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Visual Tracking on Riemannian Space Using Updated Standard Deviation Based Model

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Abstract

Object tracking using appearance based modeling from non stationary camera is one of the key aspect of visual tracking. While most of the existing algorithms are able to track objects well in controlled environments, those methods usually fail to track a longer sequence of trajectory in the presence of significant variation of the objects appearance or surrounding illumination. In this paper, we propose a new simple standard deviation based model updated method for tracking a longer sequence of trajectory for the target object. Non singular covariance based feature subspace is constructed for each candidate image region that lie on riemannian space. This feature subspace is updated by adding the vector mean difference of standard deviation between the referenced object and the detected objects, to each observation vector of the referenced model. The resultant covariance structure of this updated target reference model can be used for tracking the next sequence video frame. In the proposed model, also we use the kalman filtering for effectively handle the background clutter and temporary occlusion. Simulation result shows the current method is robust for real time tracking.

Keywords: feature matrix, covariance matrix, riemannian geometry, subspace

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1. Introduction

The ability to track and retain information about an object by finding the correspondences of the previously detected objects in the current frame has several vision applications. It plays a key role in many applications such as intelligent surveillance, human computer interface, traffic control and vehicle navigation. The main challenging issue of tracking is to handle effectively the intrinsic and extrinsic appearance variation of the object. The former is linked to the variation of object which undergoes change in the shape and pose. The letter related to the variation in the camera motion, illumination change and occlusion. Therefore, to track accurately the object, It is very crucial to design a model to represent the object which can adopted to change as object undergoes deformation to the external and internal parameter. Previously many methods were developed on vision tracking such fixed template method, prediction based filter and subspace based appearance model to track the object. Tracking with fixed templates can be reliable over short durations, but it copes poorly with appearance changes over longer durations that occur in most applications. In prediction schemes based approach, a model is first design by learning the target object and then this will use for tracking. In the recent past many filter like particle filters [1], kernel-based filters [2, 3], joint probabilistic data association filters [4] and support vector machines [5] are developed but those method are not suitable when the appearance of the object vary with respect to pose or facial expression, or to the lighting variation. In subspace based appearance model the statistical and spatial property of the image region is represented in the form of vector. Although the use of subspace based model increase the reliability and robustness of tracking [6] but still it lacks in establishing the direct local relationship of pixel present in the image region. These local relations are to a large extent, invariant to complicated environmental changes. Updating the target subspace is an important task in tracking to retain the detection accuracy of the trajectory for a longer sequence of the video. In this paper, we propose a framework for updating the subspace of the appearance model with every detected frame of the video. The object of interest is represented by its feature space,

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containing the spatial and statistical attribute of the pixel. Each of the feature in the feature space is updated in regular interval by measuring the amount of deviation of each feature from its mean. Update at every frame would result in accumulation of small errors, and eventually eliminate a target drift and loss of target information.

Our work is organized as follows. Section 2 briefly focus on the some of the related work on covariance based model tracking. Representation of the target window into a low dimensional feature space is discussed in the Section 3. Followed to this, section 4 discuss the overall frame work for the proposed model and its updated strategy. In Section 5, we compare the performance analysis of the proposed method with previous existing methods.

2. Related Work

There is a rich literature in visual tracking and a thorough discussion on this topic is beyond the scope of this paper. In this section we review only the most relevant work related to subspace based appearance model for visual tracking. We correlate our work with those methods in terms of their feature representation of image and updating the model to the variation of object. Black and Jepson [7] proposed an algorithm using a pre-trained view-based eigen basis representation and a robust error norm. This method mainly focus on the motion estimation between the frames and also it undergoes the learning a set of view based eigen bases prior to the task of tracking but these are object specific and often require training prior to tracking. Frey [8] proposed a tracker with image templates that model the mean and the variance of each pixel during tracking. T.Yu and Y.Wu [9] present an differential tracking algorithm to model both the object appearance variations and its global spatial structures. This model use the maximum likelihood matching criterion to enables the efficient recovery of all motion parameter. Mei and Ling [10] introduce sparse representation method for visual tracking. In this approach the target object is found by L_1 minimization of the sparse presentation of the space.

Ho.et al. [11] developed a tracking algorithm based on the appearance of the object. In his approach the subspace is updated at real time and tracking depend on the previous best approximation of searching the object. Hager and Belhumeur [6] developed a low dimensional subspace tracking method to effectively capture the appearance variation caused by illumination and pose change using parametric models. Their method extends a gradient-based optical flow algorithm by incorporating low-dimensional representations for object tracking under varying illumination conditions. Hypothesis based multivariate approach [12] also give significant result for the tracking. But this method is not suitable for the object undergoes continuous appearance variation. Li et al. [13] propose an incremental PCA algorithm for subspace learning. It deals with updating the mean of the multi sample image by flattening the each newly arrived image. This method is quite incapable in handling larger mean variation. In Skocaj and Leonardis [14], a weighted incremental PCA algorithm for subspace learning is presented. In their approach an incremental method is used, which sequentially updates the principal subspace considering weighted influence of individual images as well as individual pixels within an image. Although the above two process is quite robust for tracking but it lacks with capturing the spatial and statistical property of the object. This cause the method not fertile towards the illumination and change in variation of the object. In order to tackle those issues F. Porikli, O.Tuzel [15] proposed appearance based covariance matrix descriptor for capturing both the statistical as well as the spatial property of the object window. As the mean covariance matrix is possessing the property of symmetric positive definite(SPD) and also lie on the Riemannian manifold, so the statistics for covariance matrices of image features may be computed through Riemannian geometry. Appearance based model using the Riemaninan geometry is robust only when the deformation of appearance is minimal. Many different type of tracking algorithm has been developed in the recent past using this geometry. chen et al. [16] developed a tracker using a diffusion process on riemannian manifold, this dynamical model using the random walk on riemannian manifold for updating the template. Although this method is robust towards eliminating the problems such as pixel to pixel mis alignment, pose and illumination change, but still there is some difficulties in handling the diffusion speed.

Tuzel and Porikli [17] present a new algorithm for human detection using Riemanian manifolds. This method uses the covariance matrices as object descriptors and a learning algorithm on the Riemannian manifolds. Lim et al. [18] present a human tracking framework using the identification of system dynamics and nonlinear dimension reduction technique. Although log euclidean distance can be used for matching the object but those methods are lacking to obtain the optimal mean covariance of the detected region needed for the model update. Based on this log euclidean Riemannian metric [19, 20], we propose a Visual Tracking On Riemannian Space using a updated Standard deviation Based Model. The objective of the proposed method is to construct a low dimensional feature subspace to track the object by exploiting the temporal and statistical property of the pixel and also update this feature subspace of the appearance model with the addition of every new frame of the video for retaining the tracking for a longer trajectory.

Contribution Of Our Work:

I. The target object window is scale down to smaller feature image for faster computation of covariance matrix.

II. This tracked object window size is always fixed one and its observation which is described through d dimensional space is updated with addition of newly detected matching object.

III. Observation vector of target object is updated on the basis of the deviation of the object from their mean dimen-

sion
The main aim of our work is to update the referenced model which in terms depends on finding a mean covariance matrix from the set of detected covariance region. As the covariance factor is mainly depends on the deviation of each feature sample from its mean. So the key idea behind is to updated the each sample feature of the feature referenced image with a small value δ which is the mean difference of standard deviation(SD) between the referenced and detected object. This leads to minimize the variance structure between the updated referenced model and the next detected region.

3. Covariance Matrix Representation

Using Tuzzel et al. [15] covariance matrix representation, The observed Image I of $m\ X\ n$ one dimensional or three dimensional color image is converted into d dimensional feature image of size $mXnXd$. Mathematically this mapping can be written as

$$F(n,p) = \emptyset(I,r,c) \tag{1}$$

Here the function θ is a mapping function and it can be any mapping such as color,image gradient or edge magnitude. For a given rectangular region R $\subset$ I , denote the $f_{i=1....n}$ as the d dimensional feature point obtained by within R. In this paper each pixel of the object is defined through the set of feature as

$$f_k = [x, y, I(x,y), I_x, I_y, \sqrt{(}x^2+y^2), arctan\frac{I_x}{I_y}] \tag{2}$$

where x,y are the spatial coordinate and $I(x,y), I_x, I_y$ are the intensity value and its deviation of the pixel along x and y. Consequently, the image region R can be represented as dXd covariance matrix.

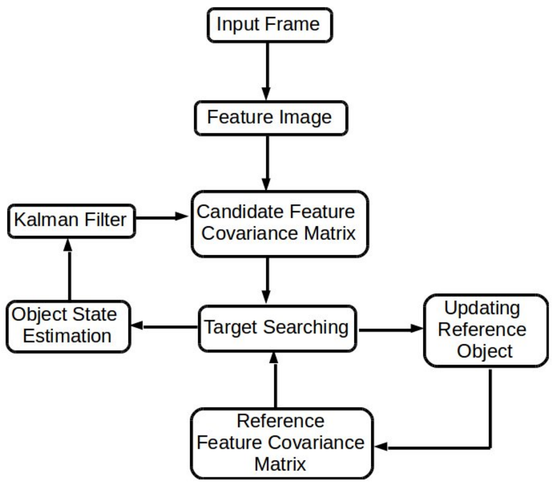

Figure 1: Proposed Model

$$S_r = \frac{1}{nm-1}\sum_{i=1}^{n}(Y_{ij}-\bar{Y}_i)(Y_{ij}-\bar{Y}_j) \tag{3}$$

The covariance matrix descriptor of a gray scale or color image region is a 7 X 7 or 17 X 17 symmetric matrix. The pixels coordinates are involved in the computation of the covariance matrix in order to include the spatial information about the image region and the correlations between the positions of the pixels and the intensity derivatives into the covariance matrix. It is also possible to compute covariance matrix from feature images in a very fast way using integral image representation [21].

4. Framework for Visual Tracking

The entire frame work of our method is passed through two stage. As shown in the figure 1, the first stage describe the construction of low dimensional feature space and the last stage use the kalman filter to predict the future location and estimate the current state from the given all the previous observations. In addition to this, the last stage also describes the updation of the target reference object with the newly added frame. This updation is carried out by by adding a small value δ . This value is the mean difference in the deviation of the so far detected region from the referenced object.

4.1. Object Representation

In this proposed appearance based model, each pixel of the object is treated as a sample or observation defined with set of spatial and statistical attributes or features. Thus a feature space can be constructed from the one dimensional intensity or three dimensional color image.Once the feature matrix is constructed then Using eq(3) a low dimensional covariance matrix is extracted from this feature image matrix.

4.2. Matching of candidate region

In every tracking framework to find the best candidate region in the target frame, one needs to compute the effective distance between the candidate covariance matrix C_i and the reference covariance matrix C_j. As the covariance matrix do not lie on the euclidean space and these are belongs to a connected riemannian manifold. so a log euclidean based forstner distance [22]can be employed for the said purpose for computing the similarity between the two matrix. This method uses the sum of the squared logarithms of the generalized eigenvalues to compute the dissimilarity between covariance matrices as

$$\rho(C_i, C_j) = \sum_{k=1}^{d}(\sqrt{log^2\lambda_k(C_i, C_j)}) \tag{4}$$

where $\lambda_k(C_i, C_j)$ are the generalized eigenvalues of (C_i, C_j) which is derived from the equation

$$\lambda_k C_i X_k - C_j X_k = 0 \tag{5}$$

Here X_k represent the generalized eigen values. The distance measure ρ satisfies the metric axioms, positivity, symmetry, triangle inequality, for positive definite symmetric matrices. The minimum ρ value for a candidate object in the searched space will be judge as the target selection for that frame.

4.3. Model update strategy

Model updated strategy is an important step required to track object that undergoes change in shape, size and appearance with respect to time. Although a straight forward solution may be to take the aggregate covariance of all the detected covariance matrix. But as the covariance matrix do not conform to euclidean space and it is confronted to a riemannian space. It can be possible to find the mean of detected covariance matrix by using the Riemannian mean. But the computational cost for this linearly grows as time progresses.

An average covariance structure can be constructed from the detected regions of the previous frame. A small value δ which is the mean difference of the standard deviation between the reference model and the detected region, is added with each sample or observation of the original reference model. A low dimensional covariance structure is then derived from this resulting updated model which can be used for the next set of successive frame.

Let R is the referential feature image region with size m X n X d . This region which is represented with d dimensional feature or attribute is updated. This model updation is carried out with estimated object region $R_1, R_2 ... R_J$. We keep set T of previous covariance matrices $[C_1, C_2 .... C_T]$ where C_i denotes the current covariance matrix of the detected region. From this set we compute sample mean covariance matrix.
Following steps are used for the model updation.

Step 1: Find the mean and variance vector for the reference feature image as
$\mu_r = \mu_{r1}\mu_{r2}\mu_{r3}.......\mu_{rd}$ and $\sigma_r = \sigma_{r1}\sigma_{r2}...........\sigma_{rd}$
Step 2: similarly find the mean and variance vector of the detected region as $\mu_d = \mu_{d1}\mu_{d2}\mu_{d3}.......\mu_{dd}$ and
$\sigma_d = \sigma_{d1}\sigma_{d2}...........\sigma_{dd}$
Step 3: Find the difference of standard deviation between the detected and the referenced model.
$\delta = \sqrt{\sigma_r} - \sqrt{\sigma_d}$
Step 4: Update each observation Y_i of the referenced model with the value δ
i.$\forall Y_{ij} = Y_{ij} + \delta_j$ if $\forall Y_{ij} > \mu_r$
ii.$\forall Y_{ij} = Y_{ij} - \delta_j$ if $\forall Y_{ij} < \mu_r$

where *i=1..MN* indicates the number of row feature vector or observation with *j=1..d* number of component.

Once the original referenced region is updated, then extract its covariance matrix of this referenced model which can be used for the next sequence of candidate object in the video.

4.4. Proposed Algorithm

step 1: Initialize $\hat{C} = C1, Y = Y1,$
step 2: Extract the variance vector σ_r *of d elements from the diagonal of reference covariance matrix* $\hat{C}$
step 3: for t=1..T do
step 4: -compute the deviation $\sigma_t = \sqrt{\sigma_r} - \sqrt{\sigma_d}$
step 5: compute $\delta = \frac{1}{2T}\sum_{t=1}^{2T}\sigma_t$
step 6: if($Y_{ij} > \mu_r$ *)*
step 7: $Y_{ij} = Y_{ij} + \delta_j$
step 8: else
step 9: $Y_{ij} = Y_{ij} - \delta_j$
step 10: $\hat{C} = COV(Y)$
step 11: end

4.5. Kalman Filter

A Kalman filter is an optimal estimator i.e infers parameters of interest from indirect, inaccurate and uncertain observations. It is recursive so that new measurements can be processed as they arrive. From the set of past observation the future state of the object can be predicted. Once the true state information is available this predicted measurement is undergoes the update phase. it is treated as an useful tool in determining the position and state of the object in the presence of the occlusion.

Each Kalman filter is configured as follows

$$X_k = AX_k + W_k \tag{6}$$

$$Z_k = HX_k + V_k \tag{7}$$

where $X = [P_x P_y V_x V_y]$
P_x P_y represent the center position of x-axis, and y-axis. Vx, Vy are the velocity of x-axis and y-axis. Matrix 'A' represents the transition matrix, Matrix 'H' is the measurement matrix,and T is the time interval between two adjacent frames.

W_k,V_k are the Gaussian noises with the error covariances Q_k and R_k.

The process of Kalman filter is as follows. The Kalman filter state prediction X_t and state covariance prediction P_t are defined by:

$$X_{k|k-1} = AX_{k-1} \tag{8}$$

$$P_{k|k-1} = AP_{k-1}A^T + Q_k \tag{9}$$

where Xt and Pt denotes the estimated state vector and error covariance matrix respectively at time t. Then the Kalman filter update steps are as follows:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + T)^{-1} \tag{10}$$

$$X_k = X_{k|k-1} + K_k(Z_k - Z_k|k-1) \tag{11}$$

$$P_k = (1 - KH)P_{k|k-1} \tag{12}$$

where K is the Kalman gain and this is depend on the accuracy of the measurement. Kalman filter algorithm starts with initial conditions with K_0 and P_0 . K_t is the Kalman gain, which defines the updating weight between the new measurements and the prediction from the dynamic model.

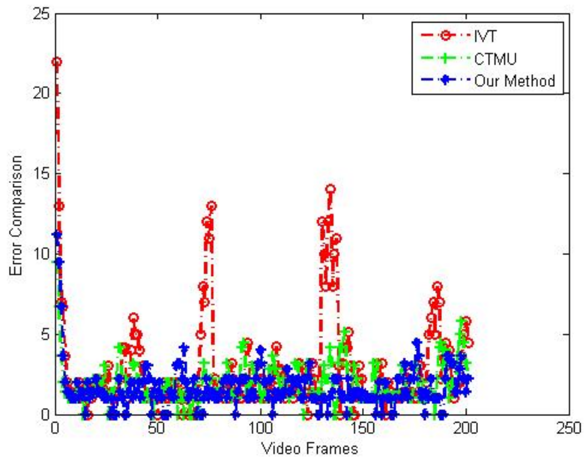

Figure 2: Quantitative Error comparison between IVT, CTMU and Our method

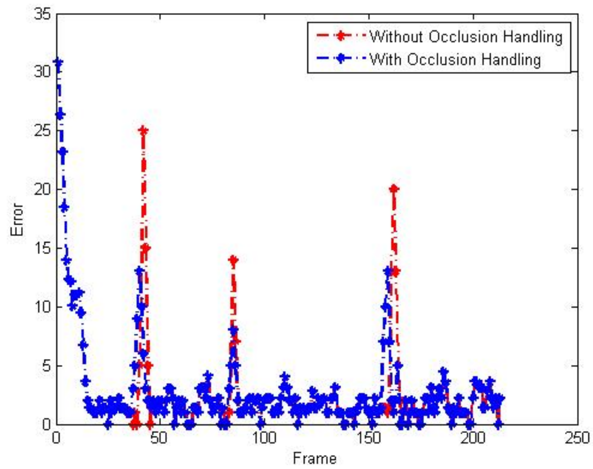

Figure 3: Quantitative Error comparison without occlusion and with occlusion handling technique

4.6. Occlusion Handling

Updating the appearance model for tracking the object under the occlusion yields inaccurate or incorrect result. In order to handle this issue,we only update the subspaces for blocks whose dissimilarity detection rate (ρ) is less than certain threshold value. During the occlusion environment kalman prediction filter is used for detecting the object in the occluded background. In this way, the appearance variations in blocks which are not occluded are learned effectively. As a result, the appearance model can be updated even in the presence of occlusions.

4.7. Time Complexity

The total time complexity of our proposed algorithm is depend on three factor. Computation time for updating the reference feature matrix which is $O(mnd)$. The time computation for finding the low dimensional covariance matrix using integral covariance representation is $O(mnd^2)$ and the forstner distance measurement to find the similarity between two covariance matrix is $O(mnd^3)$. So the total computational complexity is O$(mnd + mnd^2 + mnd^3)$. Asymptotically this complexity can be expressed as O(n^3).

5. Experimental Analysis

In order to find the performance of the proposed tracking method, experiment are carried out using the opencv -2.4.2 on Ubuntu platform. Seven number of feature where considered for each pixel of the object. A 9X9 neighborhood window size is considered for the searching of candidate object in a video frame. The experiments are carried out on different types of vision video dataset.Each experimental outcome is explained separately for clearly understanding the performance issue of the vision tracking.

Experiment 1: First experiment is carried out on moving person where the frames are captured from a stationary camera. Here we first track the single object without model update and with model update approach and also we compared the same with the traditional covariance based model approach (CTMU). In Fig4 first row and 2nd row showing our method to track the person with out and with model update method and third row shows the simulation output for CTMU. From the Simulation results we observed that our proposed method yields better tracking result.

Experiment 2: Our algorithm also applied on another two dataset,one is tracking a person on a traffic and another is the tracking a pedestrian in a shopping mall.In Figure 5,the first and 2nd row respectively showing the tracking result for the person and a pedestrian in a shopping mall.we tested this for 400 frames and simulation shows the better tracking result.

Experiment 3: Location deviation or the tracking error of our proposed method also shown in the figure 3, Experiment carried out to show the quantitative evaluation of error rate between our proposed method and the covariance tracking method using model update(CTMU) and Robust incremental method for subspace learning(IVT). The error comparison which is shown in figure 2 shows that our method has more robust and better handle the error better detection quality as compared to CTMU and IVT.

Experiment 4: Our model is also tested on face tracking under the occlusion condition. Occlusion before the tracked image introduce noise to the model. With the help of kalman prediction and threshold decision, the model restricted the subspace updation. Fig. 6 shows the results of tracking the face using our occlusion handling method. It

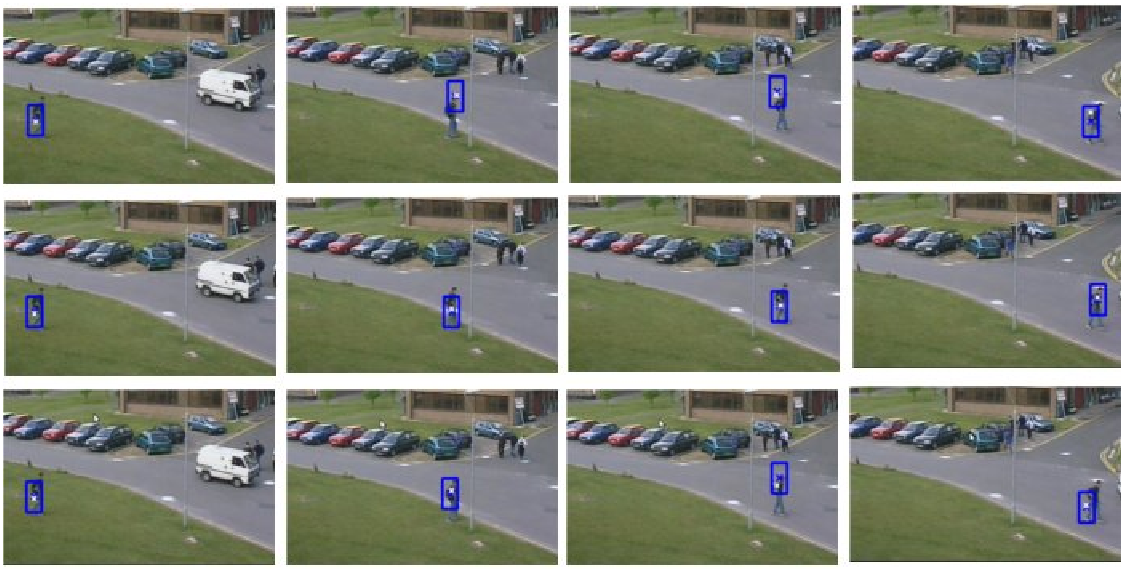

Figure 4: First row and 2nd row showing the result of our proposed method without and with model update and 3rd row showing the simulation result of existing covariance based model update method.

Figure 5: Tracking Using the Proposed method for a person and the pedestrian in a shopping mall

Table 1: Table1

Input Video	Detection Rate	No Of Trial
Moving Man Video	96.28	0.0012
Padestrain Tracking	94.43	0.0915

is seen our occlusion monitoring method successfully handles to detect the face throughout the video.
We also analyzed the number of trials to find the correct estimation. This is based on ordering the search regions according to the match scores until we find the correct estimation. We defined the metric as the ratio of the total number of trials to the total number of possible regions. we applied this to moving man video and the pedestrian tracking.

We show the output for moving object tracking on moving man video and pedestrian video.The result of those experiment reveals a good detection rate of our algorithm.

However, there are some limitations in our algorithm. As we consider covariance descriptors for constructing the feature space. so it is very important to chose a target region of good resolution in the initial frame for detecting the object in the next sequence of frame, Another limitation to the current model is in deciding the proper threshold value in selecting the candidate target object in the nearest neighborhood region. so in order to avoid the drifting of the object both the region selection and proper setting up threshold value is required for the model.

6. Conclusion

In this paper, We have presented a appearance based updated model for visual tracking the object. A log euclidean based forstner distance is employed for the similarity measurement between the objects. Our model is

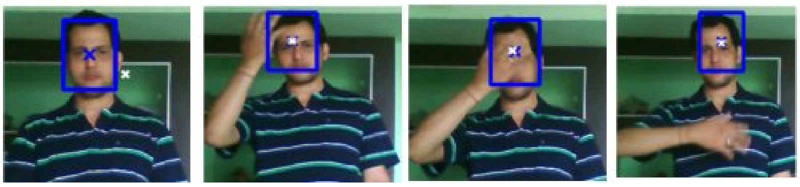

Figure 6: Tracking the face Under the hand occlusion

adaptive in nature and updated the feature space of object in the regular interval by measuring the mean deviation of the feature. Although our proposed model performs well, it occasionally drifts from the target object. With the help of kalman filters, the tracker often recovers from drifts in the next few frames when a new set of samples is drawn. Experimental results have demonstrated that, our tracking algorithm obtains more accurate tracking results when there are large variations in illumination, small objects, pose variations, occlusions. Moreover the proposed method is more promising for real time tracking. In future scope this algorithm can be extended to work on multi object simultaneously and also to to find the interval rate for updating the model for proper tracking the object.

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