

Video Image Object Tracking Algorithm based on Improved Principal Component Analysis

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Abstract—Since the existing object tracking algorithms are very difficult to adapt the object appearance changes caused by illumination changes, large pose variations, and partial or full occlusions, an object tracking algorithm based on two-dimensional principal component analysis (2DPCA) and sparse-representation is proposed in this paper. The tracking algorithm adopts 2DPCA and sparse-representation to establish object appearance model. In order to reduce dimension of object template, incremental subspace updating algorithm is introduced to online update the object template, reduce the requirement of memory space and enhance the precision of object appearance description. Experimental results show the proposed algorithm is robust for image illumination variance and object partial occlusion.

Index Terms—Object Tracking; Sparse-Representation; Incremental Learning; Subspace Updating Algorithm; Object Appearance Description

I. INTRODUCTION

Object tracking [1] in video is one of the hot topics in the field of computer vision. It has a wide variety of applications, such as video conference, robotics navigation, virtual reality etc, which has important theoretical significance and practical value. However, object tracking result is usually affected by the background, brightness, objects posture, occlusion or lighting condition and so on, which makes the tracking process more complicated and becomes a challenging task. In order to overcome these difficulties, a large collection of algorithms are proposed to improve and refine object tracking. One category of existing algorithms is to detect and track each individual object using an independent tracker where multiple object tracking is performed by using multiple independent trackers [2]. Although tracking isolated objects is relatively simple, especially in simple backgrounds, tracking multiple objects in complex backgrounds remains a challenging task [3], especially in cases of long-term partial occlusions, object intersections, object pose changes, deformations, abrupt motion speed changes, cluttered background or dynamic complex background [4]. Therefore, it is worthy of studying the topic deeply that object tracking should exactly track the selected objects [5].

The existing object tracking algorithms can be classified into three categories: Correlated-template matching based tracking methods, Adaptive filter theory tracking approaches, Classification-based tracking algorithms [6]. The tracking algorithms based on correlated-template matching can achieve a higher accuracy with simple scheme, but the model is sensitive with the situation of partial occlusion, non-rigid image deformation and natural appearance changes [7]. The tracking algorithms based on adaptive filter theory can mainly be classified into two categories: extended Kalman filter and particle filter [8]. Kalman filter can only handle the scenario with linear, Gaussian and single mode, while particle filter adapts to nonlinearity and non-Gauss object tracking [9]. Classification-based tracking algorithms are regarded as a two-classification problem, where the object is tracked through distinguishing foreground from background using two thresholds [10]. It mainly utilizes the prior knowledge of each classifier to locate the moving or still object accurately, but two groups of samples are needed to construct classifier, which it is not appropriate for real-time scenario [11]. And in the process of tracking, there must be many sudden changes in the object image, and then the reasonable updating of the reference image will be the key to the tracking problem [12].

Recently, sparse representation theory can significantly improve the robustness of tracking in cases of long-term partial occlusions, object intersections, object pose changes, deformations, abrupt motion speed changes, cluttered background or dynamic complex background and reduce the computational complexity [13], which this technology is gradually applied and spread in object tracking. Scholars have proposed a robust visual tracking algorithm by viewing tracking as a sparse approximation problem in a particle filter framework [14] [15]. In this framework, occlusion, corruption and other challenging issues are addressed seamlessly through a set of trivial templates. Specifically, in order to find the tracking target at a new frame, each target candidate is sparsely represented in the space spanned by target templates and trivial templates. The sparsity is achieved by solving a ℓ_1 -regularized least squares problem. Then the candidate with the smallest projection error is taken as the tracking target. After that, tracking is continued by using a Bayesian state inference framework in which a particle

filter is used for propagating sample distributions over time. Although the proposed approach shows excellent performance in comparison with three previously proposed trackers, it is always unstable in the case of small objects or large deformation because of its high computation complexity and complicated calculation. Based on the above analysis, an object tracking algorithm based on two-dimensional principal component analysis and sparse-representation is proposed in this paper. The tracking algorithm adopts 2DPCA and sparse-representation to establish object appearance model. In order to reduce dimension of object template, incremental subspace updating algorithm is introduced to online update the object template, reduce the requirement of memory space and enhance the precision of object appearance description.

II. OBJECT TRACKING BASED ON SPARSE-REPRESENTATION

A. Feature Subspace

Assume $\mathbf{Y}_t = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n\}$ denotes an observed sample set of object on the t frame, where $\mathbf{y}_i \in \mathbf{R}^{d \times d}$ is the i th observed sample, $\mathbf{I}_t = \frac{1}{n} \sum_{i=1}^n \mathbf{y}_i$ denotes the

means of observed sample set $\mathbf{Y}_t$. In order to reduce storage costs and computation time of computer, an object tracking algorithm based on two-dimensional principal component analysis (2DPCA) is introduced to analyze the image. In comparison with PCA, 2DPCA is based on image method, which doesn't have to be translated into vector [16] [17]. Computing covariance matrix is simple and direct, and computing feature vector has less time. 2DPCA algorithm is described as follows:

Computing the covariance matrix of observed sample set $\mathbf{Y}_t$

$$\mathbf{S}_t = \frac{1}{n} \sum_{i=1}^n (\mathbf{y}_i - \mathbf{I}_t)(\mathbf{y}_i - \mathbf{I}_t)^T = \frac{1}{n} \mathbf{Y}_t \mathbf{Y}_t^T \quad (1)$$

Computing the eigenvalue of covariance matrix [18] $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$;

Computing the unit orthogonal eigenvectors relative to eigenvalues [19] $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n$;

Retain the first k eigenvectors to constitute feature subspace $\mathbf{U} = \{\mathbf{u}_i\}_{i=1}^k$.

B. Sparse-representation

Assume the object template set and feature subspace can be denoted as $\mathbf{U} = \{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k\} \in \mathbf{R}^{d \times k} (d \gg k)$, where includes k object templates [20]. Therefore, the tracking results can use the feature subspace $\mathbf{U} = \{\mathbf{u}_i\}_{i=1}^k$ to express approximately as the nonlinear curve [21]. Let us consider the discrete signal x of size N , which can be viewed as an $N \times 1$ column vector in $\mathcal{R}^N$ with elements $x[n] \in \mathcal{R}^n$. Specifically, using the

basis matrix $\Psi = [\Psi_1, \Psi_2, \dots, \Psi_N]$ with the vectors $\{\psi_i\}$ as columns, a signal x can be sparsely expressed as

$$x = \sum_{i=1}^N s_i \Psi_i = \Psi s \quad (2)$$

$$\mathbf{y} \approx \mathbf{U} \mathbf{a} = a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2 + \dots + a_k \mathbf{u}_k \quad (3)$$

where, s is the $N \times 1$ column vector of weighting coefficients in the Ψ domain, $\mathbf{a} = (a_1, a_2, \dots, a_k)^T \in \mathbf{R}^k$ is a vector of object coefficient. Due to the interference, such as noise or occlusions in the process of object tracking, the error term is introduced, as shown as follows [22]:

$$\mathbf{y} = \mathbf{U} \mathbf{a} + \boldsymbol{\varepsilon} \quad (4)$$

where, $\boldsymbol{\varepsilon} \in \mathbf{R}^d$ is the error term caused by noise or occlusions and its non-zero element denotes the object has noise or the object is occluded. Therefore, the identity matrix $\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_d]^T \in \mathbf{R}^{d \times d}$ is introduced to the interference location [23]. So Equation (4) can be rewritten as follows:

$$\mathbf{y} = [\mathbf{U}, \mathbf{E}] \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix} = \mathbf{D} \mathbf{c} \quad (5)$$

where, $\mathbf{b} = (b_1, b_2, \dots, b_d)^T \in \mathbf{R}^d$ is noise coefficient, $\mathbf{D} = [\mathbf{U}, \mathbf{E}]$ is an over-complete dictionary, and $\mathbf{c}^T = [\mathbf{a} \ \mathbf{b}]$ is coefficient vector [24].

The signal x is K-sparse if it is a linear combination of only K basis vectors; namely, only K elements of the coefficients in (1) are nonzero and (N-K) are zero [25]. The measurement value of a signal x can be obtained by adopting nonlinear measurement, so y can be written as

$$y = \Phi x = \Phi \Psi s = \Theta s \quad (6)$$

where, Φ is an $M \times N$ measurement matrix with $M < N$. Because y is the $M \times 1$ vector and x is the $N \times 1$ column vector, so it is an underdetermined equation to recover x from only measurements y , which its exact solution cannot be obtained. If, however, x is K-sparse and the K locations of the nonzero coefficients in s are known, then the problem can be solved. According to the compressed sensing theory [26] [27], a sufficient condition for a stable solution for both K-sparse and compressible signals is that the matrix Φ satisfies RIP criterion and is incoherent with the basis matrix Ψ . So the original signal x can be precisely reconstructed by solving the following l_1 norm optimization problem [28].

$$s = \arg \min_s \|s\|_{l_1} \text{ s.t. } y = \Phi \Psi s \quad (7)$$

Applying the relaxation to the problem (5) yields a new optimization problem as follows

$$\min \|y - Dc\|_2^2 + \lambda \|c\|_1 \quad (8)$$

The linear programming technology is adopted to solve the Equation (7), so the reconstruction methods include some greedy algorithms, such as OMP [29], StOMP [11] and CP [12] have recently been proposed. Thus, we can get the sparse solution of coefficient vector $c^T = [a \ b]$

$$c^* = \arg \min_c \|y - Dc\|_2^2 + \lambda \|c\|_1 \quad (9)$$

By the solution $c^T = [a \ b]$ in above equations, reconstruction error between sample and template can be defined as

$$RE = \|y - Ua\|_2^2 \quad (10)$$

C. Incremental Subspace Updating Algorithm

Given the first n frames $A = [I_1, I_2, \dots, I_n]$, and the

corresponding mean value $\bar{I}_A = \frac{1}{n} \sum_{i=1}^n I_i$, we can get the

centered matrix $\bar{A} = [I_1 - \bar{I}_A, \dots, I_n - \bar{I}_A]$. If we denote the

singular value decomposition of data matrix $\bar{A}$ as

$\bar{A} = U_A \Sigma_A V_A^T$, where $\Sigma_A = \text{diag}(\lambda_{1,1}, \dots, \lambda_{r,1})$, $r = \min(m, n)$ and $\lambda_{i,j}$ is singular value of data matrix S_i (including zero), and U_A and Σ_A are unitary matrix and diagonal matrix, respectively. In addition, each column in matrix $\bar{A}$ is basis vector of subspace. Assume $B = [I_{n+1}, I_{n+2}, \dots, I_{n+m}]$ denotes m frames image,

the corresponding mean value $\bar{I}_B = \frac{1}{m} \sum_{i=n+1}^{n+m} I_i$, so we can

get $C = [A, B] = [I_1, \dots, I_n, \dots, I_{n+m}]$. In order to the unitary matrix U_A and diagonal matrix Σ_A of matrix C , the concrete steps are described as follows:

(1) Compute the mean value

$\bar{I}_C = \frac{fn}{fn+m} \bar{I}_A + \frac{m}{fn+m} \bar{I}_B$ of matrix C , where f is a forgetting factor and is also a non-negative number (no more than 1)

(2) Compute incremental centered matrix of B :

$$B^+ = [(I_{n+1} - \bar{I}_B), \dots, (I_{n+m} - \bar{I}_B), \sqrt{\frac{nm}{n+m}} (\bar{I}_B - \bar{I}_A)]$$

(3) Compute orthogonalization $\tilde{B}$ of $(B^+ - UU^T B^+)$

and matrix $R = \begin{bmatrix} f \Sigma & U^T B^+ \\ 0 & \tilde{B} (B^+ - UU^T B^+) \end{bmatrix}$.

(4) Decompose R in singular value decomposition to get U_R and Σ_R , thus $U_C = [U_A \ \tilde{B}] U_R$, $\Sigma_C = \Sigma_R$.

III. PARTICLE FILTER

The particle filter is an effective technique for the state estimation in non-linear and non-Gaussian dynamic systems. A novel method for object robust tracking based on particle filter has been proposed. Under the theory

framework of particle filter, the posterior distribution of the object is approximated by a set of weighted samples, while object tracking is implemented by the Bayesian propagation of the sample set. The state transition model is chosen as the simple second order auto-regressive model, and the system noise variance is adaptively determined in object tracking.

The objective of the particle filter is to estimate the values of the hidden states x_t , given the values of the observation process y_t at time t . According to the state transferring probability $p(x_t | x_{t-1})$ and the observation probability $p(y_t | x_t)$, the posterior probability $p(x_t | y_{1:t})$ can be derived and obtained by the following two steps: predict and update.

$$p(x_t | y_{1:t}) = \int p(x_t | y_{t-1}) p(x_{t-1} | y_{1:t-1}) dx_{t-1} \quad (11)$$

$$p(x_t | y_{1:t}) = \frac{p(y_t | x_t) p(x_{t-1} | y_{1:t-1})}{p(y_t | y_{1:t-1})} \quad (12)$$

The optimal Bayes estimator can be constituted by prediction equation in (10) and updating equation in (11). Each particle has an assigned weight to represent the probability of that particle being sampled from the probability density function. Weight disparity leading to weight collapse is a common issue encountered in these filtering algorithms; however it can be mitigated by introducing a re-sampling step before the weights become too uneven. In the resampling step, the particles with negligible weights are replaced by new particles in the proximity of the particles with higher weights.

Assume the particle is $\{x_t^i\}_{i=1}^N$ at time t , the normalized weight is denoted as $\{w_t^i\}_{i=1}^N$, and $\sum_{i=1}^N w_t^i = 1$. In other words, we use $\{(x_t^i, w_t^i)\}_{i=1}^N$ to describe the posterior probability.

$$p(x_t | y_{1:t}) \approx \sum_{i=1}^N w_t^i \delta(x_t - x_t^i) \quad (13)$$

In addition, the weight w_t^i of particle is updated by using the following equation:

$$w_t^i = w_{t-1}^i \frac{p(y_t | x_t^i) p(x_t^i | x_{t-1}^i)}{q(x_t^i | x_{t-1}^i, y_{1:t})} \quad (14)$$

where $\delta(\bullet)$, $q(\bullet)$ are Dirac function and importance density function, respectively. Generally, $q(x_t | x_{t-1}, y_{1:t}) = p(x_t | x_{t-1})$ is viewed as importance density function, where observations likelihood $p(y_t | x_t)$ is weight. The maximum posterior estimation can be acquired by the optimal state estimation problem of object:

$$\hat{x}_t = \arg \max p(x_t | y_{1:t}) \quad (15)$$

A. Motion Model

In the tracking framework based on particle filter, motion model is adopted to predict the available states of object between adjacent frames. Especially, rectangular box is used to locate object. The affine transformations of rectangular box are used to describe image scaling, translation, and rotation. In this paper, state vector of object is defined as

$$X_t = [x_t, y_t, \alpha_t, \beta_t, \phi_t, \gamma_t] \quad (16)$$

where six parameters correspond to six affine transformation parameters of rectangular box, and denote as the translation between two images in x , y direction, scale variation, the aspect ratio, rotation and gradient, respectively. Given the probability model of State Transition is called the normal distribution or the Gaussian distribution, namely,

$$p(X_t | X_{t-1}) = N(X_t; X_{t-1}, \Psi) \quad (17)$$

where, $N(\bullet)$ is Gaussian distribution, Ψ is a covariance matrix. In general, these parameters are independent of each other, and Ψ is a diagonal matrix where its elements are variance of affine parameters $\delta_x^2, \delta_y^2, \delta_\alpha^2, \delta_\beta^2, \delta_\phi^2, \delta_\gamma^2$, respectively.

B. Observation Model

Observation model measures the degree of similarity between candidate object region and object model. According to the Bayesian inference framework, observation model plays an important role in processing unknown scenario. Using the reconstruction error, the object observations likelihoods function can be defined as follows:

$$p(y|x) = \exp(-RE) \quad (18)$$

As we can see from Equation (18), the smaller the reconstruction error between sample and object template, so the larger its corresponding weight and the more reliable the sample will be. Our proposed tracking algorithm is given in Table 1.

IV. EXPERIMENT AND ANALYSIS

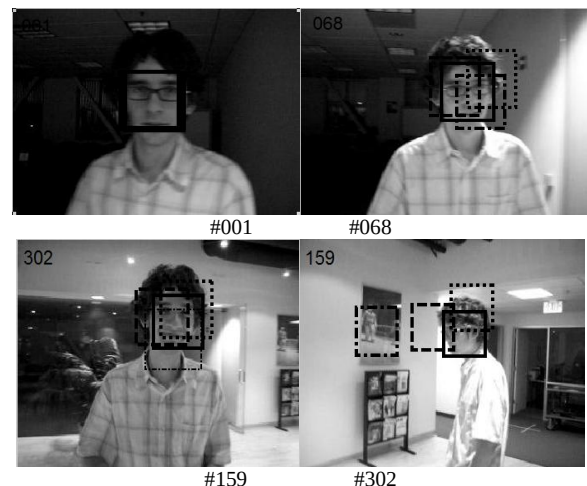
In order to validate the performance of our proposed algorithm, four standard video image sequences are selected to perform the tracking experiment. All of the experiments are run under MATLAB v7.8 (R2012a) on PCs with an Intel Pentium Dual Core CPU at 3.06 GHz and 4 GB memory. The proposed method is compared with three state-of-the-art methods which include Incremental Visual Tracking (IVT), L1tracker (L1), Multiple Instance Learning (MIL). In the actual experiment, the object position is manually selected in the first frame, the number of particle samples is 600, the dimension of object subspace is 16, and the update frequency of object subspace is set as 5. Throughout this study, the size of observatory image in our implementation is set as 32×32 .

TABLE I. OUR PROPOSED TRACKING ALGORITHM

Our proposed tracking algorithm
Input: video image sequence $\{F_t\} (t=1, \dots, T)$, the current number of particles N .
Output: object location tracked in each frame $\{x_t\} (t=1, \dots, T)$.
1. Initialization: manually choose the initial object template and disturb some pixels to generate n templates; using the affine transformation, the n templates are converted into image with the same size 32×32, then 2DPCA algorithm is adopted to generate the feature subspace U for object template set, namely, object templates set. 2. Construct over-complete dictionary: use feature subspace U and E to construct over-complete dictionary $D = [U \ E]$. 3. Generate particles: according to Gauss distribution, use the initialized affine transformation matrix to generate N particles (affine transformation parameters of candidate object templates). 4. Compute coefficient of sparse representation: minimize the Equation(8) in l_1 norm to solve sparse representation coefficient of each particle in template space, so as to get the coefficient-based affine coordinate of tracking object in the current frame. 5. Particle resample: according to the actual size of the weight, particles set is re-sampled for getting N particles in the next frame. 6. Update object template: use Maximum A Posteriori Probability to estimate the particle $\hat{x}_t$ with maximal weight, save the corresponding observation sample; at 5-frame intervals, use the updating algorithm to update object template. 7. Output result: show the tracking result in the current frame, go back to step 3.

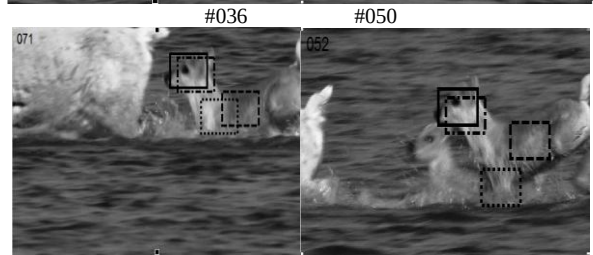
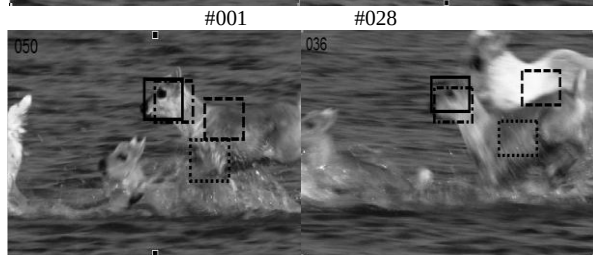
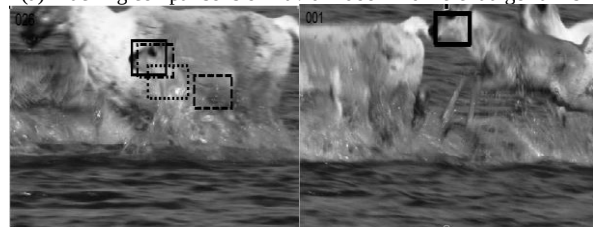
Figure 1(a) demonstrates David Indoor video sequences to evaluate the performance of tracking algorithm under the condition of illumination and posture change. In David Indoor sequence, there are two obvious light-intensity changes, and posture changes, such as picking glass and wearing glass. Throughout the whole tracking process, our proposed algorithm is not very sensitive to changes of illumination and posture, while L1, IVT and MIL algorithm show some deviation from the original object to some extent, where the MIL is more sensitive to all these influence.

In Deer video sequences shown in Figure 1(b), our proposed algorithm and MIL algorithm show a good performance. Although error tracking is appeared when the occlusion is occurred in #052 frames, MIL algorithm soon returns to the exact position. In addition, aiming at fast-moving object, LI and IVT algorithm has poor tracking performance.





(a) Tracking comparisons of David Indoor in different algorithms



(b) Tracking comparisons of Deer in different algorithms



(c) Tracking comparisons of Car4 in different algorithms



(d) Tracking comparisons of Caviar1 in different algorithms

Figure 1. Tracking comparisons of video sequences among our algorithm, IVT, L1 and MIL

As shown in Figure 1(c), our proposed algorithm and IVT algorithm show a good performance. Nevertheless, the tracking result of L1 algorithm has partial excursion after the vehicles pass over the bridge, while MIL algorithm has a larger excursion so that the tracking algorithm loses object.

Video sequences Caviar1 display the woman is walking down the aisle, as shown in Figure 1(d). The tracking result of MIL algorithm has the worst performance when appearing similar occlusion, and L1 and IVT algorithms have also some deviation from the original object to some extent, while our proposed algorithm shows a good performance in condition of partial occlusion or similar interference.

In addition, we adopt the location error to analyze quantitatively the performance of our tracker and the referenced trackers, where the location error is Euclidean distance between object location and tracking location, as shown in Figure 2. The maximum, average and standard deviation of each algorithm are listed in Table 2.

The underlined text shows the optimal result of each algorithm in Table 2, as we can see that our algorithm and L1 algorithm have the similar optimal result in David Indoor; our tracking algorithm and MIL algorithm have steady tracking performance when appearing the occlusion in Deer; comparing with the other three algorithms, our tracking algorithm shows a good performance when processing Deer and Car4 video sequences; our tracking algorithm acquires the least means and standard deviation in Caviar1 sequences. According to the overall performance, our proposed

algorithm yields the best performance in the process of object tracking.

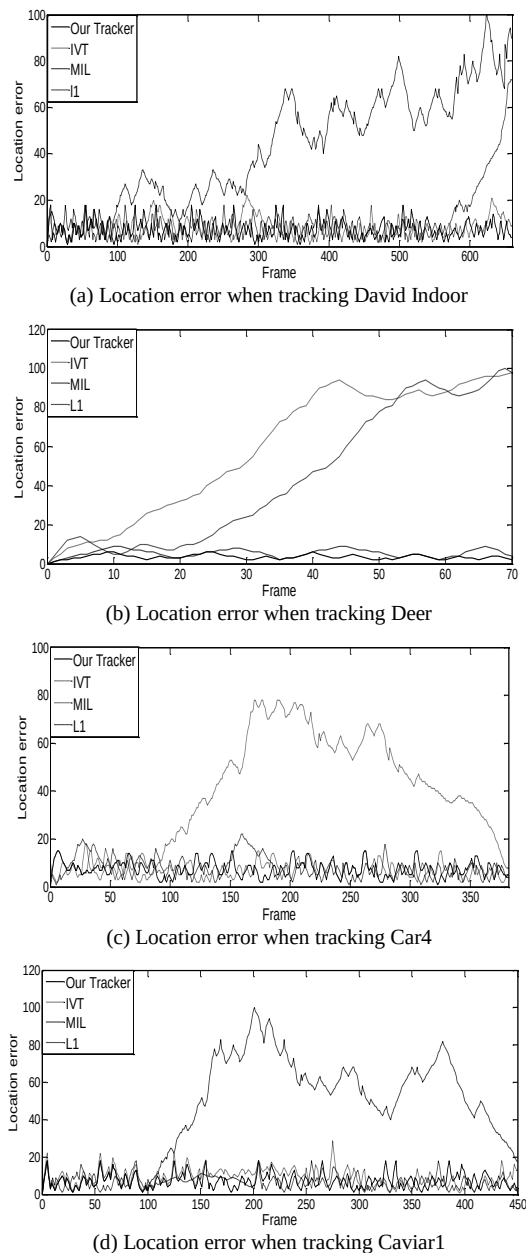


Figure 2. Quantitative evaluations in terms of center location error (in pixel). The proposed algorithm is compared with, IVT, L1 and MIL on four challenging image sequences

TABLE II. LOCATION ERROR

		David Indoor	Deer	Car4	Caviar1
IVT Tracker	Max	28.55	102.34	22.36	15.20
	Mean	9.18	59.10	8.39	7.50
	Std	4.45	32.82	4.22	3.16
MIL Tracker	Max	98.88	9.24	103.21	78.43
	Mean	45.25	5.46	42.46	38.61
	Std	27.22	2.09	24.38	21.82
L1 Tracker	Max	20.02	97.88	72.44	22.58
	Mean	6.77	44.01	10.72	8.15
	Std	3.35	34.63	10.91	4.48
Our Tracker	Max	21.23	6.35	18.21	15.32
	Mean	7.30	3.57	7.37	7.48
	Std	3.64	1.28	3.45	3.13

V. CONCLUSION

An object tracking algorithm based on two-dimensional principal component analysis (2DPCA) and sparse-representation is proposed in this paper, which adopts 2DPCA and sparse-representation to establish object appearance model and avoid to process high dimensional data. In order to reduce dimension of object template, incremental subspace updating algorithm is introduced to online update the object template, reduce the requirement of memory space and enhance the precision of object appearance description. Experimental results show comparing with IVT, MIL and L1 algorithm, the proposed algorithm can track the object accurately and is also robust for image illumination variance and target partial occlusion. However, our algorithm only uses the global feature, which makes full occlusion hasn't been effectively solved. Therefore, local features have reasonably been combined to better describe object and the improvement of our proposed algorithm will be the next research priority.

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