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Unsupervised Tracking, Roughness and Quantitative Indices

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Abstract. This paper presents a novel methodology for tracking a single moving object in a video sequence applying the concept of rough set theory. The novelty of this technique is that it does not consider any prior information about the video sequence unlike many existing techniques. The first target model is constructed using the median filtering based foreground detection technique and after that the target is reconstructed in every frame according to the rough set based feature reduction concept incorporating a measure of indiscernibility instead of indiscernibility matrix. The area of interest is initially defined roughly in every frame based on the object shift in the previous frames, and after reduction of redundant features the object is tracked. The measure of indiscernibility of a feature is defined based on its degree of belonging (DoB) to the target. Three quantitative indices based on rough sets, feature similarity and Bhattacharya distance are proposed to evaluate the performance of tracking and detect the mis-tracked frames in the process of tracking to make those corrected. Unlike many existing measures, the proposed ones do not require to know the ground truth or trajectory of the video sequence. Extensive experimental results are given to demonstrate the effectiveness of the method. Comparative performance is demonstrated both visually and quantitatively.

Keywords: Rough Set, Unsupervised Tracking, Feature Reduction, Bhattacharya distance, moving object segmentation.

1. Introduction

In computer vision detection and tracking of moving objects is a very important problem. Application of object tracking in video sequences has been studied over the years. It is used to perform the tasks like

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motion based recognition, traffic monitoring and automated surveillance [29, 27, 13, 15]. In the task of object tracking there are different types of uncertainties and ambiguities. These arise due to the reasons like loss of information caused by projection of the 3D world on a 2D image, noise, complex object motion and presence of regions with similar features.

The ambiguities and uncertainties are handled in various ways, e.g., using statistical and probabilistic methods, fuzzy sets and fuzzy logic [8], kernel based method [5, 23]. Over the years researchers have been trying to improve the accuracy and speed both in detection and tracking. These methods can broadly be of two types. In one kind of approach prior knowledge about the number and the size of objects, or the object appearance and shape were required [29]. The other approach is based on background estimation [3, 25, 6, 12] which, in turn, needs several input frames available to approximate the background model. But, in practical scenario the prior knowledge is not always available. There may also not be enough input frames to estimate the background. We have taken into account the aforesaid issues and proposed a method for tracking which does not need prior knowledge about the sequence. We have shown rough set theory as an effective tool for handling the uncertainties.

Theory of rough sets [17] has recently become a popular mathematical framework for image processing problems [22, 16]. The focus of the theory is on the ambiguity caused by limited discernibility of objects in the domain of discourse. Its key concepts are those of object 'indiscernibility' and 'set approximation'. The primary use of rough set theory has so far mainly been in generating logical rules for classification and prediction [24]; thereby making it a prospective tool for various tasks including pattern recognition, image processing, feature selection, data mining and knowledge discovery from large data sets. Use of rough set rules based on reducts has significant role for dimensionality reduction/feature selection by discarding redundant features [26]; thereby having potential application for mining large data sets [11]. Rough set theory is an intelligent technique for managing uncertainty that is used for the discovery of data dependencies, to evaluate the importance of attributes, to discover patterns in data, to reduce redundancy, and to recognize and classify objects [9, 26, 28, 18]. Though the concept of rough set has been applied in several areas of pattern recognition, its use in the problem of object tracking has not been addressed adequately. For example, Dai *et al.* [7] used rough set rule reduction concept to control moving camera, Jalal *et al.* [10] performed the task of tracking using rough entropy in wavelet domain. Reduction of knowledge is very necessary to solve the problem of object tracking and rough set theory is proven to be effective for this task.

The objective of the present paper is to develop an unsupervised method using the concept of feature reduction in rough set theory for object tracking from a video sequence shot by a still camera without having any prior knowledge about the sequence and the object. It is assumed that, the object is moving neither very fast nor very slow from frame to frame initially; there is not much feature variation among object model in the initial frames neither due to external effect (such as, lightning change) nor due to object movement (such as change in color or shape); the object does not have huge color variation within itself and it does not have similar features as the background. The initial target is modeled using the median filtering based background estimation technique [6]. The problem of tracking has been depicted as a task of reducing a set of pixels from the current frame as closed to that in the target model using rough set theory. Here the degree of belonging (DoB) of a pixel to the object region is determined in terms of its color and spatial information. So, the issue of reduction of knowledge plays the key role here. This method of reduction of features also eliminates the other objects that might appear in the region of interest. Three measures based on rough set theory and pixel distribution to evaluate the performance of tracking have been defined. Unlike other measures [13, 2, 14, 15], the

proposed ones do not require the information of ground truth or the trajectory of the sequence. These indices reflect nearly similar results to those obtained by the measure based on ground truth (centroid distance). The measure based on Bhattacharya distance considers bins of unequal size to represent the target. Its appropriateness and effectiveness in detecting the mis-tracked frames vs. bins of equal size is also experimentally demonstrated. This measures are also used to detect the mis-tracked frames in the process of tracking and those results are corrected then by using the magnitudinous and directional object shift information from the previous frames.

The article is organized as follows. In Section 2 we have described the basic concepts and features of rough set theory required for the development of the proposed methodology. In Section 3 we have explained the method of tracking along with a block diagram. Section 4 describes the corresponding algorithm. Three new measures to evaluate the performance of tracking are defined in Section 5. Details of experimental results on different types of data sets with comparison are shown in Section 6. Comparison is made with mixture of Gaussian (MoG) and mean shift tracking methods. Section 7 concludes the article.

2. Rough Sets: Reduct and Core

Let $\mathcal{A} = \langle U, R\rangle$ be an information system. For a given set S, a subset of attributes, let R determines the approximation space $RS = (U, IND(R)$ in S. Let X be a set in universe U ($X \subseteq U$) to be approximated based on the set of equivalent relations ($[x]_R$) defined over R. Then, X is approximated as *R-lower approximation* $\underline{R}X$ and *R-upper approximation* $\overline{R}X$ in RS. They are defined as follows:

$$\underline{R}X = \{x \in U : [x]_R \subseteq X\} \tag{1}$$

$$\overline{R}X = \{x \in U : [x]_R \cap X \neq \emptyset\} \tag{2}$$

The pictorial representation of a rough set is shown in Figure 1. Here, the oval shaped area represents the set X to be approximated over the small rectangles or the set of equivalent relation $[x]_R$. The upper approximation $\overline{R}X$ of the set is represented by the larger light gray rectangular region and the lower approximation $\underline{R}X$ is represented by the dark gray and smaller rectangular region.

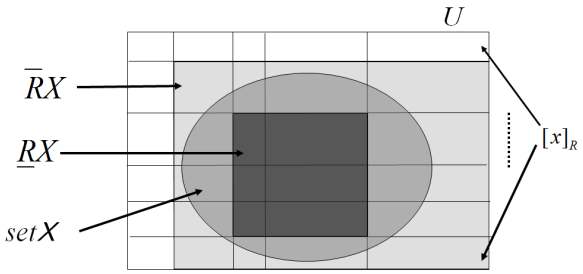


Figure 1. Rough representation of a set X

The equivalence relation plays an effective role to approximate a set. As one can see the equivalence relation is defined based on the subset of attributes R. All the attributes may not be necessary to define a proper equivalence relation. Certain attributes in an information system may be redundant and can

be eliminated without losing the essential classificatory/ discriminatory information. The procedure of eliminating those redundant equivalence relation from the point of view of rough sets is as follows.

Let **R** be a family of equivalent relations and let $R \in \mathbf{R}$. R will be said *dispensable* in **R** if $IND(\mathbf{R}) = IND(\mathbf{R} - \{R\})$, otherwise R is *indispensable* in **R**. The family of **R** is *independent* if each $R \in \mathbf{R}$ is indispensable in **R**, otherwise it is dependent. Suppose, $\mathbf{P} \subseteq \mathbf{R}$, **P** is independent and $IND(\mathbf{P}) = IND(\mathbf{R})$; then, **P** is called a *reduct* of **R**. **R** may have more than one reduct. The set of all indispensable relations in **R** is called the *core* of **R**. It can be shown that $CORE(\mathbf{R}) = \bigcap RED(\mathbf{R})$. This is how the knowledge can be reducted from a knowledge base [17].

2.1. Partial Dependency in Knowledge Base

Theorizing based on drawing inference about the world is another (other than classification) important task. In other words, the problem is - how knowledge can be induced from a given knowledge base.

If there is not enough information available for classifying all the data points in a given set, then some part of that set can be classified by employing the knowledge of some other classifications. That part of the set is known as *positive region* of the classification with respect to the other classification. It can be expressed as:

$$POS_P(Q) = \bigcup_{X \in U/Q} \underline{P}X \tag{3}$$

where, *P* and *Q* are equivalence relations over *U* and Equation (3) denotes *P* positive regions of *Q*. The dependency between P and Q is measured according to:

$$k = \gamma_P(Q) = \frac{cardPOS_P(Q)}{cardU} \tag{4}$$

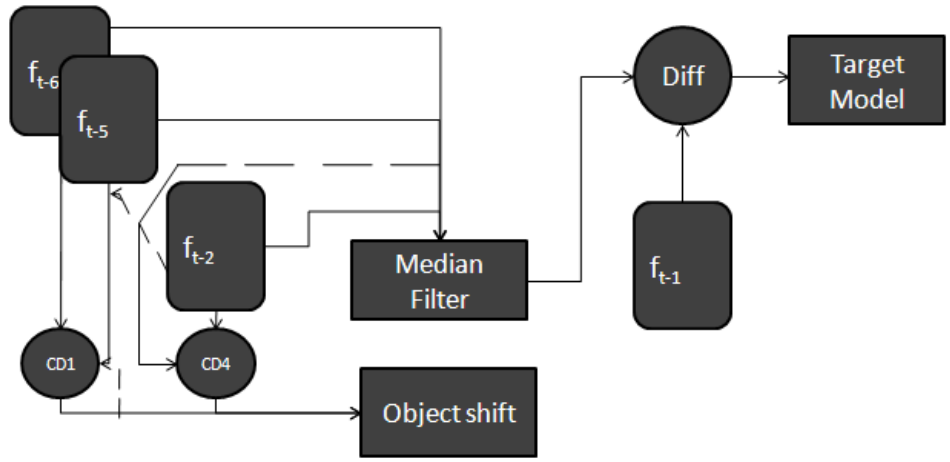
If $k = 1$ then all elements in the universe can be classified to the elementary categories of U/Q by emplyoing the knowledge of P. If $k \neq 1$ then only the elements within $POS_P(Q)$ can be classified.

All these concepts deal with incompleteness of knowledge. In case of object tracking in video sequences the knowledge is also incomplete. For example, the object location, its shape and size, and appearance of any other object in the area of interest may not be known to the tracker. To deal with these kinds of incompleteness we model the aforesaid concepts of rough set theory in order to track an object. It is expected that, the moving object will have almost similar features throughout the sequence and hence the reduct and core features of frames may give an idea about the object model. In case of practical application, the features with exactly same feature values may not be present in all the frames, rather it will deviate a bit from frame to frame. Hence, the concept 'Measure of Indiscernibility'is introduced here, based on which the reduct and core are found out in video . The details of all the implementations are discussed in the following section.

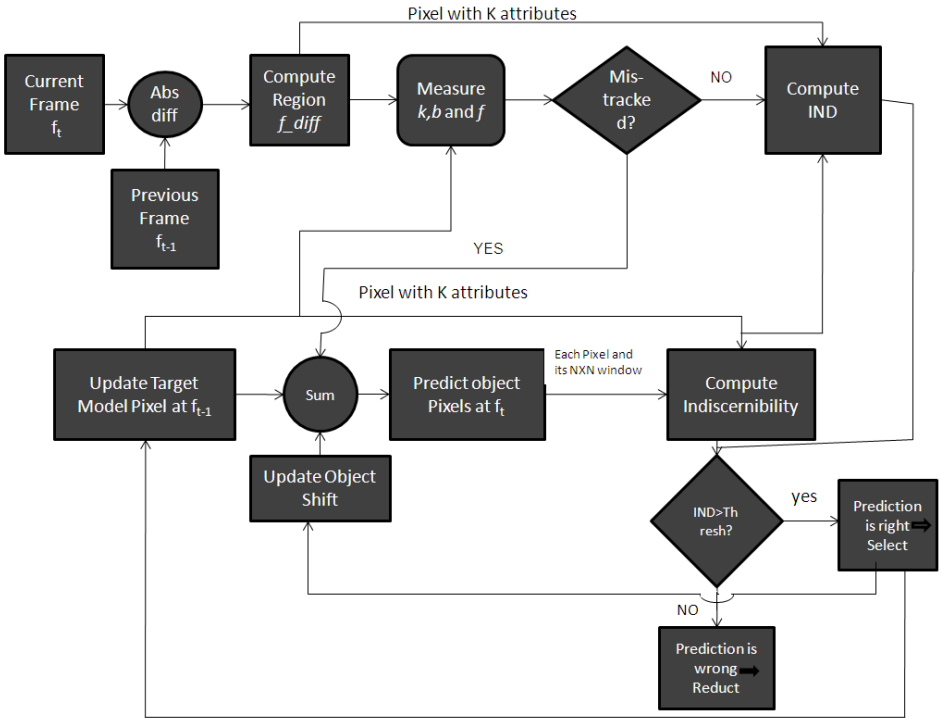
3. Object Extraction and Tracking

To track an object, proper design of the tracker or the tracking window is very necessary. The pixels within the tracker are considered as object pixels to locate and reconstruct the object in the next frame. So, the proper selection of the pixels within the tracker also plays a very important role in tracking. Some unwanted object may appear within the tracker and that may lead to mis-tracking.

Our aim is to extract out an object from a video sequence shot with still camera without having any prior knowledge about the sequence. In the process we want to avoid the unwanted regions within the tracker at the time of reconstructing the object. These are discussed in the following sections.



(a)



(b)

Figure 2. Block diagram of the proposed methodology (a) Initial estimations (b) Tracking

3.1. Methodology

The proposed method of video tracking is shown in a block diagram in Figure 2. The first step involves modeling of the moving object. We have considered the simple and popular background estimation method: median filtering [6] to estimate the the background and extract the initial target model. This is shown in Figure 2(a). This way we can reduce the possibility of distortion caused by noise. We have considered previous five frames in this approach. The difference regions between two consecutive frames for those frames have been extracted. So, there will be $n-1$ nos. of difference images if n previous frames are considered. The rectangular region (assuming that the tracker is rectangular) containing the largest two segments from each difference image is considered as the object of interest of that frame. The shifts (i.e., magnitude and direction) of the centers of those rectangles are then calculated and the median of the shifts is obtained. This information is used to form the search window for pixels if some frame with noise is present in the sequence. Otherwise, the consecutive frame difference will be considered.

To perform the task of tracking the object in the current frame the changed area between the current frame and the previous frame is extracted out. But, the difference area or region of interest (ROI_t) may be mislead due to presence of noise in the frame. The quantitative indices described in Section 5 are used to determine the presence of noise in a certain frame. That is, if noise is present in a frame the difference region of that frame is equivalent to mis-tracked one, and k, f and b values or at least one of them between the changed region and T_Mod will reflect that. If the difference of a frame is found to be mis-tracked, that region will not be considered as ROI_t, rather the probable location for each pixel will be predicted based on its shift information as shown in Figure 2(b) and that predicted region will be treated as ROI_t for that particular frame.

Then, the degree of belonging (DoB) of each pixel in the ROI_t with respect to the target model (T_Mod) is compared, and if the DoB value of a pixel is within a pre-specified threshold, then, it will be selected as a non-redundant feature, otherwise deducted.

The set of pixels in the region of interest (ROI_t) is treated as the conditional feature set. The set of pixels present in the target model is treated as the decision feature set or the set of attributes required to define the equivalence relation. Here, each pixel is treated as a feature with N attributes as shown in Figure 3. We therefore need to eliminate those pixels or features which are redundant to object background classification.

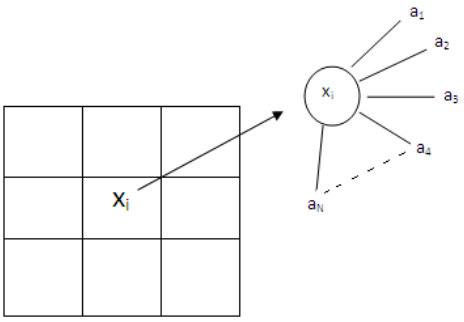


Figure 3. A pixel (feature) X_i with its N attributes

In case of video tracking each pixel in the object region in the current frame needs to be recognized as a non-redundant feature, as well as the pixels other than those of the object region are to be recognized as

redundant features. We have considered the object model and the region of interest in the current frame as two families of equivalence relations. In other words, we have a set of feature values of T_Mod, and we need to select those features from ROI_t which resemble the T_Mod closely in terms of N attributes, the remaining features need to be deducted. The said method of pixel reduction is performed based on the measure of degree of belonging (DoB). The DoB of a pixel in ROI_t to the target model is computed using the N attributes of the pixels at the same and surrounding locations in T_Mod. The details of the measure have been discussed in Section 3.3. If the value of DoB is greater than a certain threshold then the feature will be selected, otherwise deducted.

3.2. Object of Interest as a Rough Set

As mentioned before, in case of video tracking we do not know the exact location, color or size of the moving object in the current frame. So, we can say that, the moving object in the current frame is an unknown set to be approximated. The target model can be considered as an equivalence class. This equivalence class may not necessarily be a subset of the region of interest (ROI_t), but it must have a non zero intersection with it. So, ROI_t can be treated as the upper approximation of the object. We need to find out such an equivalence class which will entirely be a subset of ROI_t. To do that, we first reduce the redundant pixels from the upper approximation of the object and define a new equivalence class which will entirely be a subset of ROI_t. The minimum region within which the new equivalence class belongs will be treated as the lower approximation of the object and it will be tracked in the t^{th} frame.

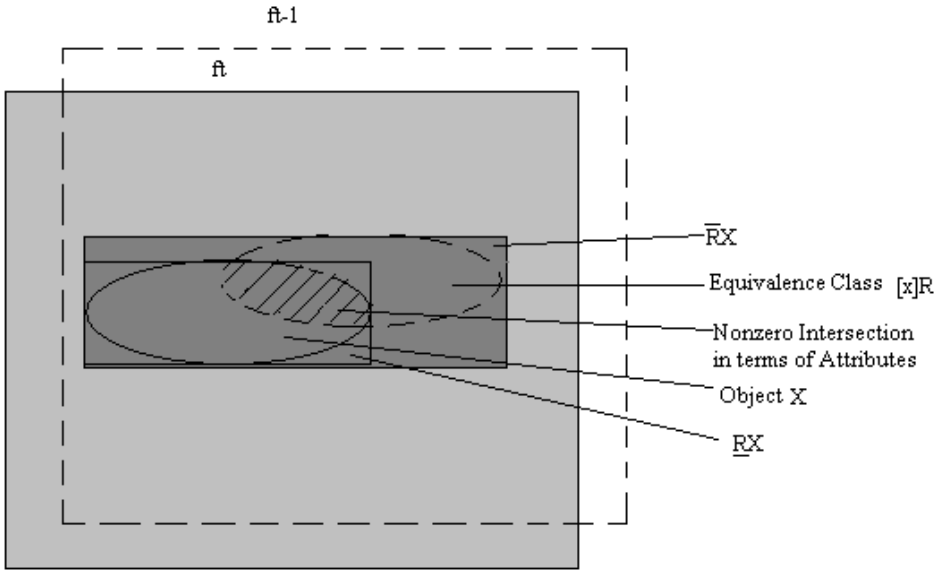


Figure 4. Object of interest as a rough set

For example, in Figure 4 the solid lined elliptical region denotes the object of interest in the current frame, that is, the unknown set X, the dotted elliptical region denotes the object in the previous frame, that is, the equivalence relation $[x]_R$, the light gray region denotes the current frame f_t, and the dotted rectangular region denotes the previous frame f_{t-1}. As we can see from the figure, the region which

has a nonzero intersection with $[x]_R$ is the dark gray region or ROI_t. So, the dark gray region in f_t is treated as upper approximation of X or $\overline{R}X$. The minimum region that contains the set of features after deduction, that is, the smaller rectangle in the darker gray region is treated as the lower approximation of the object or $\underline{R}X$.

3.2.1. Reduct and Core in Video

We can see from the earlier section that initially for a certain frame we are given with the upper approximation $\overline{R}X$ and the set of equivalence relation defined over the set of features R_{t-1}. As we are dealing with the video sequence, all the features in the previous frame (R_{t-1}) may not be present in the ROI_t or in the upper approximation. So, we need to find out the features similar to R_{t-1} in ROI_t, in order to compute the lower approximation of X. From Section 2 we know that a *reduct* of knowledge is its essential part, which suffices to define all the basic concepts occurring in the considered knowledge. Let, the set of features in $\overline{R}X$ be defined as $\mathbf{P}_t$. We need to find out a R_{t-1}-reduct of $\mathbf{P}_t$ where each feature is represented in terms of N attributes. This is done according to the forthcoming criterion. A feature $P_t \subseteq \mathbf{P}_t$ will be reducted if and only if

$$POS_{(\mathbf{P}_t - P_t)}(R_{t-1}) = POS_{\mathbf{P}_t}(R_{t-1}). \tag{5}$$

The intersection of all the reducts is treated as the core (Section 2). Accordingly, the R_{t-1}-core of $\mathbf{P}_t$ will be treated as the reduced set of features for the new target model and will be treated as R_t at the time of computing $\underline{R}X$.

	P1	P2	P3	P4
R=r1	yes	no	yes	yes
G=g1	yes	yes	no	no
B=b1	yes	yes	yes	yes
X=x1	yes	yes	no	no
Y=y1	yes	no	no	no

R={P1, P2, P3, P4}
IND(**R**)={r1, g1, b1, x1, y1}
IND(**R**-{P1})≠*IND*(**R**)
IND(**R**-{P2})=*IND*(**R**) ⇒ Reduct1={P1, P3, P4}
IND(**R**-{P3})=*IND*(**R**) ⇒ Reduct2={P1, P2, P4}
IND(**R**-{P4})=*IND*(**R**) ⇒ Reduct3={P1,P2,P3}

CORE= Reduct1 ∩ Reduct2 ∩ Reduct3
= P1
Pixel P1 will be selected

Figure 5. An example: Reduction of pixels based on indiscernibility

In Figure 5 an example is shown how redundant pixels can be deducted based on indiscernibility. Here **R** is the set of features and $IND(\mathbf{R})$ is the indiscernibility matrix of it. There are three reducts of **R**, that is, three sets of features with the same indiscernibility matrix after reducing feature(s). The core obtained here is $P1$. From this figure, it can be noted that, the reduction of the core feature does not result in the same indiscernibility matrix. In the problem of video tracking we need to find those pixels or features to keep indiscernibility the same. But, this kind of pixels reduction is not possible in practical scenario of videos. The exact indiscernibility matrix may not be available for any of the features in the current frame. Because, the information of previous frame may get deviated in the current

frame due to the change in object color/ shape/ size. Therefore the concept of exact matching (or exact similarity) between frames is not appropriate or meaningful, rather a degree of matching or similarity may be used. To make this process suitable to videos, we have defined a measure of indiscernibility rather than considering the exact indiscernibility matrix. The said measure of indiscernibility is referred as *degree of belonging* (DoB) for feature reduction. In the next section we discuss the measure.

3.3. Measure of Indiscernibility (Degree of Belonging) for a Feature

Let, a feature in the current frame (f_t) be represented as M and the set of features similar or nearer to it in the target model (T_Mod) be denoted by N. Let the distance between them be expressed as:

$$d = Dist(M, N) \tag{6}$$

Where, $Dist(.)$ is the distance function used to compute the distance between M and N. If the information on M is exactly the same as that of a features in N, then d will be zero. As the similarity between M and N decreases, d increases, the maximum value being unity. Therefore, lower the value of d, better is the DoB of M to the T_Mod.

In case of human vision system (HVS), in a certain range of features, HVS is very sensitive, after or before that the change in response is less. This characteristics may be incorporated in defining the function d to compute the DoB. In case of our experiment, we have used Zadeh's S-function [30] as the distance function.

We are given with an equivalence relation ($Targ\_Mod$) and a set of features, that is, the probable target area. We need to eliminate those features which are redundant with respect to new equivalence relation to be formed in the current frame. After considering a feature, that is, a pixel in T_Mod, we measure the degree of belonging (DoB) with respect to ROI_t. This can be done based on pixels' attributes. Several attributes could be used depending upon the problem. We have considered seven attributes: x, y, R, G, B, ev, eh of a feature to define the distance function. Here, x and y denote the spatial location of a feature (pixel) at ROI_t, R, G, B are color values and ev, eh are the vertical and horizontal edges obtained by using Sobel operator. Further, pixels may not be in the same position at ROI_t as it is predicted to be. Rather it may get shifted due to its change in velocity or shape or size. So, consideration of a window around the spatial location in ROI_t will be more effective than considering a single pixel. Accordingly, we considered a window of size $w1 \times w2$ centered at its corresponding location of ROI_t and the feature in the equivalence relation (target model).

Again, it can be said that, some spatial change from the estimated location is more probable, while, the change in other attributes (e,g., color) is less likely. Therefor, to measure the DoB (Equation 10) more weight on the color-edge distance than the spatial distance of pixels has been given in order to have their proper impact. In our experiment, we have measured the distance in terms of color and edge attributes (denoted by dcl) and in terms of spatial location (denoted by dsp) between the input feature and the features within the window on ROI_t as:

$$dcl = min_{i \in (w1 \times w2)} \left(\frac{\sum\limits_{c=(R,G,B,ev,eh)} |T\_Mod_c(x_i, y_i) - ROI_{t_c}(x, y)|}{3} \right) \tag{7}$$

$$dsp = max(|x' - x_s|, |y' - y_s|)/(w/2) \tag{8}$$

where (x_s, y_s) is the location of the pixel within the window from which the color-edge distance of the input feature is minimum and x', y' is its location at ROI_t and w is either $w1$ or $w2$ depending on which axis is giving maximum distance.

Let the distance of the input feature and the features in the window of the target model be defined (using the aforesaid S-function, and Equations (7) and (8)) as:

$$d = \begin{cases} 0 & \text{if } dcl \leq \alpha \\ \frac{dsp+2(\frac{dcl-\alpha}{\gamma-\alpha})^2}{2} & \text{if } \alpha < dcl \leq \beta \\ \frac{dsp+(1-2(\frac{dcl-\gamma}{\gamma-\alpha})^2)}{2} & \text{if } \beta < dcl \leq \gamma \\ 1 & \text{if } dcl > \gamma \end{cases} \tag{9}$$

The degree of belonging (DoB) of the input feature is measured as:

$$DoB = 1 - d \tag{10}$$

The values of α, β and γ may be chosen by the user. The choice of these values depend on the area of application. For example, in case of the current scenario, these values should lie between 0 to 255. Let, only the color distance be considered. It can be said that, if the variation in color value less than five is negligible, whereas more than fifteen denotes different value. In this case, the values of α, β and γ will be 5, $(5 + 15)/2 = 10$, 15 respectively. Figure 6 shows the characteristics of the proposed distance measure, that is, how the feature distance varies with color distance and spatial distance when, $\alpha = 10; \beta = 120$ and $\gamma = 240$.

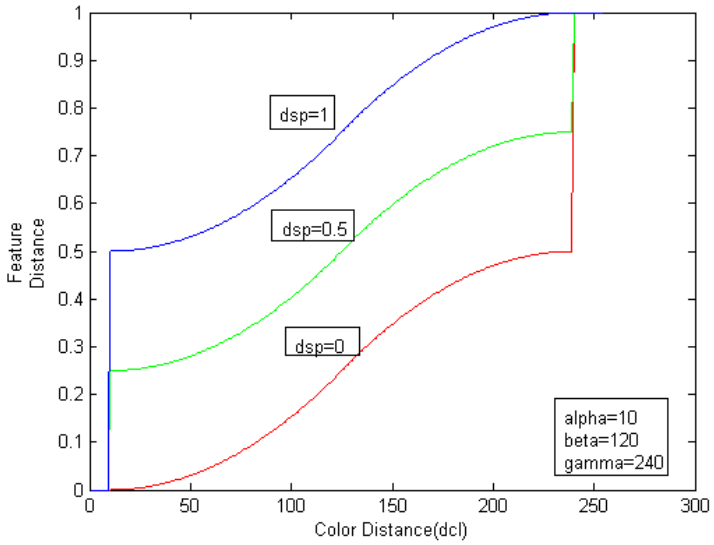


Figure 6. Variation of feature distance (d) with respect to color- edge distance (dcl) and spatial distance (dsp)

Using the measure, the system is able to eliminate the unnecessary features in the current frame and reconstruct the object automatically. The reconstructed object will then be treated as the target model in the next frame.

4. Algorithm for Tracking

We have considered the tracker to be rectangular in shape. We have taken the median of the first four frames to model the background and subtract it form the fifth frame to find out the target model. The minimum rectangular region that we have after segmentation of the foreground image is treated as the initial target model T_Mod. Then find out the changed regions between the initial frames and compute the shifts of the centroids between the changed regions of consecutive frames. Compute the median of the shifts of the centroids. The searching procedure of a pixel from ROI_t is shown in Figure 7. Every pixel location at T_Mod has a predicted location in ROI_t. From Figure 7 it can be seen that, the shifts between the objects at f_{t-2} and f_{t-1} frames is denoted as s. So, the predicted object at f_t will also shift by s distance. The search region for a certain pixel is shown by the dark gray rectangle. Here, it is assumed that, a certain object pixel will not deviate more than 25% of the shift from its predicted location.

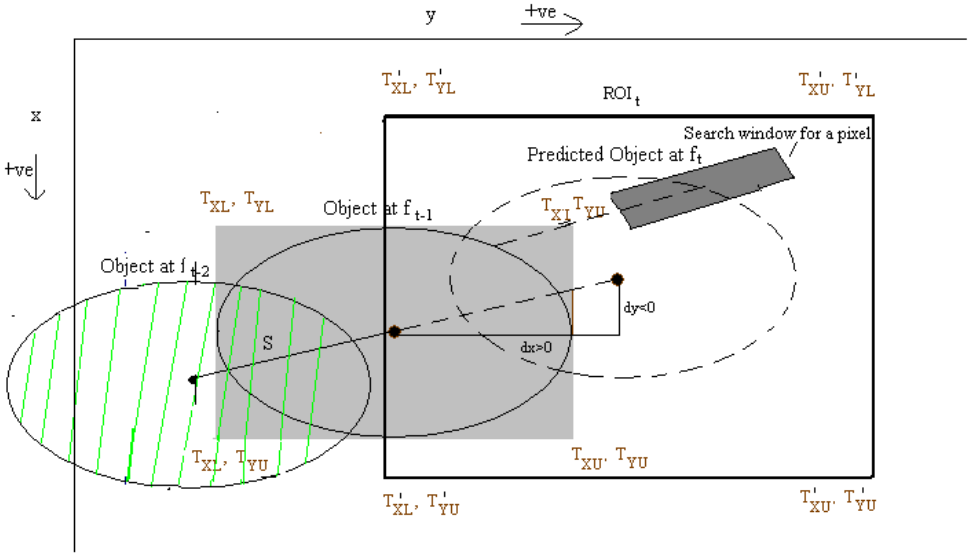


Figure 7. The pixel searching procedure in ROI_t

Then, select the difference region of interest in the current frame f_diff by considering the difference region between the current and previous frame, and perform the following operations:

Step 1: Compute the k, f and b values, according to Section 5, between T_Mod and f_diff. *IF* $k < th1$ or $f > th2$ or $b > th3$ then, ROI_t=T_Mod+s *ELSE* $ROI_t = f\_diff$ The vertices of this region are denoted as $((T_{XL}, T_{YL}), (T_{XU}, T_{YL}), (T_{XU}, T_{YU})$ and $(T_{XL}, T_{YU}))$.

Step 2: Consider a pixel P_1 of T_Mod as a feature with attributes x, y, R, G, B, eh, ev. Where, (x, y) denotes its spatial location, that is, (1,1) for the first pixel, and (R, G, B) are the color and eh and ev are the edge values of the pixel.

Step 3: Construct a window of size $w1 \times w2$ in ROI_t with the center of the window at (x',y'). Where, $w1 = 0.25 * dx$ and $w2 = 0.25 * dy$. dx and dy are the same as in Figure 7.

Step 4: Calculate the color-edge distance (dcl) between P_1 and all the pixels in the window of the ROI_t according to Equation (7).

Step 5: Calculate the spatial distance (dsp) according to Equation (8).

Step 6: Compute DoB with Equation (10).

Step 7: Repeat *Step 2* to *Step 6* for every pixel in T_Mod.

Step 8: Select a threshold (Th) for those features with DoB value neither 0 nor 1. (Select it as the the lower quartile value of those DoB values assuming that more than 75% pixels will be the object pixels.)

Step 9: Reduct the pixels with DoB less than the threshold (Th), and select the remaining to reconstruct the object model which will be treated as T_Mod (size $T_x \times T_y$) in the next frame. Track this region.

Step 10: Design the tracker according to the following in the next frame
IF $d_x > 0$ then, $T_{xu} = T_{xu} + 1.25s$ and $T_{xl} = T_{xl} - 0.75s$ *ELSE* $T_{xu} = T_{xu} + 0.75s$ and $T_{xl} = T_{xl} - 1.25s$
IF $d_y > 0$ then, $T_{yu} = T_{yu} + 1.25S$ and $T_{yl} = T_{yl} - 0.75s$ *ELSE* $T_{yu} = T_{yu} + 0.75s$ and $T_{yl} = T_{yl} - 1.25s$.
Here, $T_x = T_{xu} + T_{xl}$ and $T_y = T_{yu} + T_{yl}$.

Step 11: Calculate the frame difference within this rectangular region only and treat it as f_diff.

Step 12: Repeat *Step 1* to *Step 11* for each frame in the video sequence.

5. Measures of Tracking

As we mentioned before, our aim is to find out a way of tracking a moving object without having any prior knowledge about the video sequence. There exist many techniques to evaluate the performance of tracking. These are mainly of two types. One is based on ground truth and the other one is based on the trajectory of the sequence [13, 2, 14]. Here we propose three measures (k-index, f-index and b-index) to evaluate the tracking performance without having the knowledge about either ground truth or trajectory.

5.1. Using Partial Dependency of Knowledge

As mentioned in Section 2, $POS_{R_t-1}(\mathbf{P}_t)$ is the set of all objects which can be classified to elementary categories of knowledge $\mathbf{P}_t$, employing knowledge R_t-1. We have evaluated the set of attributes T_Mod based on the knowledge of previous frame. Here, we can consider, T_Mod as $R_t - 1$ and ROI_t as $\mathbf{P}_t$. Similarly, the set which is treated as the reconstructed target model is considered to be $POS_{R_t-1}(\mathbf{P}_t)$. It is assumed that the moving object model in the frames have several common features, throughout the sequence, and there will be very less change in target models between two consecutive frames as only a few features are likely to be affected. So, the measure of how much part of knowledge of $\mathbf{P}_t$ has been evaluated from knowledge R_{t-1} can be a good measure to evaluate the tracking performance. In rough set theory, the aforesaid concept is defined as:

$$k = \gamma_{R_t-1}(\mathbf{P}_t) = \frac{cardPOS_{R_{t-1}}(\mathbf{P})}{cardU} \tag{11}$$

where $card$ denotes the cardinality of the set. The higher the value of k is, the more is the dependency. If $k = 1$, the entire knowledge of $\mathbf{P}_t$ has been evaluated by employing the knowledge R_{t-1}.

Here, we consider the union of T_Mod and ROI_t as the universe of classes. The k-value reflects how properly the T_Mod can reconstruct the target model in the current frame, thus evaluates the performance of T_Mod. That is, if there is any fault in selection of T_Mod, then $card(POS_{R_t-1}(\mathbf{P}_t)))$ will be small and $card(U)$ will be large; thereby giving smaller value of k in the t^{th} frame. So, if a frame has smaller k- value, then we can conclude that, the frame is mis-tracked or over-tracked or under-tracked. In other words, the k-measure can automatically determine if the target model has been reconstructed properly in the current frame using the information of the previous frame.

5.2. Using Ratio of Feature Distance to Total Feature

This measure is computed as the ratio of the summation of the feature distance and the total no. of features in ROI_t. It can be written as:

$$f = \frac{\sum_{i=1}^{F} Dist_i}{F} \tag{12}$$

Where, F is the total no. of features and $Dist$ is the same as in Equation 6. It is expected that, all the pixels of object model in the previous frame will be present in the current frame with a certain shift in the current frame. Then, the feature distance will be zero for each feature. Henceforth, it can be concluded that, if the summation of feature distance is small, then, the value of f will also be small. That means there exist more pixels with value of DoB high. So, the lower value of f for a frame indicates the better tracking in the frame. Any frame having a value of f greater than a certain threshold will be said to be mis-tracked or over-tracked (the tracker contains more redundant features) or under-tracked (the tracker does not contain sufficient features to define the equivalence classes).

5.3. Using Target Representation and Bhattacharya Distance

The color distributions of the target model and reconstructed object are considered in this measure. Here, a target is represented based on the distributions of the levels in the target model and the tracked region. We have divided the total range of levels into m number of bins/ segments. The size of a bin is dependent on the no. of occurrence of the pixels of the levels within that bin; thereby making it wider for levels with higher number of occurrence.

In case of video tracking, the object model region and tracked region are supposed to contain pixels with similar levels. It can be said that the levels where the occurrences of pixels are maximum in both the target model and tracked region are similar. Further, the probability of deviation in the levels with such maximum occurrence of pixels would be higher than those for the levels with less occurrence of pixels.

Let, p_u be the occurrence of pixels in the u^{th} bin and be represented as: $p_u = \sum_{i=1}^{n} \delta[bin(x_i) - u]$ with δ: Kronecker delta function, $bin(x_i)$: the bin where the i^{th} pixel is and n: total number of pixels in the region. Then, the sizes of the bins are defined in terms of the following ratio: $u_i : u_2 : .. : u_j : .. : u_m =$

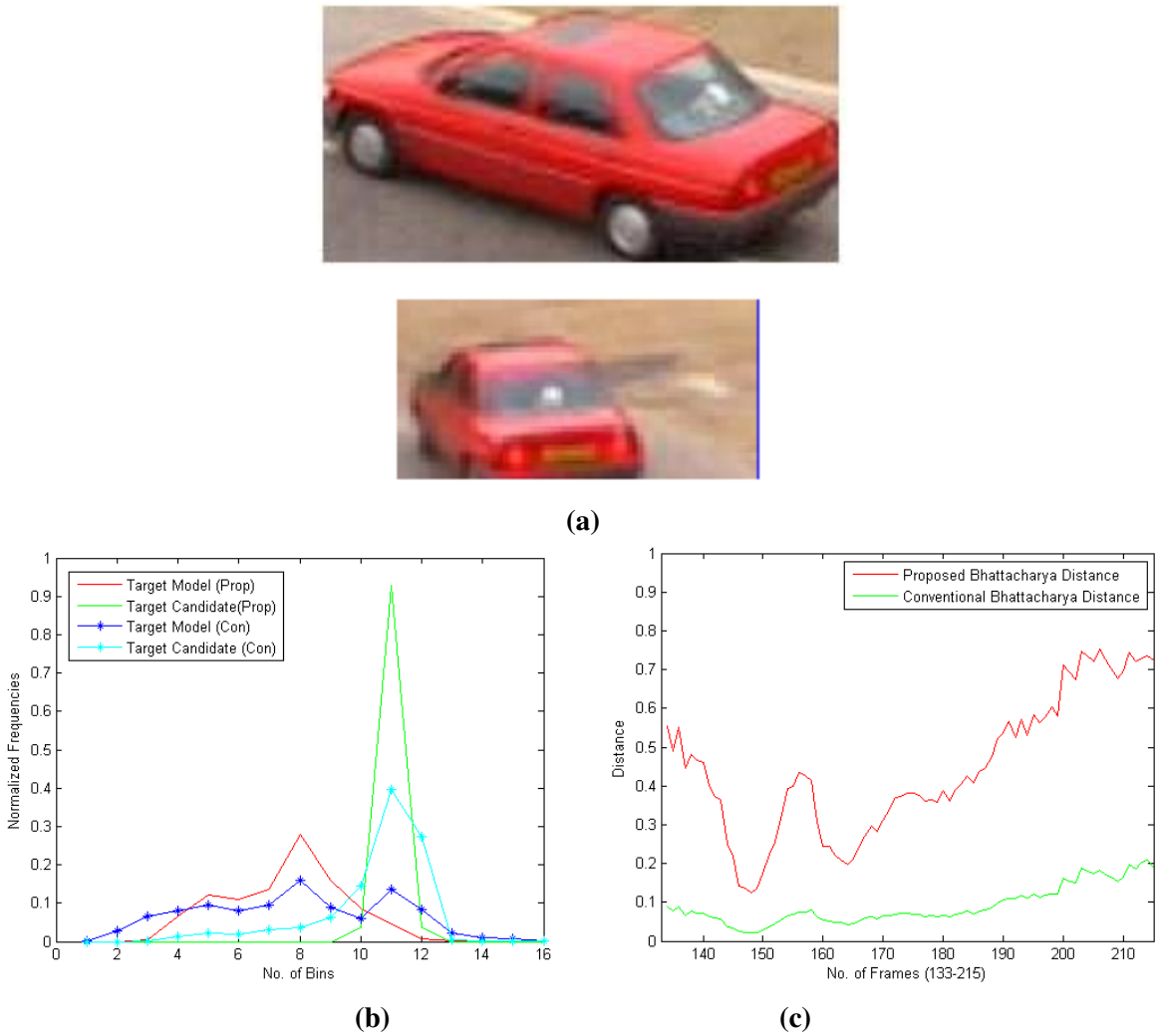
$p_1 : p_2 : .. : p_j : .. : p_m$. The target model is represented as:

$$p_{u_j} = \sum_{i=1}^{n} \delta[bin(x_i) - u_j] \tag{13}$$

Let q_{u_j} characterize the tracked regions corresponding to the u_j^{th} bin. Then Bhattacharya distance between p_{u_j} and q_{u_j} is:

$$b = 1 - \sum_{j=1}^{m} \sqrt{(p_{u_j} q_{u_j})} \tag{14}$$

As b represents the distance between two distributions, lower value of b reflects better tracking.



(a) **(b)** **(c)**

Figure 8. (a) Target model and tracked region (b) their representation (c) comparison between two approaches for frame nos. 134-215 of the*Surveillance Scenario Sequence* from PETS-2000

Note that, a method for object tracking based on Bhattacharya distance was explained by Commanicu *et al.* [5]. However, unlike our approach, the object was represented with bins of equal size. We can see from Figure 8 that the consideration of unequal histogram bins results in more clear seperability between the target model and the target candidate (tracked region). Here, frame nos. 134-215 of the*Surveillance Scenario Sequence* from PETS-2000 are shown, as an example. From Figure 8(b) the seperability corresponding to the target model and tracked region (as in Figure 8(a)) is seen to be much larger, while in Figure 8(c) the Bhattacharya distance throughout the sequence is seen to be much higher with clear peaks and valleys; thereby making it easier to find out the mis-tracked frames.

Note: From the above three indices of tracking, it can be noted that, k-index measures the knowledge dependency between the target model and tracked region. The resulting decision on tracking using k-index may be wrong if the size of the object changes rapidly. For example if the object appears suddenly much bigger than it was in the previous frame, then without having the whole object as the tracked region, or having the same sized tracked region as it was there in the previous frame, the k-value may get higher which should not be the case. f-index determines the pixel-wise similarity between these two regions considering the neighborhood effect. This measure may also fail similarly if the background contains similar attributes. b-index is based on the similarity between color histograms of the two regions. If there is a huge change in color between two frames' object model, then, tracking the right object may be detected as mis-tracked by this measure. Though the three indices of tracking have some limitation individually, they may be used together to supplement the other. For example, the sudden change in object size can be detected by b-index, while the huge change in color can be detected by k-index. None of the measures could be claimed as the best among the three in all scenarios as these are strongly application dependent.

6. Results and Discussions

Experiments were conducted to demonstrate the effectiveness of the proposed method in: removing the unwanted regions within a tracker automatically and reconstructing the object, tracking the moving object, and identifying the mis-tracked frames. The new quantitative indices (k-index, f-index and b-index) based on rough sets are used to measure the performance. Comparative results with two other popular techniques are also shown.

We have performed our experiments with different types of data sets from PETS-2000 [19], PETS-2001 [20], PETS-2004 [21], AVSS-2007 [1]. However, to limit the size of the paper, we have shown some of the results only.

6.1. Reconstruction

The procedure of reconstruction has been discussed previously. This section will show how our proposed algorithm can eliminate the unwanted regions as redundant features.

In Figure 9(a), the region labeled as 'unwanted region', that is regions with some other object(s) represents the set of redundant features in ROI_t. Those are deducted at the time of reconstruction as shown in Figure 9(b). Here the target models correspond to the frame nos. 147, 150 and 152 of the data set *Surveillance Scenario Sequence* obtained from PETS-2000 [19].

We have shown another result in Figure 10 obtained after applying this algorithm to *Data1 sequence* from [20]. In this sequence one man is walking. The moving object is very small compared to the rest of

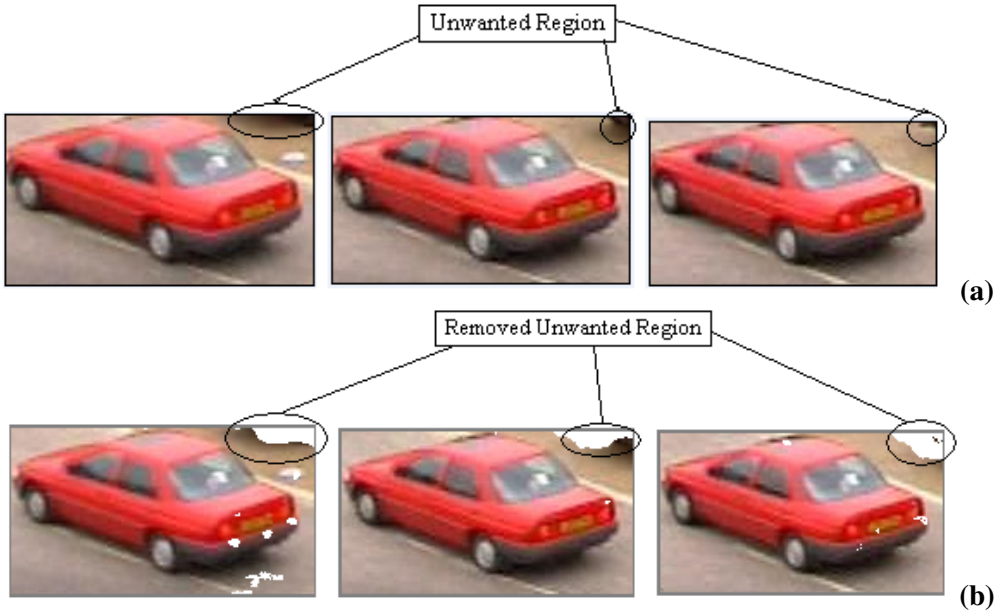


Figure 9. The reconstruction results on frame nos. 147, 150, 152 from the *Surveillance Scenario Sequence* from PETS-2000: (a) ROI_t, (b) after feature reduction

the frame and several unwanted areas within ROI_t are present there (some of the original frames of the sequence are shown in Figure 11.iii(a)). We can see form Figure 10(b) that the unwanted areas within the ROI_t have also been removed.

Figure 10. The reconstruction results on frame nos. 343, 350, 355, 366 from the *Data1 sequence* from PETS-2001: (a) ROI_t, (b) after feature reduction

6.2. Tracking

Here we have shown some results corresponding to four kinds of data sets.

Let us consider Figure 11.i(a) which represents four frames of a video sequence where one man is walking. The data is taken from AVSS-2007 [1] data set, where each frame has a size of 576×720 pixels. Figure 11.i(b) represents the corresponding four tracked frames. Here, the object motion is slower and no unwanted area appears within the region of interest. Figure, 11.ii shows the tracking results corresponding to four frames taken from PETS-2000 [19] where each frame is of size 576×768 pixels. Here, the motion of the object is faster and in certain frames there are some unwanted areas within

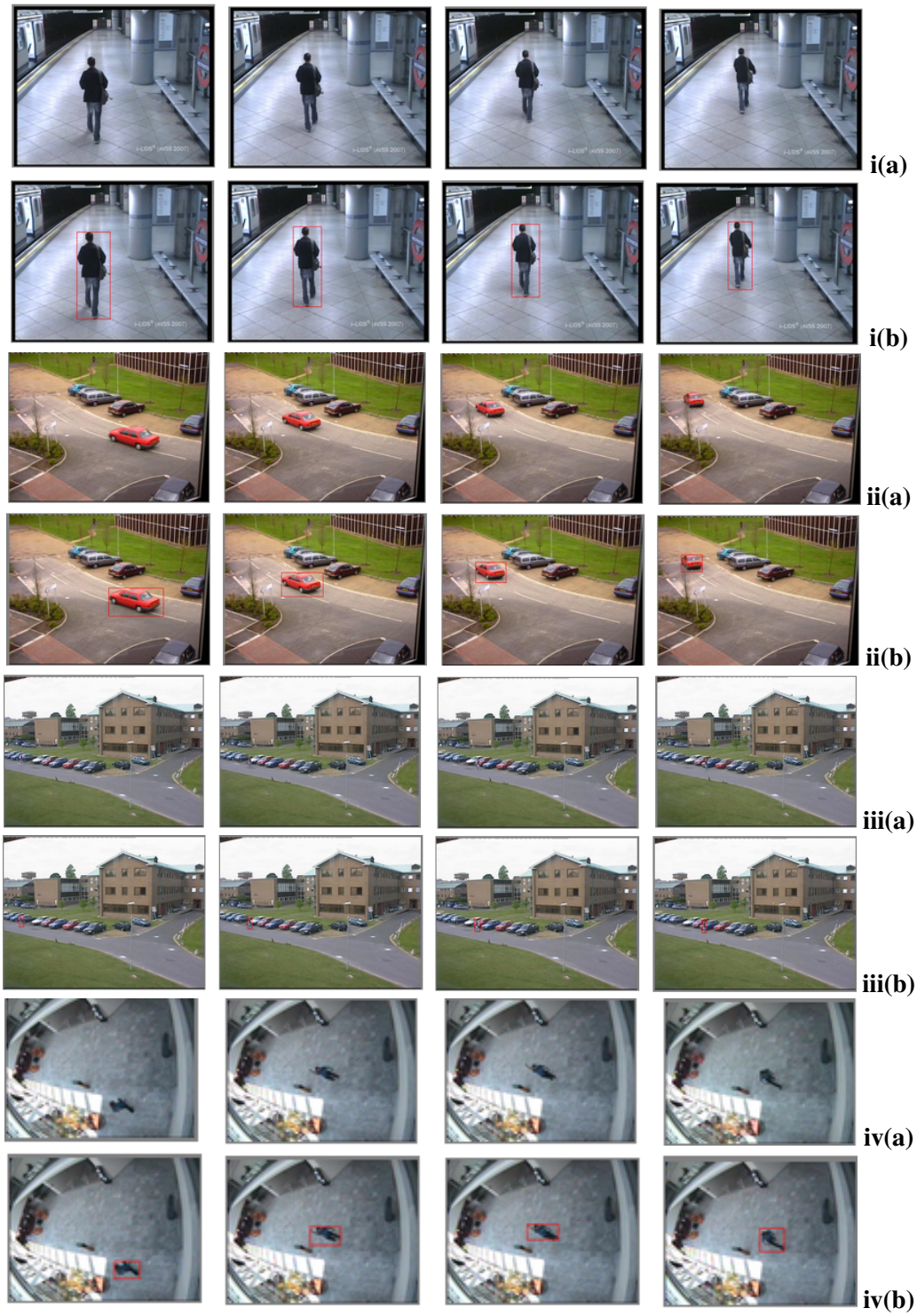


Figure 11. Tracking Results for different video sequences: (i) Frame nos. 1305, 1317, 1331, 1347 from the *Baggage Detection Sequence* from AVSS-2007 (ii)Frame nos. 134, 154, 174, 194 from the*Surveillance Scenario Sequence* from PETS-2000 (iii) Frame nos. 221, 281, 331, 371 from the*Data1 sequence* from PETS-2001 (iv)Frame nos. 66, 104, 114, 145 from the*Walk3 sequence* from PETS-2004 (a) Original and (b) Tracked

the region of interest. In case of both the data sets (Figs 11.i and 11.ii) the area of object region is larger, whereas in case of Figure 11.iii the object is much smaller. The data set is taken from PETS-2001 [20] (each frame of size 576×768 pixels). Here, there is a person walking in front of several standing cars. So, several unwanted objects within the Region of Interest are present there. The object area is very small as well as the object is not crisply separable from the background even by human eyes. The moving object is also smaller in case of Figure (11.iv). This data set is taken from PETS-ECCV-2004 [21] (each frame of size 384×288 pixels). There is a person walking through B-line. The person is walking, standing, waving his hands throughout the sequence. In all the aforesaid data sets, the results of tracking are satisfactory and are shown in corresponding figures (Figs 11.i(b),11.ii(b), 11.iii(b), 11.iv(b)).

6.3. Evaluation of Mis-tracked Frames

Here we have shown how the proposed measures (Section 5) can detect the over-tracked or under-tracked frames. According to them the lower value of k or higher value of f and b denotes the less accurate tracking. We have shown some mis-tracked frames according to all the three measures. Frame nos. 249, 326, 385, 415 from [20] and frame nos. 75, 84, 125, 176 from [21] which are detected as 'mis-tracked' are shown in Figures 12 and 13 respectively, as two examples.

Figure 12. The mis-tracked frames on frame nos. 249, 326, 385, 415 from the*Data1 sequence* from PETS-2001: (a) Original, (b) Mis-tracked (c)Zoomed frames

For instance, in Figure (12), the frames where more background areas are included either horizontally or vertically by the tracker are detected as mis-tracked frames. Zoomed version (Figure 12(c)) is shown for convenience.

In Figure (13) the frames detected as mis-tracked are those frames where huge portion of the background is included in the tracker, or the object (person) itself is not being entirely covered by the tracker. So, both the cases of under tracking and over tracking are seem to be detected by the measures.

One may note that, all of the measures are dependent upon the object model in the previous frame. So, if the target gets mis-tracked in any one of the frames, these measures can detect, but, if the tracker

Figure 13. The mis-tracked frames on frame nos. 75, 84, 125, 176 from *Walk3 sequence* from PETS-2004: (a) Original, (b) Mis-tracked

is continuously mis-located to some other object, these measures may fail. So, in the proposed method of tracking, these measures are used as error detector in each frame, and if mis-tracking is detected in any certain frame, then, the error gets corrected immediately, as discussed in Section 4. The values of $th1$, $th2$ and $th3$ are chosen as 0.9, 0.25 and 0.3 respectively. It can be seen in Figure 14(a) that the frame was initially mis-tracked. The values of k, f and b were 0.984, 0.2353, 0.3625 respectively. The b index reflects its mis-tracking and hence it gets corrected. The tracking result after correction is shown in Figure 14(b). This way every mis-tracked frame gets corrected in the process of tracking and we have a satisfactory tracking result throughout all the sequences.

Figure 14. Frame no. 1299 from the *Baggage Detection Sequence* from AVSS-2007 (a) mis-tracked frame and (b) corrected

6.4. Comparison

We have compared our method with two popular exiting methods, viz, Mean Shift tracking (MS) [4] and Mixture of Gaussian based background adaptation (MoG) [25]. The comparisons are made visually as well as quantitatively with the proposed three measures. We have shown the comparative results for two sequences (*Surveillance Scenario Sequence* from PETS-2000, the *Walk3 sequence* from PETS-2004), as an example. The visual comparative results are shown in Figure 15. The values of k, f and b obtained

according to Equations (11, 12, 14) for the two sequences applying the three defined methods (viz. proposed, mean-shift and MoG) are shown in Figures 16, 17 and 18 respectively. One more numerical comparison is done based on the centroid distance, i.e., how far the tracker centroid is from the ground truth object centroid. Euclidian distance metric is used here. This is a popular measure to evaluate the tracking performance. In Figure 19 the centroid distance measures for the said two sequences and three methods are shown. As seen from these figures, the proposed method results in higher value of k, and lower values of centroid distance, f and b; thereby signifying more accurate tracking than the other two methods. For example, it can be seen from Figure 15(i) that in case of *Surveillance Sequence* the tracking results show that meanshift (MS) method provides the worst result whereas MoG gives better result than MS and the proposed method provides the most accurate result among the three methods. The visual results are reflected in quantitative measures also. The ground truth based measure depicted in Figure 19(a) shows the same. In Figure 16(a) it can be noticed that the average value of k is the lowest for meanshift (MS) method, higher than MS but lower than the proposed one for MoG and the highest for the defined one. From Figure 17(a) the f-values, as expected, are lower for proposed method and higher for meanshift and MoG. The average b-values are the lowest for the proposed method, higher than the proposed but lower than MS for MoG and the highest for MS and shown in Figure 18(a). One tabular expression expression is shown in Table 1 where the columns denote the best (Rank1) to worst (Rank3) methods among the three decided according to the average values of k ($k_{proposed}$, k_{MS}, k_{MoG}), f ($f_{proposed}$, f_{MS}, f_{MoG}) and b($b_{proposed}$, b_{MS}, b_{MoG}) indices in the respective rows.

Table 1. Accuracy of The Three Methods According to k-index, f-index and b-index for *Surveillance Scenario*, and *Walk3* sequences

Surveillance Scenario	$Rank1$	$Rank2$	$Rank3$
k-index	$k_{proposed}$	k_{MoG}	k_{MS}
f-index	$f_{proposed}$	f_{MS}	f_{MoG}
b-index	$b_{proposed}$	b_{MoG}	b_{MS}
Decision	Proposed	MoG	MS
Walk3 Sequence			
k-index	$k_{proposed}$	k_{MoG}	k_{MS}
f-index	$f_{proposed}$	f_{MoG}	f_{MS}
b-index	b_{MoG}	$b_{proposed}$	b_{MS}
Decision	Proposed	MoG	MS

So, it can be said that, the measures defined here are effective to evaluate the performance of tracking quantitatively.

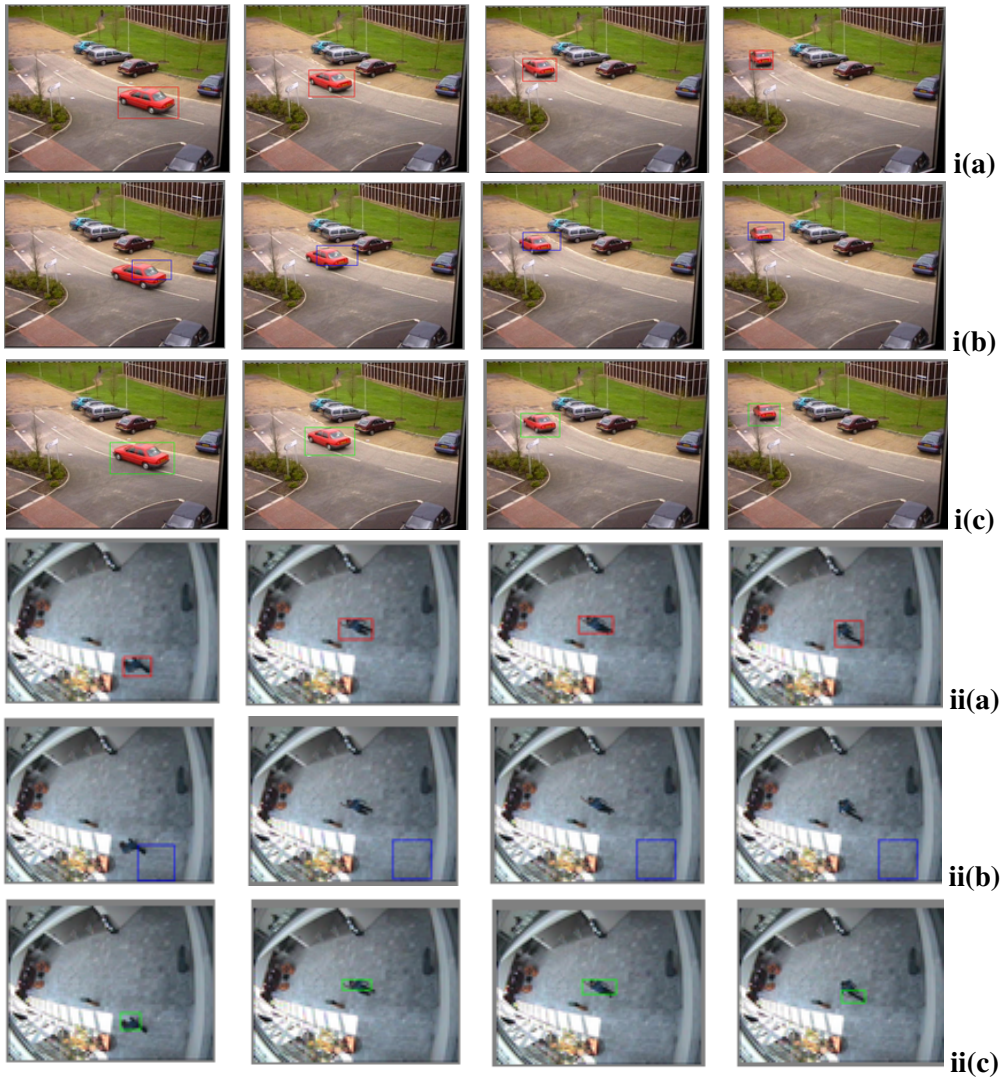
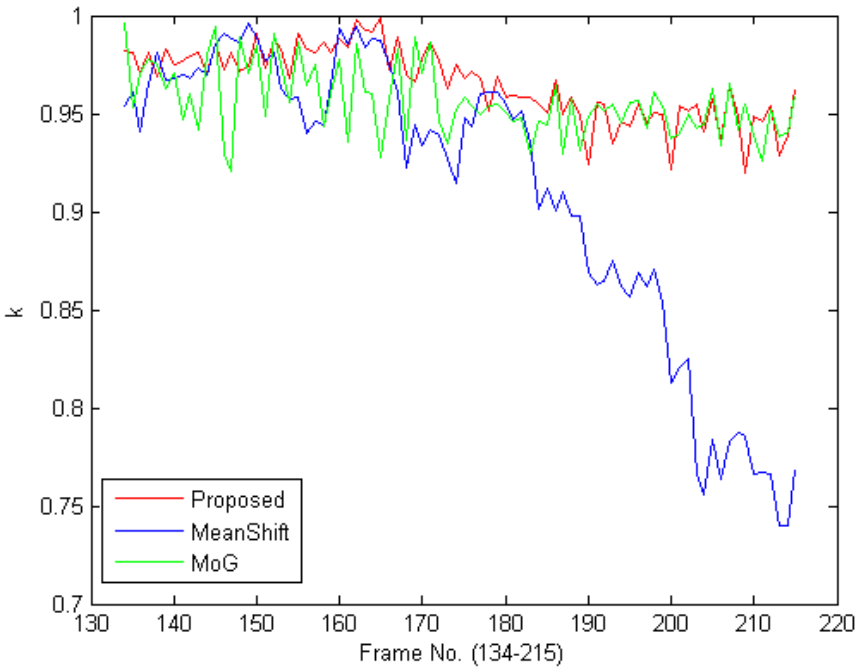
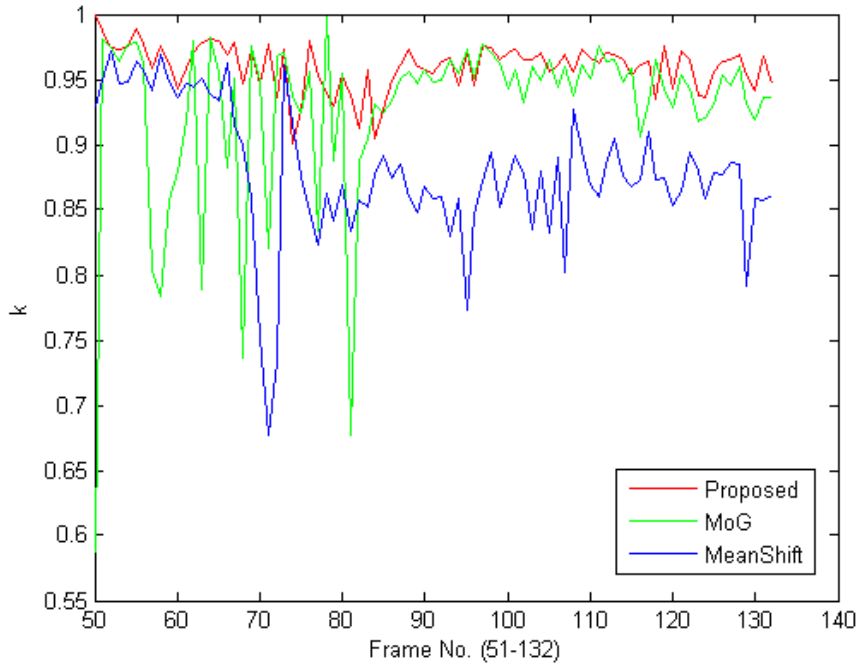


Figure 15. Comparative Tracking Results for video sequences: (i)Frame nos. 134, 154, 174, 194 from the*Surveillance Scenario Sequence* from PETS-2000 (ii)Frame nos. 66, 104, 114, 145 from the*Walk3 sequence* from PETS-2004 (a) Proposed (b) Mean Shift (c) MoG

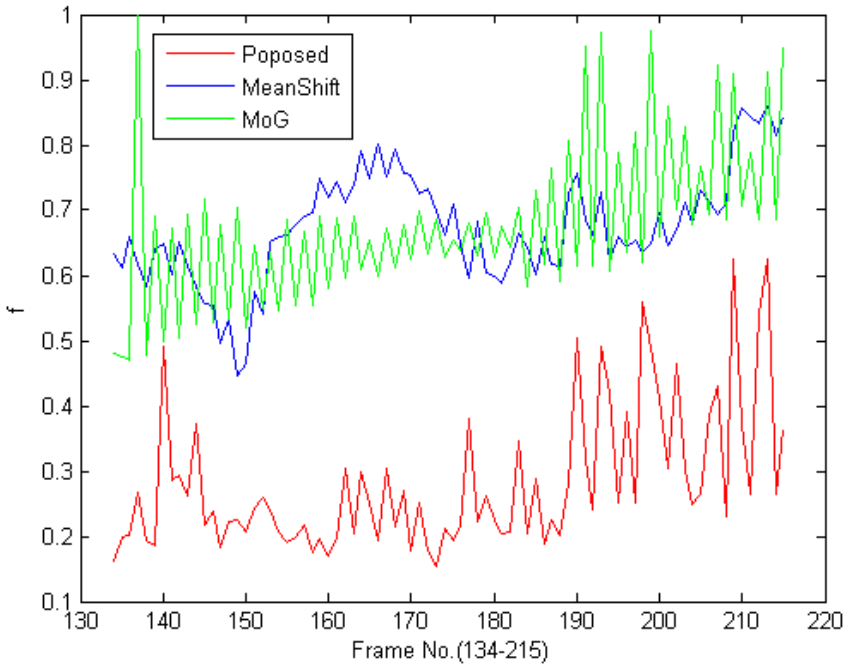


(a)

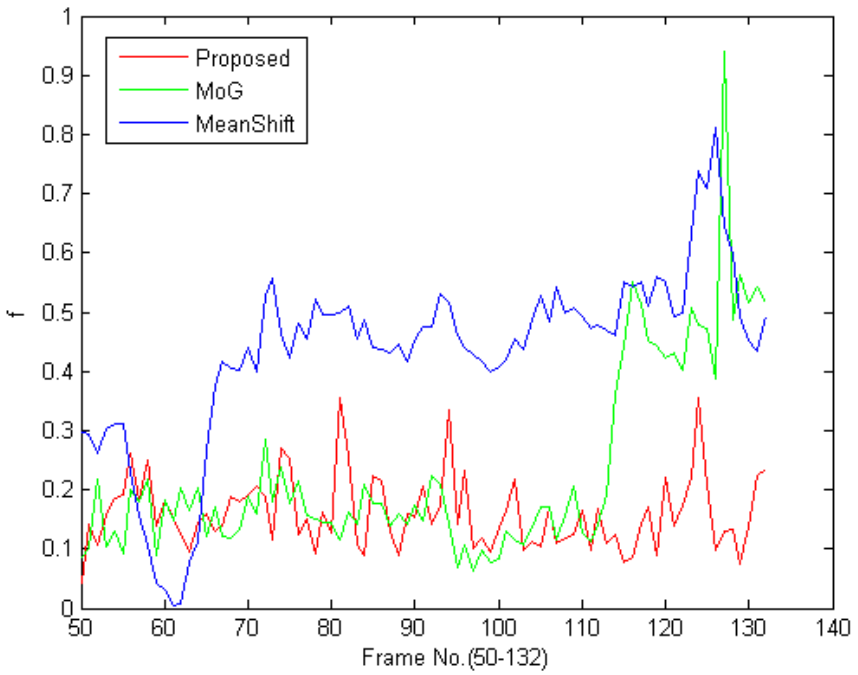


(b)

Figure 16. Values of k obtained for: (a)Frame nos. 134-215 from the*Surveillance Scenario Sequence* from PETS-2000 (b)Frame nos. 50-132 from the*Walk3 sequence* from PETS-2004

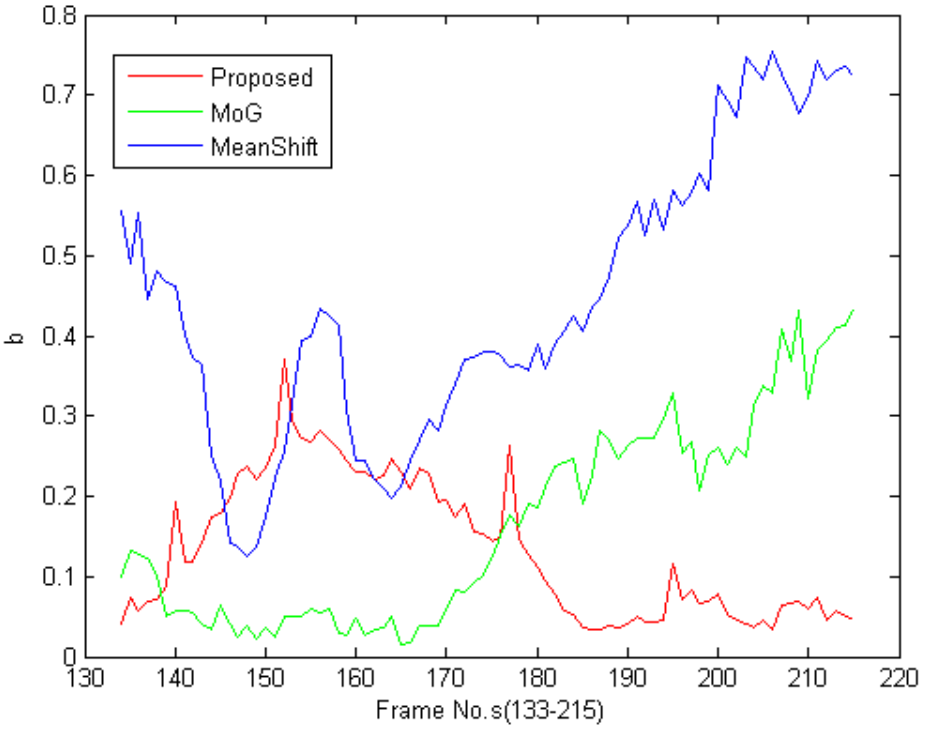


(a)

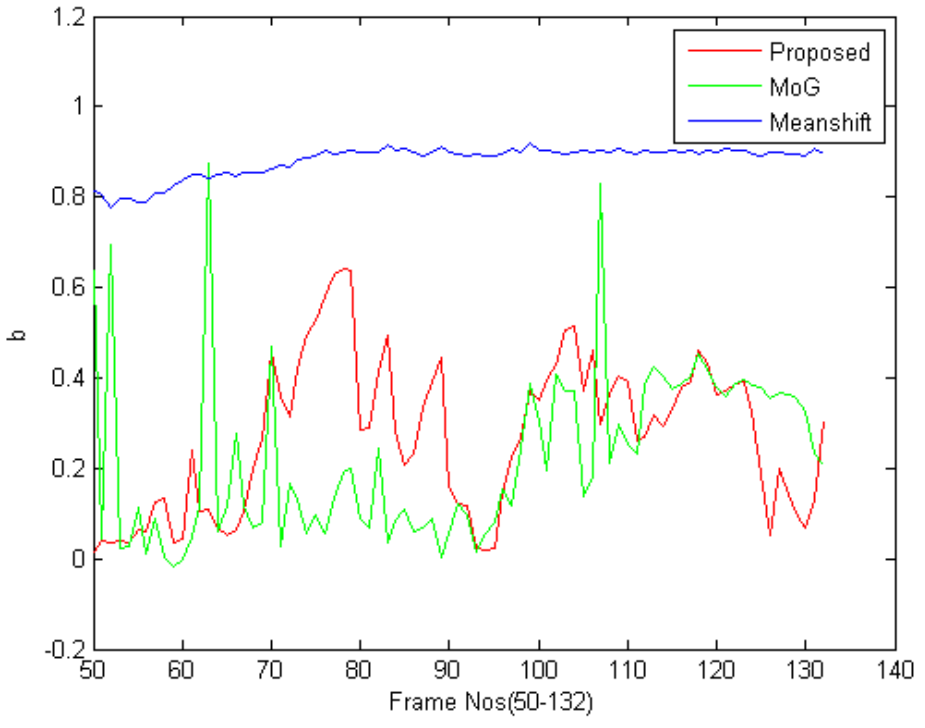


(b)

Figure 17. Values of f obtained for: (a)Frame nos. 134-215 from the*Surveillance Scenario Sequence* from PETS-2000 (b)Frame nos. 50-132 from the*Walk3 sequence* from PETS-2004



(a)



(b)

Figure 18. Values of *b* obtained for: (a)Frame nos. 134-215 from the*Surveillance Scenario Sequence* from PETS-2000 (b)Frame nos. 50-132 from the*Walk3 sequence* from PETS-2004

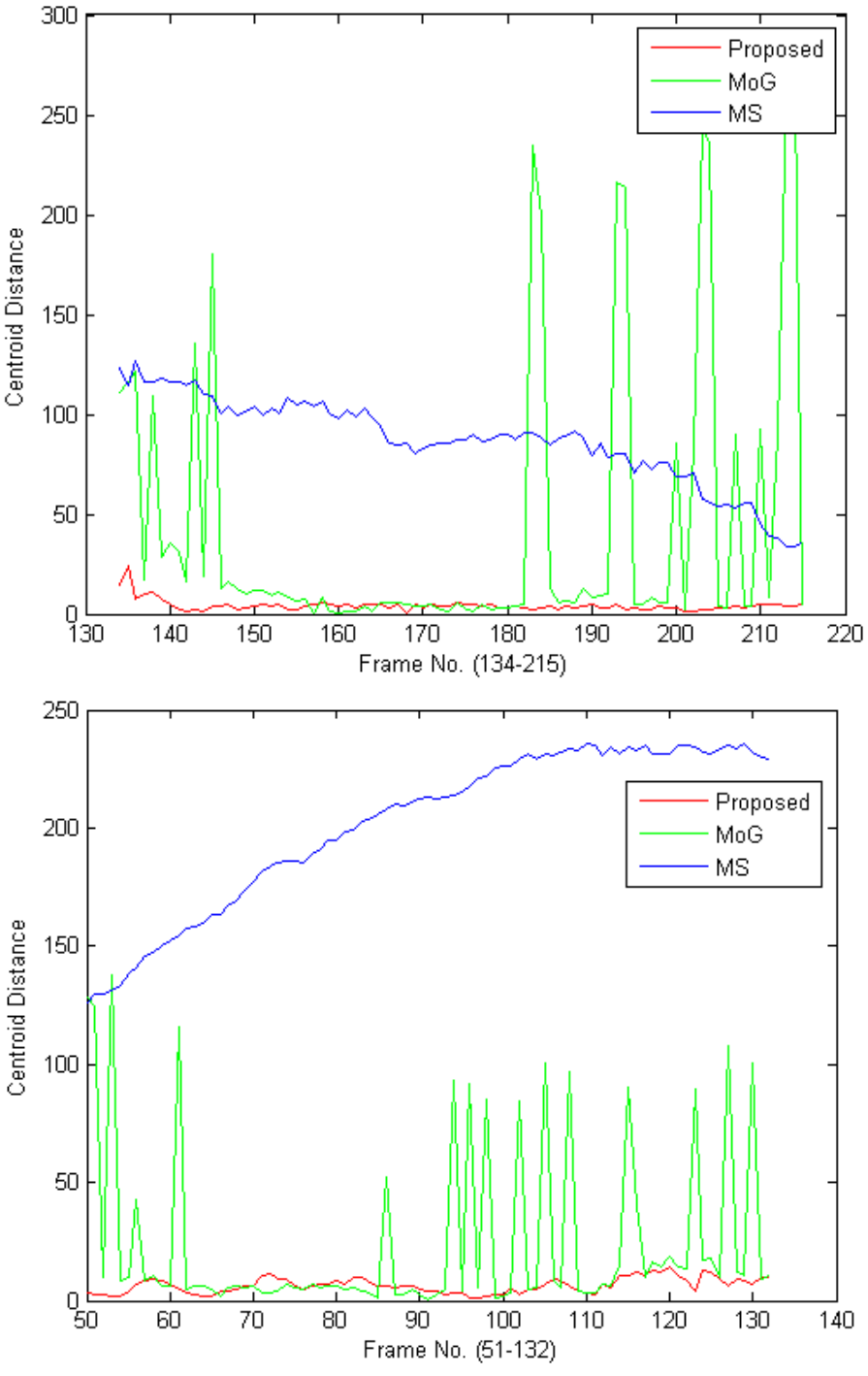


Figure 19. Values of *Centroid Distance* obtained for: (a)Frame nos. 134-215 from the*Surveillance Scenario Sequence* from PETS-2000 (b)Frame nos. 50-132 from the*Walk3 sequence* from PETS-2004

7. Conclusions

In this paper we have described a method using the concept of rough set based feature reduction along with a measure of indiscerniblity for tracking a moving object in a video sequence. We have used median filtering method for initial object modeling to reduce the effect of noise. We have also proposed three new measures to evaluate the performance of tracking. We have used these measures in the process of tracking to determine the mis-tracked frames and making them corrected. This way, the over all performance of tracking gets improved. We have implemented our algorithm on several data sets and have satisfactory results. The proposed method is seen to be more efficient for tracking as compared to mean-shift and MoG. The method does not require any prior knowledge about the video sequence or the object and it can reconstruct the desired object in the current frame. The reconstructed object is more reliable as the method includes the neighborhood information of a pixel predicted from the object shift information in the previous frames, in addition. The proposed measures are able to find out the mis-tracked frames successfully, which shows their effectiveness to make the process corrected and to evaluate the quality of tracking. Appropriateness of a particular index in evaluating the tracking is application oriented. These measures are also unsupervised and do not require any knowledge about the ground truth. k-index reflects the knowledge dependency between the target model and tracked region. f-index determines the pixel-wise similarity in terms of these two regions considering the neighborhood effect. b-index measures the similarity between color histograms of the two regions. The superiority of considering unequal bins over equal bins in computing Bhattacharya distance for determining the mis-tracked frames is also established. The values of the indexes reflect nearly similar results to a ground truth based measure. This shows its effectiveness towards performance evaluation of tracking. The method can be extended for tracking multiple moving objects.

8. Acknowledgement

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