A Rapid Anomalous Region Extraction Method by Iterative Projection onto Kernel Eigenspace

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Abstract

In computer vision, background subtraction method is widely used to extract a changing region in a scene. However, it is difficult to simply apply this method to a scene with moving background object, because such object may be extracted as a changing region. Therefore, a method has been proposed to estimate both current background image and occluding object region simultaneously by using eigenspace-based background representation. On the other hand, image completion method using eigenspace have been extended to non-linear subspace using kernel trick, however, such existing method takes large computational cost. Therefore, in this paper, we propose a method for rapid simultaneous estimation of a background image and occluded region in non-linear space, using the kernel trick and iterative projection.

1. Introduction

Detecting an anomalous object in a captured image is one of the important task on the field of computer vision. Especially, background subtraction is the most popular technique to extract the region of the object from a background image taken under the static condition. Though, such condition is rare for practical use; a real scene often contains known moving object. Thus the system must have the ability to distinguish unfamiliar object from moving objects with known motion.

There are several methods to extract anomalous region using a kind of database of known background images. In particular, eigenspace derived from the principal component analysis (PCA) is vastly used because of its simplicity and an easiness of analysis. However, adopting this subspace assumes that a set of sample image has linearity among the images. Except some photometric changes caused by illumination varieties, a general image sequence with moving object has non-linearity within each other. Therefore, In this paper, we propose a method for rapid anomalous region extraction with better handling of a background database using kernel PCA.

2. Anomalous Region Extraction from Dynamic Scene using Eigenspace

Inclusive model of the background is a natural extension of the simple background subtraction method from the viewpoint of the representation of known information. Eigenbackground [4] by Oliver et al. is one of the popular method to extract the region of object using eigenspace as a model of background. Projecting newly captured image onto eigenspace makes an estimation of the background image in the sense of least square error. Therefore, we can easily estimate a background by the projection of an input image onto the eigenspace followed by its back-projection to image space. However, since an anomalous object in a scene partially occludes background objects, the projection onto eigenspace leads an erroneous estimation result.

In the area of image inpainting, there are some better methods to estimate an occluded region by explicitly exclude the occluded region from the computation of estimation using eigenspace. Amano et al. proposed BPLP (Back Projection for Lost Pixels) method for inpainting in offline [1]. The estimation can be formulated as:

$$\hat{\boldsymbol{p}} = \left(E^T \Sigma^T \Sigma E\right)^{-1} E^T \Sigma^T \Sigma \tilde{\boldsymbol{x}}, \quad (1)$$

where $\hat{\boldsymbol{p}}$ is an estimated point in eigenspace, E a matrix arranged eigenvectors, Σ a occlusion mask, and $\tilde{\boldsymbol{x}}$ input image with an anomalous object. The occlusion mask Σ is the diagonal matrix in which each element has 0 if the pixel is occluded, 1 otherwise.

Since the eq. (1) contains an inversion and multiplications of large matrices, the method can not be applied for a real-time extraction of an anomalous object region. Therefore, we proposed iteration based approach which allows update of an occlusion mask during computation of a background image estimation [3], and realize simultaneous estimation of a background image and an occluded region by an anomalous object in real time. However, it has a limit of estimation result derived by the linearity assumption.

Using the kernel PCA [5], sample background image set can be described as a subspace in higher-dimensional feature space. The feature space is corresponding to kinds of nonlinear subspace in an original image space.

Amano et al. have proposed kBPLP nonlinear extension of BPLP using the kernel trick [2]. In the kBPLP, they introduced the following new feature description which is stacked pixel value $\boldsymbol{\zeta}$ in occluded region and feature value $\boldsymbol{\xi}_\phi$ of pixel value $\boldsymbol{\xi}$ in observable region.

$$\boldsymbol{y}_i = \begin{bmatrix} \boldsymbol{\xi}_{\phi i} \\ \boldsymbol{\zeta}_i \end{bmatrix}. \tag{2}$$

In the subspace constructed from this feature points $\boldsymbol{y}_i$, the pixel values in occluded region $\boldsymbol{\zeta}$ can be estimated from feature values of observable region $\boldsymbol{\xi}_\phi$, since there is a linear relationship between $\boldsymbol{\xi}_\phi$ and $\boldsymbol{\zeta}$. Actually, an estimation equation of occluded values can be represented by:

$$\tilde{\boldsymbol{\zeta}} = ZV\left(V^{\mathrm{T}} K_\phi(X,X)V\right)^{-1} V^{\mathrm{T}} K_\phi(X,\tilde{\boldsymbol{\xi}}) \tag{3}$$

where $K_\phi(A,B)$ is a kernel matrix having the value of kernel function k_ϕ; $\{k_\phi(\boldsymbol{a}_i,\boldsymbol{b})_j\}_{ij}$, and V is a collection of eigenvectors of $K_\phi(X,X)$.

As shown in eq. (2), kBPLP classifies pixels into two groups beforehand. Thus when a occluded region changes, the kernel matrix $K_\phi(X,X)$ and its eigenbases must be recalculated using a newly classified X. While BPLP for linear subspace works as a constant for various occlusion masks, it is difficult for kBPLP to estimate image in realtime due to the computational cost.

3. Proposed Method

The BPLP with linear eigenspace is the method that uses a eigenspace calculated by PCA of sample images, and estimates occluded values by fitting the input image to the subspace without concerning various occluded region. On the other hand, since kBPLP reconstructs a subspace according to the specific occluded region, the method is not a direct extension of BPLP as to this point. Hence, we modify the kBPLP framework to make a natural extension of BPLP by applying our iteration method.

3.1. Modified kBPLP (m-kBPLP)

Here, we introduce the following feature Y, which has whole pixel value X and its high-dimensional nonlinear feature value X_ϕ.

$$Y = \begin{bmatrix} X_\phi \\ X \end{bmatrix} = UDV^{\mathrm{T}} = \begin{bmatrix} U_\phi \\ U_X \end{bmatrix} DV^{\mathrm{T}} \tag{4}$$

here we obtain

$$Y^{\mathrm{T}}Y = K_\phi(X,X) + X^{\mathrm{T}}X, \tag{5}$$

And we call this new kernel matrix $K_Y(X,X)$. Using this matrix, the point $\boldsymbol{p}$ on the eigenspace corresponding to $\boldsymbol{x}$ is computed by,

$$\boldsymbol{p} = U^{\mathrm{T}}\boldsymbol{y} = D^{-1}V^{\mathrm{T}}K_Y(X,\boldsymbol{x}). \tag{6}$$

In addition, we can compute a back-projection linearly using this feature $\boldsymbol{p}$ as follows:

$$\boldsymbol{x} \approx U_X\boldsymbol{p} = XVD^{-1}\boldsymbol{p}. \tag{7}$$

Similarly, an estimated point $\hat{\boldsymbol{p}}$ of given occluded image $\Sigma\tilde{\boldsymbol{x}}$ can be computed as

$$\hat{\boldsymbol{p}} = \left(D^{-1}V^{\mathrm{T}}K_Y(\Sigma X,\Sigma X)VD^{-1}\right)^{-1} D^{-1}V^{\mathrm{T}}K_Y(\Sigma X,\Sigma\tilde{\boldsymbol{x}}). \tag{8}$$

In next section, we will apply the iterative projection technique to realize faster estimation.

3.2. Rapid Calculation of m-kBPLP using Iterative Projection

In the m-kBPLP, the estimation process is done linearly because there is a linear relationship between a feature vector $\boldsymbol{y}$ and image vector $\boldsymbol{x}$. So we can apply the iterative projection method [3] to m-kBPLP.

Regarding an input image $\tilde{\boldsymbol{x}}$ as fully observable ($\Sigma = I$), the projected point on feature space $\hat{\boldsymbol{p}}$ and the back-projected point of it $\hat{\tilde{\boldsymbol{x}}}$ can be computed as same as eq. (6) and eq. (7),

$$\hat{\boldsymbol{p}} = D^{-1}V^{\mathrm{T}}K_Y(X,\tilde{\boldsymbol{x}}) \tag{9}$$

$$\hat{\tilde{\boldsymbol{x}}} = U\hat{\boldsymbol{p}} \tag{10}$$

$$= XK_Y^{-1}(X,X)K_Y(X,\tilde{\boldsymbol{x}}) \tag{11}$$

Then we iterate the background estimation by projecting to nonlinear eigenspace and back-projection, and replace pixel value in occluded region with estimated using the following recurrence equation:

$$\hat{\hat{\boldsymbol{x}}}_k \leftarrow X K_Y^{-1}(X,X) K_Y(X, \hat{\boldsymbol{x}}_k) \tag{12}$$

$$\hat{\boldsymbol{x}}_{k+1} \leftarrow \Sigma \tilde{\boldsymbol{x}} + (I - \Sigma)\, \hat{\hat{\boldsymbol{x}}}_k \tag{13}$$

3.3 Updating Occlusion Mask

Both kBPLP and our method needs information of the region occluded by an anomalous object, Σ. Unfortunately, this matrix Σ is originally unknown because the objective of our research is to estimate the silhouette of the anomalous object. Therefore, we calculate the mask Σ by using a simple background subtraction as

$$\Sigma = \mathrm{diag}(\sigma_0, \ldots, \sigma_n) \tag{14}$$

$$\sigma_i = \begin{cases} 1 & \text{if } |\tilde{\boldsymbol{x}}(i) - \hat{\boldsymbol{x}}(i)|^2 < \frac{\tau^2}{3} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

where τ is a threshold and $\boldsymbol{x}(i)$ denotes rgb value of i-th pixel. Of course, the estimated background $\hat{\boldsymbol{x}}$ is varied when the occlusion mask Σ changes, therefore, background estimation by eq. (13) and background subtraction by eq. (15) must be iterated.

The sequence of simultaneous estimation of background and object region is summarized as follows.

(0) Initialize: set $\Sigma_0 = I, \hat{\boldsymbol{x}}_0 = \mathbf{0}$,
(1) Capturing input image $\tilde{\boldsymbol{x}}$,
(2) Replacing former occluded region $(I - \Sigma)$ in the input image with previously estimated image $\hat{\hat{\boldsymbol{x}}}$ (eq. (13)),
(3) Updating estimated image $\hat{\hat{\boldsymbol{x}}}$ using the image $\hat{\boldsymbol{x}}$ in step (2), (eq. (12)),
(4) Updating occlusion mask Σ by comparing input image and estimated background,
(5) Back to step (1).

4. Experiments

In advance, we define the matrix X composed from given background sequence $\{\boldsymbol{x}_i\}_{i=1}^{s}$.

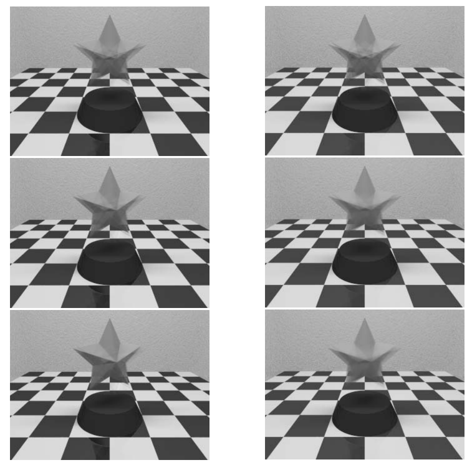
$$X = [\boldsymbol{x}_1 - \bar{\boldsymbol{x}}, \ldots, \boldsymbol{x}_s - \bar{\boldsymbol{x}}], \tag{16}$$

where $\bar{\boldsymbol{x}}$ denotes mean image of the sequence, i.e. $\frac{1}{s}\Sigma \boldsymbol{x}_i$. Then we obtained the sample data by normalizing X so as to Frobenius norm of X $\|X\|_{\mathrm{F}}$ is equal to s.

$$X := \frac{s}{\|X\|_{\mathrm{F}}} X = \frac{s}{\sqrt{\mathrm{tr}(X^{\mathrm{T}} X)}} X \tag{17}$$

Table 1. num of dim. of subspace

$k_Y(\boldsymbol{x}, \boldsymbol{y})$	p	dim.	c.p.
$\boldsymbol{x}^{\mathrm{T}}\boldsymbol{x}$	–	182	0.990218
$(1 + \boldsymbol{x}^{\mathrm{T}}\boldsymbol{y})^p + \boldsymbol{x}^{\mathrm{T}}\boldsymbol{x}$	3	219	0.990456
$\exp\left(-\frac{\|\boldsymbol{x}-\boldsymbol{y}\|^2}{p^2}\right) + \boldsymbol{x}^{\mathrm{T}}\boldsymbol{x}$	1.5	200	0.990303



(a) kBPLP (b) Proposed

Figure 1. Estimated image with updating mask

In kernel PCA, the relationship between the number of dimension and cumulative proportion differs for each kernel function. Therefore, we decided the dimension of eigenspace to the smallest number to exceed 0.99 of c.p.. The threshold to extract the unseen object is set to $\tau = 0.13$. For the measurement of processing time, we used a computer with Dual Xeon 3.6GHz CPU and 2GB RAM.

At first, we compare the proposed method and kBPLP using a CG sequence at a view of square error and computational time. We set $\Sigma = I$ (no occluded region) as an initial state. Table 1 shows the dimension of eigenspace with each kernel function.

Fig. 1 shows the estimation result of each method. Though kBPLP computes better result per iteration, they lives in different time scale. In Fig. 2, the time scale for kBPLP is 100 times longer than proposed method, and proposed method almost converges in 10 seconds, while kBPLP takes more than 500 seconds. When the occlusion mask is not given, the final result may differ each other, since the method uses a different mask in iteration.

Then, we applied proposed method to a real se-

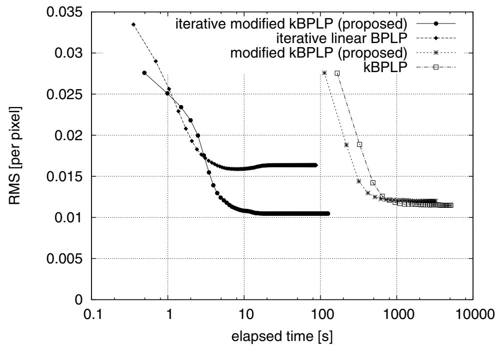


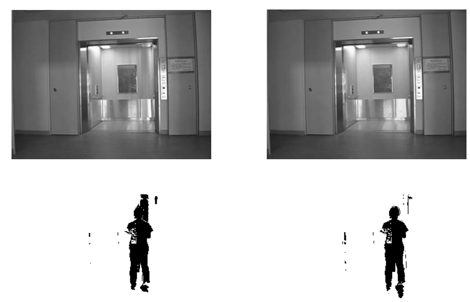
Figure 2. Estimation error in revising mask

quence taken by digital video camera, and we compared our nonlinear method with traditional linear iterative method. At first, we extract 256 frames without human from a sequence taken in front of a lift as background images (Fig. 3(a)). Then we carried out the kernel PCA, and we decide the dimension of eigenspace so as to satisfy the 0.99 of c.p.. We have 112 dimensional eigenspace (c.p.: 0.990273) at this moment.

The input sequences for the estimation is shown in Fig. 3(b). In this case, we switch input frames per iteration, this is equivalent to compute the result in $1/30$ seconds. The result of estimated background and extracted object region for each method is shown in Fig. 4. There is an object having similar intensity of lift's door, thus we find stripe-like estimation error with liner estimation method. On the other hand, nonlinear version has lesser error comparing to the linear method.

(a) Background images (b) Input images

Figure 3. Background and input sequence



(a) Linear (b) Gaussian ($p = 0.7$)

Figure 4. Estimated background image and object region

5. Conclusion

In this paper we propose an extraction method of an anomalous object region from a dynamic scene using nonlinear feature space. We modeled the dynamic scene by eigenvectors derived by the kernel PCA of a background sequence. This feature subspace is superior to linear subspace by PCA as to describe a background image set. Then we adopt the iterative method for faster estimation than the simple inversion-based approach. This proposed method indicates more stable results than a linear method in real scene.

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