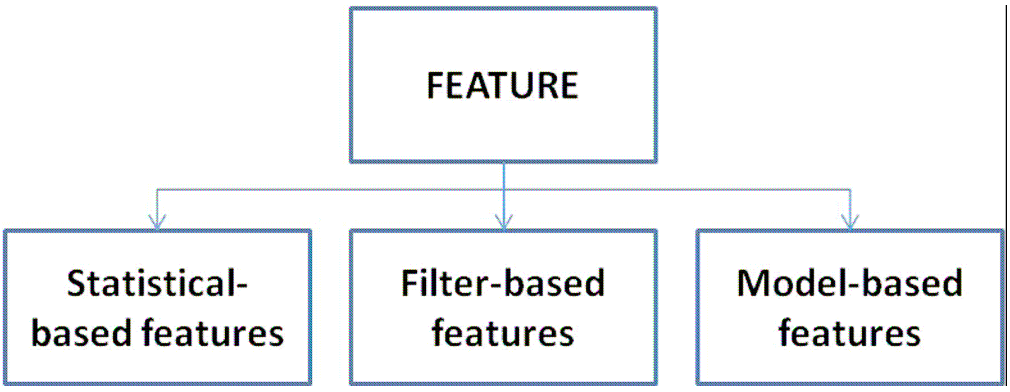


***Figure 3**: Classification of features into three areas*

4.1.1 Statistical methods:

Statistical-based features can be arranged in threedifferent types, namely – 1st-order statistics, 2nd-orderstatistics and higher-order statistics (Fig. 3). In thissection, we present key statistically-produced features.

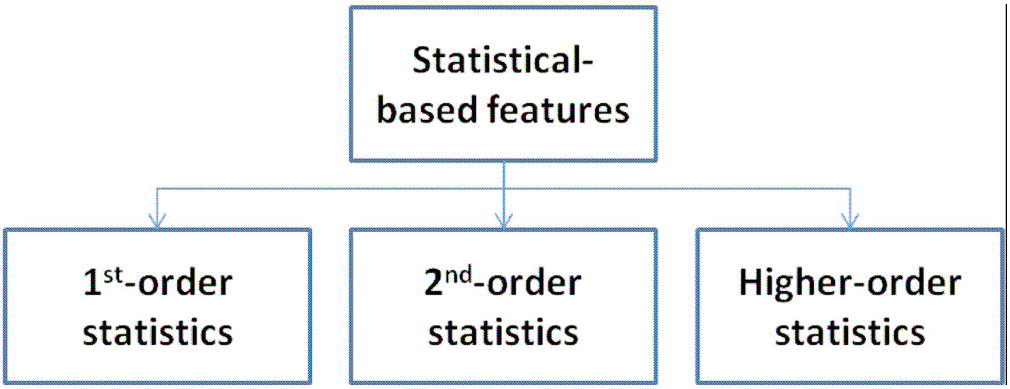


***Figure 4:** Statistical-based features.*

4.1.1.1 First Order Histogram Based Features:

First Order histogram provides different statisticalproperties such as 4 statistical moments of the intensity histogram of an image. They depend only onindividual pixel values and not on the interaction orco-occurrence of neighbouring pixel values. Four firstorder histogram statistics are Mean, Variance, Skewness and Kurtosis.A histogram h for a gray-scale image $I$with intensity values in the range $I(x, y) \in [0, K-1]$would contain exactly K entries, where for a typical8-bit gray scale image, $K = 2^8 = 256$. Each individualhistogram entry is

defined as,$h(i)$ = the *number* of pixels in I with the intensity value I for all $0 \leq i < K$. We can redefine histogram as,

$h(i) = card\{(x, y) | f(x, y) = i\}$ (10)

Where$card\{\ldots\}$ denotes the number of elements("cardinality") in a set. The standard deviation (s.d.) andskewness of the intensity histogram are defined as:

$$\ldots = \sqrt{\Sigma(\ ,\ ) - \ )^2} \qquad (11)$$

$$= \frac{\Sigma(\ ,\ ) - \ )^3}{(\ .\ .)^3} \qquad (12)$$

4.1.1.2. Second Order Grey Level Co-occurrence Matrix Features:

The GLCM is a well-established statisticaldevice for extracting second order texture informationfrom images. Second order statistics, called Gray LevelCo-occurrence Matrix (GLCM). It is a way of extracting2nd order statistical texture features. A GLCM is amatrix where the number of rows and columns is equalto the number of distinct gray levels or pixel values inthe image of that surface. GLCM is a matrix thatdescribes the frequency of one gray level appearing in aspecified spatial linear relationship with another graylevel within the area of investigation.

Given an image, each with an intensity, the GLCMis a tabulation of how often different combinations ofgray levels co-occur in an image or image section.Texture feature calculations use the contents of theGLCM to give a measure of the variation in intensity(i.e., image texture) at the pixel of interest. Typically,the co-occurrence matrix is computed based on twoparameters, which are the relative distance between thepixel pair d measured in pixel number and their relativeorientation θ. Normally, θ is quantized in four directions(e.g., 0º, 45 °, 90 ° and 135 °), even though various othercombinations could be possible.

If we have animage that contains $N_g$gray levels from 0 to N_g–1, and ifwe consider $f(p,q)$ is the intensity at sample p, line qofthe neighborhood, then we can have the gray levelco-occurrence matrix as,

$$(, |\Delta ,\Delta) = \quad (, |\Delta ,\Delta) \tag{13}$$

Where

$$= \frac{1}{(-\Delta)(-\Delta)} \text{and} \quad (, |\Delta ,\Delta) = \sum_{=1}^{-\Delta} \sum_{=1}^{-\Delta}$$

$$= \begin{cases} 1 & (,) = \quad (+\Delta , \ +\Delta) = \\ 0 & \end{cases}$$

Where *(m,n)* is the size of the target, *(p,q)* is the gray level target and *f* is the gray level image. To use this co-occurrence matrix,fourteen metrics have been defined by Haralick [26] , whichcorrespond to global descriptions metrics of texture in specificareas (i.e. these metrics describe the nature of the spatialdependencies between the set of pixels which composes the target). The most useful features [25] out of fourteen features are: angular second moment (ASM), contrast, correlation, entropy, Inverse difference moment and dissimilarity.

Angular second Moment (ASM):

$$= \sum_{=1} \sum_{=1} \quad ^{2} \tag{14}$$

It is also known as energy, uniformity, and uniformity ofenergy, returns the sum of squared elements in theGLCM. ASM ranges from 0.0 for an image with manyclasses and little clumping to 1.0 for an image with asingle class.

Contrast:

$$= \sum_{=1} \sum_{=1} (-)^{2} \quad ^{2} \tag{15}$$

It provides a measure of the intensity contrast between apixel and its neighbour over the whole image. Contrast isalso known as variance and inertia.

Correlation:

$$= \sum_{=1}\sum_{=1} \frac{(-)*(-)*}{^{2}} \quad (16)$$

Where $= \sum_{=1}\sum_{=1} *$ and $= \sum_{=1}\sum_{=1} *(-)^{2}$

It returns a measure of how correlated a pixel is toits neighbor over the whole image.

Entropy:

$$= -\sum_{=1}\sum_{=1} *\log( ) \quad (17)$$

Entropy is a measure of information content. Itmeasures the randomness of intensity distribution. It is astatistical measure of randomness that can be used tocharacterize the texture of the input image. Thenormalized GLCM is the joint probability occurrence ofpixel pairs with a defined spatial relationship havinggray level values of an image.

*Inverse Difference Moment:*periodic texture in the direction of the translation.

$$= \sum_{=1}\sum_{=1} \frac{}{1+| - |^{2}} \quad (18)$$

Dissimilarity: low value characterizes the homogeneous texture of the target.

$$= \sum_{=1}\sum_{=1} *(-) \quad (19)$$

4.1.1.3 Gray Level Run Length Matrix Features:

The grey level run-length matrix (RLM) is definedas the numbers of runs with pixels of gray level *i* andrun length j for a given direction. GLRLMgenerate for each sample image fragment. A set of consecutive pixels with the same gray level is called agray level run. The number of pixels in a run is therun-length. In order to extract texture features gray levelrun length matrix (GLRLM) are computed. Eachelement, *ij r* of the GLRLM

represents the number ofruns of gray level *i* having length *j*. GLRLM can becomputed for any direction. Five features derived fromthe GLRLM. These features are: Short Runs Emphasis(SRE), Long Runs Emphasis (LRE), Grey LevelNon-Uniformity (GLNU), Run Length Non-Uniformity(RLNU), and Run Percentage (RPERC). They are quiteimproved in representing binary textures.

4.1.1.4. Local Binary Pattern (LBP) Features:

Local binary pattern (LBP) operator is introducedas a complementary measure for local image contrast. The LBP operator associate statistical andstructural texture analysis. LBP describes the texturewith smallest primitives called *textons*(or, histograms oftexture elements). For each pixel in an image, a binarycode is produced by thresholding its neighbourhood (forinstance, the closest 8 pixels) with the value of thecenter pixel. A histogram is then assemble to collect upthe occurrences of different binary codes representingdifferent types of curved edges, spots, flat areas, etc.This histogram is arrangement as the feature vectorresult of applying the LBP operator. The LBP operatorconsiders only the eight nearest neighbours of each pixeland it is rotation variant, but invariant to monotonicchanges in gray-scale can be applied. Thedimensionality of the LBP feature distribution can becalculated according to the number of neighbours used.LBP is one of the most used approaches in practicalapplications, as it has the advantage of simpleimplementation and fast performance.

4.1.1.5. Autocorrelation Features:

An important characteristic of texture is therepetitive nature of the position of texture elements inthe image. Based on observation the autocorrelationfeature is computed that some textures are repetitive innature, such as textiles. The autocorrelationfeature of an image is used to evaluate the fineness orroughness of the texture present in the image. Thisfunction is related to the size of the texture primitive forexample the fitness of the texture. If the texture is roughor unsmooth, then the autocorrelation function will godown slowly, if not it will go down very quickly. Fornormal textures, the autocorrelation

function will show peaks and valleys. It has relationship with powerspectrum of the Fourier transform. It is also responsiveto noise interference.

4.1.2 Filter based methods:

4.1.2.1. Law's Texture Energy Features:

Laws presented his novel texture energy approach to texture analysis. According to the methodproposed by Laws, textural features that certainoperators such as Laplacian and Sobel operatorsaccentuated the underlying microstructure of texturewithin an image. This is the basis for a featureextraction scheme based a series of pixel impulseresponse arrays obtained from combinations of 1-Dvectors.

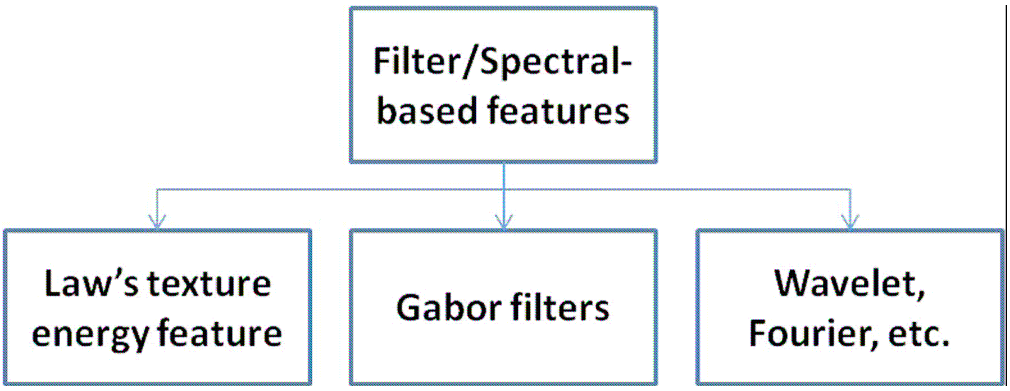


***Figure 5**: Filter or spectral-based features.*

The Law's masks are constructed by convolvingtogether just 3 basic 1x3 masks:

L3 = [1 2 1]

E3 = [-1 2 -1]

S3 = [-12 -1]

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

L5 = [14 6 4 1]

E5 = [-1 -2 0 2 1]

S5 = [-1 0 2 0 -1]

R5 = [1 -46 -4 1]

W5 = [-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 lettersare as before with the addition of Ripple detection andWave detection. These masks are subsequentlyconvolved with a texture field to highlight itsmicrostructure giving an image from which the energyof the microstructure arrays is measured together withother statistics.

4.1.2.2. Gabor Filter-based Texture Features:

The 2-D Gabor filters have been proved to be animportant tool in texture analysis. Theyconsist of a sinusoidal plane wave of some frequencyand orientation modulated by Gaussian envelope. AGabor filter is a band-pass filter which can be used toextract a specific band of frequency components from an image. Gabor functions appear to share manyproperties with the human visual system.Bank of Gabor filters are used to extract localimage features. An image is convolved with a 2D Gaborfunction to obtain a Gabor feature image, and byvarying spatial frequency and orientations, a bank ofdifferent Gabor filters can be produced. There arevarious Gabor features that can be exploited for featureanalysis, e.g., linear Gabor features (symmetric,anti-symmetric), thresholded Gabor features (symmetric,anti-symmetric), Gabor-energy features, etc. An inputimage $f(x, y)$, $x, y \in \Omega$ (Ω - the set of imagepoints), is convolved with two-dimensional Gaborfunction $g(x, y)$, $x, y \in \Omega$, to obtain a Gabor featureimage $r(x, y)$ as follows:

$$(,)=\iint(,)(-,-) \qquad (20)$$

The filter responses that result from the applicationof a filter bank of Gabor filters can be used directly astexture features, though none of the approachesdescribed in the literature employs such texture features.

4.1.2.3. Wavelet-based Feature:

Some transforms are developed to characterizelocalized frequencies specific to each pixel locationbased on various wavelet transform methods. Wavelettransform characterizes multiscale frequency content,called, wavelet coefficients, at each spatial location of an image. It can decompose image texture scale, i.e.,it can characterize textures at multiple scales. Themulti-resolution properties of Wavelet transforms arebeneficial for

accomplishing segmentation,classification and subtle discrimination of texture.However, the Wavelet transforms are usually computationally taxing. A tree-structured wavelettransform is proposed for texture analysis and classification.A simple Discrete Wavelet Transform representationcan capture small differences in rotation or scale. Someother representations on Wavelet transform can beDiscrete Wavelet Frame Transform (DWFT),Discrete Wavelet Packet Transform (DWPT),Modulus Maxima of a Continuous Wavelet Transform (MMWT), Multi-Orientation Wavelet Pyramid,Dual-Tree Complex Wavelet Transform, or scale,rotation, and translation invariant wavelets.

4.1.3. Model based methods:

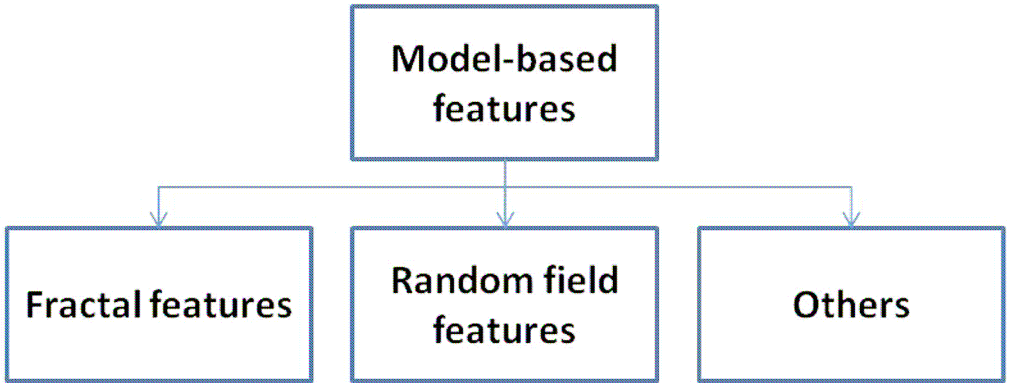


Figure 6: *Model Based Features*

4.1.3.1. Random Field Feature:

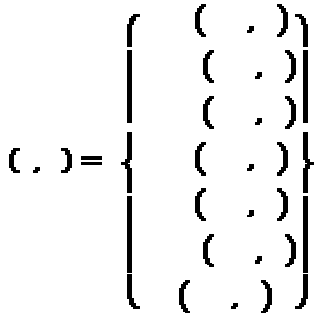
In some cases, image textures are modeled as aMarkov random field of pixels gray level. In thisapproach, relationships between the gray level ofneighboring pixels are statistically characterized.For example, a Gauss-Markov random field-basedprobabilistic texture model is developed to characterizehyperspectral textures. Another similar model isproposed for texture classification and texture segmentation. For Markov random field (MRF)models, the sufficient statistics of each sub-window canbe considered as the feature vector. There are few otherapproaches based on random fields. However,usually it is noticed that feature-based approaches areless computationally-expensive as well as moreeffective than Markov random field-based approaches.

4.1.3.2 Fractal Feature:

Fractal features can be considered to developdiscriminative and invariant features for textureclassification, especially in cases where scale changes are prominent in textures. Such variations canbe handled by choosing local interest points andselecting their characteristic scales. But, apart from theproblems related to have suitable local interest points, itis difficult to have an optimized characteristic scale thatcan be suitable for different textures of varied scales. It is found that fractal features demonstratepromising results while handling scaling constraint.However, fractal-based classification approaches do notconsider statistical characterizations of textures by usingglobal features. Moreover, they cannot differentiatebetween key texture elements (e.g., edges, corners, etc.).These issues can be overcome by evaluating denselylocal fractal features. It is shown that the local fractaldimension is invariant to local bi-Lipschitztransformations whereas its extension is able tocorrectly distinguish between fundamental texture primitives. Fractal models can classify irregulartextures too. A multi-fractal analysis is also proposed for texture descriptor.

4.2 Target representation:

Target representation with Haralick texture features, proposed by Bousetouaneet. al [21], is based on co-occurrence distribution and the spatial dependencies between the set of pixels with in the interest target region. It is represented by a vector of six selected Haralick texture features along with a metric computed by the combination of six selected features. The metric calculated is invariant to rotation, translation and scale change.All the features have been calculated in previous section (from equation (13) to equation (18)) from gray level co-occurrence matrix (GLCM) are Angular second moment (ASM), Contrast (CONT), Correlation (CORR), Entropy (ENT), Inverse difference moment (IDM), Dissimilarity respectively.The texture base target representation is denoted as



(20)

$$(\ ,\ +1)=\begin{Bmatrix}(\ ,\ +1)\\(\ ,\ +1)\\(\ ,\ +1)\\(\ ,\ +1)\\(\ ,\ +1)\\(\ ,\ +1)\\(\ ,\ +1)\end{Bmatrix} \qquad (21)$$

Where the vector $(\ ,\ )$ aggregates the selected Haralick texture features computed within the reference target region at time t. The target representation vector at time t+1 is computed within the candidate target region denoted by $(\ ,\ +1)$. In practice, vector model is the normalized with the help of mean and variance of vector as

$$\cdot = \frac{-}{\quad}, \ i = 1,2,\ldots\ldots,7 \qquad (22)$$

Here denotes the mean and is the standard deviation of the feature vector.

4.3 Similarity measurement for texture properties:

In basic mean shift, we calculate the similarity measurement between the reference target and the candidate target using Bhattacharya coefficient for the convergence of the classical mean shift tracker. Similarly in [21] Mahalanobisdistance [27] has been used to estimate the similarity measurement in the target representation at time $+1$ the vector $(\ ,\ +1)$ computed within the target region with reference target representation at time the vector $(\ ,\ )$ for convergence of the mean shift tracker.

4.3.1.Mahalanobis Distance:

Mahalanobis distance [28] is a distance measure introduced by P. C. Mahalanobis in 1936. It is based on correlations between variables by which different patterns can be identified and analyzed. It gauges similarity of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant.

In order to use the Mahalanobis distance to classify a test point as belonging to one of N classes, one first estimates the covariance matrix of each class, usually based on samples

known to belong to each class. Then, given a test sample, one computes the Mahalanobis distance to each class, and classifies the test point as belonging to that class for which the Mahalanobis distance is minimal. Mahalanobis distance and leverage are often used to detect outliers, especially in the development of linear regression models. A point that has a greater Mahalanobis distance from the rest of the sample population of points is said to have higher leverage since it has a greater influence on the slope or coefficients of the regression equation. Mahalanobis distance is also used to determine multivariate outliers. Regression techniques can be used to determine if a specific case within a sample population is an outlier via the combination of two or more variable scores.

4.3.2 Similarity measurement:

Target representation, containing 7 so-scaled Haralick texture features, represents the texture properties of the reference target at time t with vector $(\ ,\ )$ and at time time $+1$ the candidate target $(\ ,\ +1)$. For computing the distance between two targets representation vectors, Mahalanobis distance is given by

$$(\ ,\ _{+1}) = \sqrt{(\ -\ _{+1})\ ^{-1}[(\ ] -\ _{+1})} \qquad (23)$$

Where $= \frac{1}{-}\sum_{=1}(\ -\ )(\ -\ )$ and $= \frac{1}{-}\sum_{=1}$

Where is the mean vector and S is the covariance matrix of size n x n.

With the help of some experiments, Bousetouaneet al. [21] showed that the texture vector representation of target is better than color and some other descriptors also, and this is due to the proper exploitation of invariant and discriminant internal properties of the target computed through co-occurrence distribution and Haralick texture features such as: local variation of target intensity, disorder degree, local contrast distribution, organization degree of target texture, etc. All of these properties are discriminant and specific for any objects in the scene. The discriminatory and the invariance ability of the proposed target representation based texture features can be used for target description in other conditions

and configuration such as multi-target re-identification and inter-cameras matching in visual sensor network with overlapping or non-overlapping field of views.

Besides all these advantages, the algorithm [21] is unable to track the object if it changes the speed abruptly. So with the help of frame differencing for only those frames in which object's speed has been changed suddenly, we will be able to track the object. In next section we describe frame differencing in detail and the use of it in integrating with the color and texture in tracking algorithm.

5. Conclusion

Despite the improved mean shift algorithms presented by many researchers, proved to be robust in many tracking scenarios. However, there are many cases where the target location not defined when it is out of bound of window, or target represented by isolated pixels such as color histogram and texture that lacks of spatial dependencies between pixels, is still insufficient such as light change, non-homogeneous target, textured background, or the target location changes abruptly etc. we have presented a new mean shift tracking algorithm, In this paper, integrating texture and color features with frame differencing. The proposed frame differencing, that is able to find the location of target in case when it is lost due to abrupt motion change, with color and texture-based target representation based on co-occurrence distribution and discriminant Haralick texture features that are more appropriate for tracking the target in complex situations. Many experimental results and data show the effectiveness and the satisfaction of the proposed algorithm even in other capturing modalities. The proposed frame differencing with texture-based target representation and its combination with color distribution makes the classical mean shift more consistent and robust against very complex conditions. However, the proposed algorithm still has some limitations especially when the moving object is too small to be detected or the objects have same size and same color and texture as well. In other case if there is sudden change in location of object and background is dynamic as well, then frame differencing used in this technique fails because moving background is also treated as objects. These limitations can be solved by improving object's location finding algorithm and adding other information to the interested moving object such as a high-level spatial configuration of the tracked target. So, whatever, it would have its own texture model and spatial information that is different from the background and each other's objects. By considering these limitations and implementing some improvements to our algorithm, including the speed up of the processing time, could lead to some improvements in any tracking system. Future work includes making the object extraction algorithm using frame differencing more robust and exploring new criteria to measure the reliability of each feature and extending this framework to multiple object tracking.

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