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Incremental Learning of Weighted Tensor Subspace for Visual Tracking

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***Abstract*—Tensor analysis has been widely utilized in image-related machine learning applications, which has preferable performance over the vector-based approaches for its capability of holding the spatial structure information in some research field. The traditional tensor representation only includes the intensity values, which is sensitive to illumination variation. For this purpose, a weighted tensor subspace (WTS) is defined as object descriptor by combining the Retinex image with the original image. Then, an incremental learning algorithm is developed for WTS to adapt to the appearance change during the tracking. The proposed method could learn the lightness changing incrementally and get robust tracking performance under various luminance conditions. The experimental results illustrate the effectiveness of the proposed visual tracking Scheme.**

***Keywords*—visual tracking, Retinex, incremental learning, weighted tensor subspace, particle filter**

I. Introduction

A long-standing task of pattern recognition and machine vision is to explore an effective object representation, which is able to describe the object in a cluttered world accurately and efficiently. However, due to the influence of the exoteric condition (e.g. illumination variation) and intrinsic factor (e.g. pose and expression change), the object in real world takes on various appearances. Consequently, object tracking is confronted with even rougher challenge, because the object in natural video is actually a non-stationary data and presents more complicated appearance change than in still image. Therefore, effectively modeling the object appearance plays an important role in tracking research.

In recent years, many works have been done in object tracking based on the appearance modeling and feature extraction, such as, integration of shape and color [4, 6], background/foreground model[7], subspace-based appearance method [1, 2], parametric template [5], illumination invariant [24]. However, those algorithms usually train the appearance model of the tracking object in advance, and then apply the trained model to real tracking without accounting for the appearance change and adaptively updating the model during the tracking. Actually, the appearance often drifts far away from the initial one after some period of time.

Considering the limitation of the fixed appearance model, the Condensation [3], support vector machine [9], kernel-based tracking [10], active appearance mode [8], spatial-appearance model [19], online-updating sparse Bayesian classifier [20], are proposed to deal with the problem of the appearance shift. Especially, the online/incremental subspace learning based methods [12,13,14,15,17] achieve the superior tracking performance. However, since the above methods [1,2,5,8,12,13,14, 15,17,20,24] take the image-as-vector formulation, the local spatial information of object is almost lost, which reduces the reliability of visual tracking.

Consequently, more recent works model the object appearance with high-order tensors. Sun *et al.* [25, 26] proposed the dynamic and streaming tensor analysis to deal with the learning of dynamic/online data. Later, series of discriminant methods for tensor analysis and their applications in retrieval [27, 28], video semantic [29], gait recognition [30] were developed. Li and Lee [31] presented a motion saliency based visual tracking. Li *et al.* [33] employed a three-dimensional temporal tensor subspace learning for visual tracking. Tao *et al.* [34, 35] proposed a Bayesian tensor analysis method and applied it to 3-D face modeling, as well as the kernelization [36] and probabilistic [37] version. Shao *et al.* [38] developed an appearance-based method using the three-dimensional trilinear tensor. It should be noticed that all those methods above have the following characters:

- They have the common assumption of the constancy and slowness in appearance variation.
- They did not deal with the effect of drastic and asymmetric illumination on the object representation. Although some of them [5][23][24] make effort on the modeling the illumination variant, the pre-training process is inevitable still.

Note that, most of the above algorithms obtain robust visual tracking under the well-controlled environment. In real world,

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the constancy does not often come into existence, while the inconstancy or drastic change is ubiquitous, for example, illumination. Thus the problem of modeling the object appearance under drastic change in our formulation is reduced to what feature/information insensitive to illumination can be used to construct the high-order tensors, and how to model the object appearance and learn the appearance change during the tracking.

Motivated by the high dimensional algebra [25], incremental learning [15], the Retinex algorithm [23, 24] and the particle filter [3], a weighted tensor subspace (WTS) is defined by combining the Retinex algorithm with the original image, and an incremental learning algorithm is developed for WTS to adapt to the appearance change during the tracking. In contract to the incremental subspace learning [15], our algorithm extends the image-as-vector to the image-as-tensor form. At the same time, we build a weighted three-order tensor model by combining the original intensity with Retinex image, and assign weights to the two images firstly. The proposed tensor model could capture the perception of human eye on the luminance, and describe the brightness change during constructing the tensor subspace. Then by modifying the dynamic tensor analysis (DTA) [25, 26], we develop an incremental weighted tensor subspace learning method with consideration of the mean and variance updating. Finally, we apply the proposed incremental learning in the frame of particle filter to track the interesting object to update/learn the appearance variation online. The experimental results show the obvious tracking performance under the condition of the drastic and asymmetric illumination.

The rest of this paper is organized as follows: The details of the proposed incremental weighted tensor subspace learning algorithm are explained in section 2, where we propose the construction of a weighted tensor representation, and incremental tensor subspace learning method. Then we present the proposed tracking algorithm in section 3. The experimental results are presented in section 4. Finally we conclude this paper with remarks on potential extensions for future work.

II. Weighted Tensor Subspace based Incremental Learning

Tensor as a multilinear algebra is an effective tool to analyze ensembles of images resulting from the interaction of any number of underlying factors [32]. In this section, we first introduce a novel weighted tensor based object appearance, which is insensitive to the illumination change by considering the variant into the construction of the weighted tensor representation. Then we propose an incremental tensor subspace learning algorithm for the defined weighted tensor subspace (WTS) with the modification of mean and covariance updating.

A. A weighted tensor representation

A tensor can be regarded as a multidimensional matrix. A gray image can be seen as a two order tensor only including the intensity information. However, illumination changes can drastically influence the appearances of objects in the image as shown in Fig.1 (a). Inspired by the performance of the Retinex algorithm, we introduce the Retinex algorithm to compensate the illumination. Given an intensity image $I(x,y)$, which can be seen as product $I(x,y)=R(x,y)L(x,y)$, where $R(x,y)$ is the reflectance and $L(x,y)$ is the illuminance at each location (x,y). The Retinex algorithm [21, 22] estimates the reflectance $R(x,y)$ as the ratio of the image $I(x,y)$ and its low pass version that serves as estimate for $L(x,y)$. In Fig 1(b), we can see the brightness difference of the Retinex images according to the illumination condition of the first row. Therefore, it is an effective feature insensitive to illumination to represent object appearance.

Fig.1 (a) the original image and (b) the Retinex image

However, the Retinex image loses the contract information, while obtaining the illumination compensated image. The simple utilization of the Retinex image is not enough to describe the facial appearance. It is necessary for constructing tensor representation to add original image, so that a weighted three-order tensor representation is modeled, as shown in Fig 2.

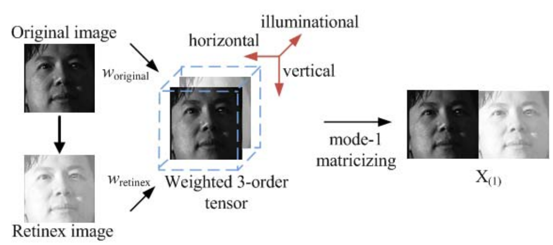

Fig. 2 The weighted tensor representation model

Here we denote the proposed weighted *3*-order tensor as $\boldsymbol{\chi} \in \Re^{N_1\times N_2\times N_3}$, each element of which is $\chi_{x,y}^{N_3}\Big|_{x=1,\dots,N_1,y=1,\dots,N_2}^{N_3=1,2}$. In the tensor terminology, each dimension of a tensor is associated with a "mode". In our proposed tensor model, there are three modes in tensor construction:

$$\chi_{x,y}^{1} = I(x,y) * w_{original}, \tag{1}$$

$$\chi_{x,y}^{2} = R(x,y) * w_{retinex}, \tag{2}$$

where N_1 and N_2 are the row and column number of image $I(x,y)$, respectively, N_3 is the image number of construction tensor representation. Due to the Retinex image is the reflectance image $R(x,y)$ separated from the original image $I(x,y)$, while the transition from the original image $I(x,y)\rightarrow R(x,y)$ is the process of removing the luminance $L(x,y)$, so the third mode is the illumination variable, simulating the perception changing of human eyes. As shown in fig.2, the weights w_{original} and w_{retinex} for the original and the Retinex image are empirically selected to control the proportion of the two components, and the right arrow is an example of the mode-1 matricizing of the tensor. Thus the weighted tensor representation is built, and the subspace based on this representation is defined as weighted tensor subspace (WTS).

B. Incremental tensor subspace learning

Here we present an incremental tensor subspace learning for WTS, which modified the dynamic tensor analysis (DTA) [25, 26] with mean and covariance updating. In the DTA algorithm, data are assumed with mean removed or mean at zero. Unfortunately, this assumption leads to failure of tracking subspace variability. Particularly, the mean of the d*th* mode is updated as:

$$\overline{\mathrm{X}}_d = \frac{\lambda n \overline{\mathrm{X}}'_d + m \overline{\mathrm{X}}''_d}{\lambda n + m}. \tag{3}$$

where

$$\overline{\mathrm{X}}'_d = \frac{1}{n}\sum_{i=1}^{n} X_{i(d)}, \overline{\mathrm{X}}''_d = \frac{1}{m}\sum_{j=1}^{m} X_{j(d)}. \tag{4}$$

Input:

New tensor data $\boldsymbol{\chi}_j\big|_{j=1}^{m} \in \Re^{N_1 \times \ldots \times N_3}$

The number of the new arrival tensor m

Old projection matrices $\mathbf{U}_d\big|_{d=1}^{3} \in \Re^{N_d \times R_d}$

Old energy matrices $\mathbf{E}_d\big|_{d=1}^{3} \in \Re^{R_d \times R_d}$

Old data mean $\overline{\mathrm{X}}'_d\big|_{d=1}^{3} \in \Re^{\left(\prod_{i \neq d} N_i\right) \times N_d}$

Old number of tensor data received n

Algorithm:

For *d*=1 to 3

Mode-*d* matrix χ_j as $\mathbf{X}_{j(d)} \in \Re^{\left(\prod_{i \neq d} N_i\right) \times N_d}$, *j*=1,…,*m*

Compute the new variance matrix $\mathbf{C}''_d$

Reconstruct variance matrix $\mathbf{C}'_d \leftarrow \mathbf{U}_d \mathbf{E}_d \mathbf{U}_d^T$

Update variance $\mathbf{C}_d \leftarrow \lambda^2 \mathbf{C}'_d + \mathbf{C}''_d + \mathbf{C}'''_d$

Decomposition $\mathbf{U}_d \mathbf{E}_d \mathbf{U}_d^T = \mathbf{C}_d$

Compute $\mathbf{U}_d$ and $\mathbf{E}_d$

Get new number of tensor data $n \leftarrow \lambda n + m$

End

Output:

New projection matrices $\mathbf{U}_d\big|_{d=1}^{3} \in \Re^{N_d \times R'_d}$

New energy matrices $\mathbf{E}_d\big|_{d=1}^{3} \in \Re^{R'_d \times R'_d}$

New data mean $\overline{\mathbf{X}}_d\big|_{d=1}^{3} \in \Re^{\left(\prod_{i \neq d} N_i\right) \times N_d}$

New number of tensor data received *n*

Fig.3 The Incremental weighted tensor subspace learning algorithm

where $X_{i(d)} \in \Re^{\left(\prod_{i \neq d} N_i\right) \times N_d}$ is the mode-*d* matricizing of the tensor χ_i. $\overline{\mathrm{X}}_d$, $\overline{\mathrm{X}}'_d$ and $\overline{\mathrm{X}}''_d$ are the total mean of the *d*th mode so far, the old mean and the mean of the new arrival data respectively, with forgeting factor λ, old data number *n* and new data number *m*. And the mode-*d* variance can be updated incrementally without storing the old tensor data, as follows:

$$\mathbf{C}_d = \lambda^2 \mathbf{C}'_d + \mathbf{C}''_d + \mathbf{C}'''_d \tag{5}$$

where

$$\mathbf{C}'_d = \mathbf{U}_d \mathbf{E}_d \mathbf{U}_d^T. \tag{6}$$

$$\mathbf{C}''_d = \sum_{j=1}^{m} \left(X_{j(d)} - \overline{\mathbf{X}}_d\right)^T \left(X_{j(d)} - \overline{\mathbf{X}}_d\right), \tag{7}$$

$$\mathbf{C}'''_d = \frac{mn}{m+n}\left(\overline{\mathbf{X}}'_d - \overline{\mathbf{X}}''_d\right)^T \left(\overline{\mathbf{X}}'_d - \overline{\mathbf{X}}''_d\right), \tag{8}$$

where $\mathbf{C}_d$, $\mathbf{C}'_d$, $\mathbf{C}''_d$ and $\mathbf{C}'''_d$ are the total variance of the *d*th mode, the old variance, the new variance and the modification term respectively. The pseudo code of the modified incremental tensor subspace learning algorithm is listed in fig.3.

III. ADAPTIVE TRACKING BASED ON INCREMENTAL LEARNING

In visual tracking, the motion of object from one frame to the next can be modeled by a one-order Markov model with hidden state variables. The state variable $\mathbf{H}_t$ describes the affine motion parameters of the object at time *t*. Given a set of observations $\mathbf{X}_t = \{X_t^1, \ldots, X_t^N\}$ obtained from the frame at time *t*, where *N* is the samples number in particle filter, we want to estimate the hidden state variable X_t^k, $k = 1, \ldots, N$. According to Bayesian theorem, we have,

$$p\left(\mathbf{H}_t \middle| X_t^k\right) \propto p\left(\mathbf{H}_t \middle| X_t^k\right) \int p\left(\mathbf{H}_t \middle| \mathbf{H}_{t-1}\right) p\left(\mathbf{H}_{t-1} \middle| X_{t-1}^k\right) d\mathbf{H}_{t-1}, \tag{9}$$

where

$$p\left(\mathbf{H}_t \middle| \mathbf{H}_{t-1}\right) = \mathrm{N}\left(\mathbf{H}_t; \mathbf{H}_{t-1}, \Psi\right), \tag{10}$$

$$p\left(\mathbf{H}_t \middle| X_t^k\right) \propto \exp\left(-\left\| \left(X_t^k - \overline{\mathbf{X}}_d\right) - \left(X_t^k - \overline{\mathbf{X}}_d\right) \prod_{d=1}^{M} \times_d \left(\mathbf{U}_d \mathbf{U}_d^T\right) \right\|_F^2\right), \tag{11}$$

where $\mathrm{N}(\cdot)$ is a Gaussian distribution of each parameters in $\mathbf{H}_t$ modeled independently, around its counterpart in $\mathbf{H}_{t-1}$ with variance Ψ, and $\|\cdot\|_F^2$ is Frobenius norm. X_t^k is obtained by sampled with affine parameters warping in current frame image, $\Psi = \left(\sigma_x^2, \sigma_y^2, \sigma_r^2, \sigma_s^2, \sigma_\rho^2, \sigma_\varphi^2\right)$ is a diagonal covariance matrix whose elements are the corresponding variances of $\mathbf{H}_t = \left(x_t, y_t, r_t, s_t, \rho_t, \varphi_t\right)$, each parameters in which denotes the *x*, *y* translations, the rotation angle, the scale, the aspect ratio and the skew direction at time *t*. The tracking process is outlined in Fig. 4.

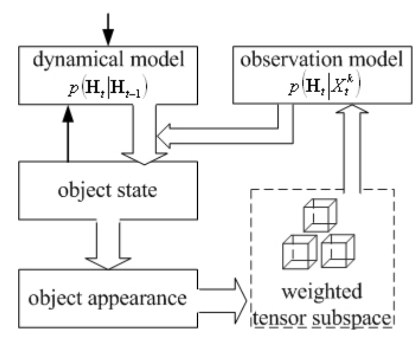

Fig. 4 The main flow of the proposed tracking method

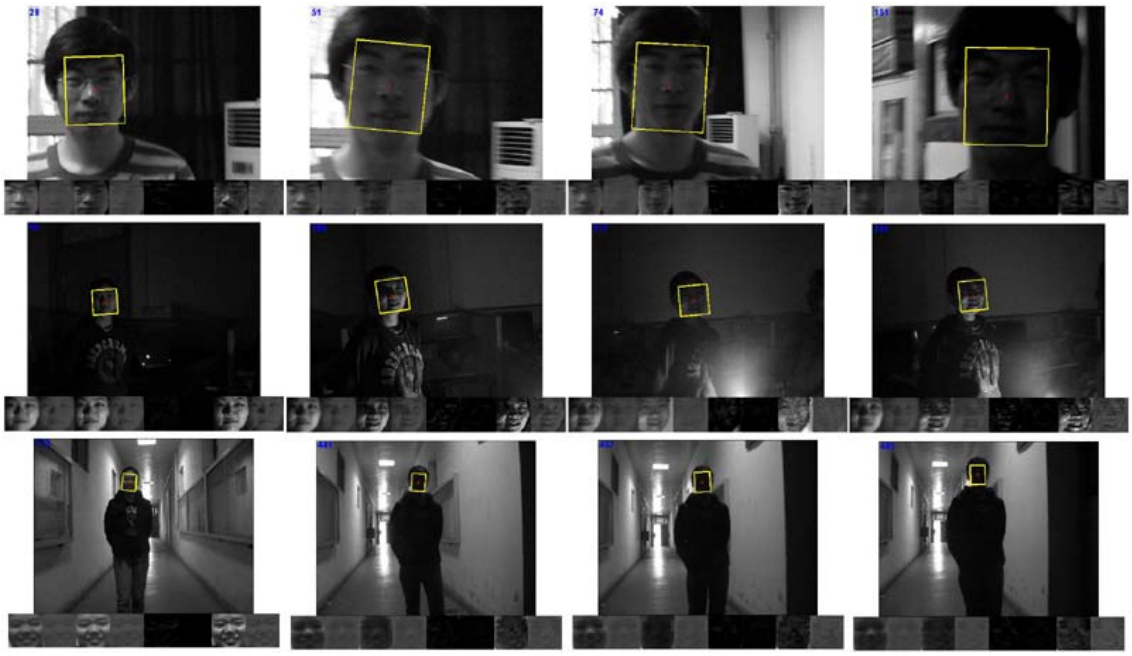

Fig. 5 the tracking results on three nature videos. The images in the middle row of each frame are: the original mean, the Retinex mean, the tracked patch, the tracked patch by Retinex, the error image, the error Retinex, the reconstructed image and the reconstructed Retinex, respectively. The red cross is the center location of the yellow box.

IV. Experiments

A. Experimental results

In order to evaluate the performance of the proposed tracking scheme, three video sequences including a human face are used in the experiments. These videos are captured indoor under drastic illumination change. The object , i.e., face, in video 1 moves fast towards the camera and has a large scale variant, at the same time, the appearance of the object undergoes sharp change caused by the blur of moving camera, and the movement from a bright scene to a dark one. The motion in video 2 is gentle and the environment is dark all the time, with a weak light source from a lamp, so the illumination on the object appearance changes slowly but asymmetrically. In video 3, the object appearance experiences a low lightness variation to too dark a circumstance to hardly recognition the facial structure. The weight w_{original} and w_{retinex} for tensor representation is 0.7 and 0.3 for the intensity and Retinex image, respectively. The forgetting factor in incremental subspace learning is 0.95. The tensor subspace is updated every 5 frames. For the particle filtering in the object tracking, the particle number is 400.

As shown in Fig 5, the object appearance in the top row in video 1 is affected by the motion blur, scale change and especially the drastic illumination variation. The proposed tensor representation simulates the adaptivity of human visual perception, can hold the spatial information of the two-dimensional appearance, and model the variant of the illumination on the object. In the middle row, the appearance undergo the asymmetric brightness in the dark room, our method can be still robust to the asymmetric change on the appearance. Similarly, the object in video 3 in the bottom row can be tracked under the dark condition, even the human face hardly recognized.

B. Qualitative comparison

As a qualitative bench work, we ran two approaches: the ISL algorithm [15] and tensor representation based incremental subspace learning [33].

The ISL algorithm [15] is proposed to incrementally tracking object with the image-as-vector formulation, by using a modified sequential Karhunen-Loeve method to construct and update the appearance subspace of object.

In essence, the method in [33] is almost equivalent to two order tensor representation based subspace learning. The former one [33] takes a three dimensional tensor, which consists of a block of temporal frames, as a processing unit; the latter method operates on a block of two order tensor, so the two approaches are different in dimension but equally satisfactory in result. Both the two tensor formulation are calculated on the intensity. However, the operation complexity of the former are higher than the latter one, due to the third dimension need to be computed and projected when the reconstruction error wanted, as well as the space consumption. In order to know from our proposed method, this method is named as ITL for short.

As shown in Fig.6 and Fig.7, each row is the tracking result in ISL, ITL and our proposed method, respectively, with red, green and yellow box located the object.

The vector-based method fails to track the object robustly, which has been reported in [33]. In Fig.6 and Fig.7, the track is lost in around 119^{th} frame of video 1 and 447^{th} frame of video 3 in the middle row. It is the same conclusion we could make for the advantage of tensor over vector. It is because the object in

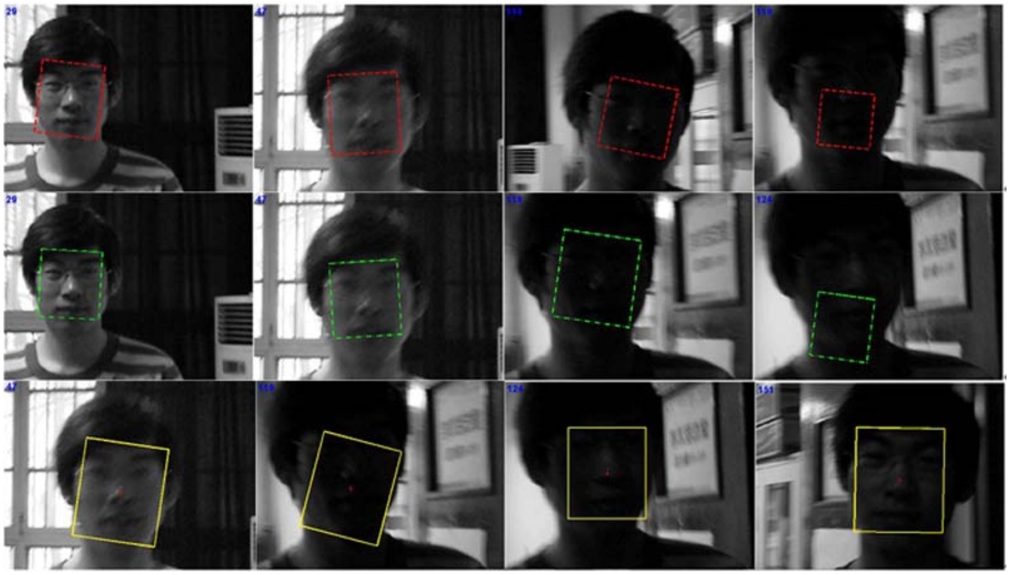

Fig.6 the comparison of the tracking performance of the ISL [15], ITL [33] and the proposed method in video 1. The top, middle and bottom row is the tracking results by ISL, ITL and the proposed algorithm, respectively.

Fig.7 the comparison of the tracking performance of the ISL [15], ITL [33] and the proposed method in video 3. The top, middle and bottom row is the tracking results by ISL, ITL and the proposed algorithm, respectively.

image takes on two-dimensional information, which could be kept by tensor form.

In Fig.6 and Fig.7, although the superior performance over the ISL, the ITL method lost the object in around 124th frame and 454th frame in the middle row, respectively. The main reason for that is the only information the ITL use is intensity, which tends to sensitive to the illumination variation. We could observe that the performance of the proposed method over the ITL [33], under the illumination undergo drastic and sharp change. It mainly owes to the construction of the weighted tensor representation. Our proposed weighted tensor model can capture the illumination variation along the third dimension, while this variation is similar to the process of human eyes apperceiving illumination change; the Retinex image embedded in the tensor presentation is able to neutralize the effect of the drastic illumination variation by the weighting the original image and the Retinex one; and the weights control the contribution of the original intensity and Retinex image in constructing the tensor subspace.

It should be mentioned that the tracking efficiency for the proposed methods is a little slower than the others, because the outnumbering consumption mainly focus on the Retinex algorithm compared to the ITL, while the operations for tensor analysis are a little more time-consuming than the ISL.

V. CONCLUSION AND FUTURE WORK

We have proposed an illumination-invariant-oriented robust object tracking, which can incrementally learn the object structure information and illumination variant. Whereas most algorithms tracks on the premise that the appearance or ambient environment lighting condition do not change as time progress, but they are still sensitive to the drastic illumination, our method adapts the weighted tensor to model the change of the light reflectance on the object appearance, incrementally update the light variant in tensor subspace. The experiments show the robustness of the proposed algorithm to tracking object undergoes ambient lighting.

Although our method could track object well, we have to point out the proposed method is a little slower than the vector-based method, such as ISL algorithm, therefore a fast implementation is needed. Moreover, the weight on the tensor representation is empirically decided, an adaptive way is required.

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