Proc. VIIth Digital Image Computing: Techniques and Applications, Sun C., Talbot H., Ourselin S. and Adriaansen T. (Eds.), 10-12 Dec. 2003, Sydney

A Mean Eigenwindow Method for Partially Occluded/Destroyed Objects Recognition

M. Masudur Rahman, Seiji Ishikawa

Department of Mechanical and Control Engineering
Kyushu Institute of Technology
Sensuicho 1-1, Tobata, Kitakyushu 804-8550, Japan
rahman@is.cntl.kyutech.ac.jp

Abstract This paper describes a method for recognizing partially occluded and/or destroyed objects using an eigenspace method referred to as a '*mean eigenwindow*' method that stores multiple partially occluded/destroyed objects in an eigenspace. We have proposed to store similar poses, that may include disturbed shapes, of an object in a particular window referred to as the '*eigen window*' and, finally, mean of appearances of each window is taken into consideration in order to obtain a generalized eigen window called the '*mean eigenwindow*'. This mean eigenwindow is further used for recognizing an unfamiliar pose, including partially occluded or destroyed shapes, and the object type itself. We have applied the proposed approach to various image situations and the method has successfully performed recognition of an object with up to 20% of occlusion and/or destruction.

Index Terms: Object recognition, eigenspace, eigenwindow, pose detection, PCA algorithm, computer vision.

1 Introduction

Object recognition is a promising area of research in computer vision fields and it has various industrial and military applications such as object picking, automatic target recognition and surveillance and monitoring, etc. The main difficulties for such tasks include: real-time performance, difficulty in segmentation, tracking object's poses in occluded environments, and difficulty in obtaining appropriate models of the objects. Recently, visual learning methods based on eigenspace analysis [2-5, 6-9] have shown the potential to solve some of these problems. These methods learn object models from a series of pose images taken in the same environment as in the recognition mode. Thus, these methods overcome the difficulty related to object tracking and modeling. Furthermore, since such methods store an object model as a vector in a low dimensional feature space and recognize objects by comparison of the model and image vectors, recognition speed is very high and it can achieve real-time performance.

The eigen window method was initially proposed by K. Ohba and K. Ikeuchi [2] for stable verification of partially occluded objects where the conventional eigenspace method was firstly proposed by H. Murase [1]. Ohba and K. Ikeuchi proposed to collect various parts (particularly edges) of objects and put into a particular window called the 'eigen window' and, then, the best matching among the object's parts is the recognized object or pose. However, partial segmentation contradicts with the concept of conventional eigenspace technique and it makes complicated to collect similar parts of objects in a particular window. In addition, we cannot handle partially or largely occluded or destroyed objects using a conventional eigenspace methods [1].

In order to employ the eigenspace method to recognition of partially occluded/destroyed objects, we propose to collect various similar appearances/image views from the partially occluded/destroyed object's shapes into an individual window, referred to as an "eigen window". Therefore, respective sets of similar images create various eigen windows. We, then, calculate a mean of each eigen window with respect to the collected/obtained poses, referred to as a "mean eigen window". This mean eigen window represents various object's appearances in a generalized form. **Figure 1** shows an eigenspace with highlighting an eigen window. An eigen window having

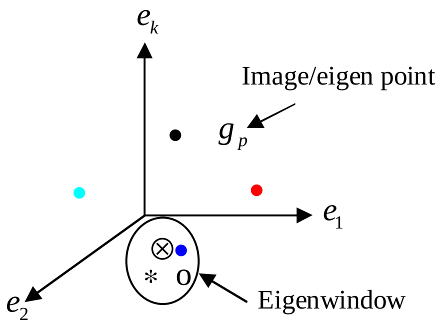


Figure 1. Demonstration of an eigen window.

four similar poses is indexed of a particular object.

In Section 2, we review eigenspace method, discuss the limitations of eigenspace method, and explain how to overcome these limitations using the mean eigenwindow method. Section 3 shows some of the experimental results and evaluates the performance. A concluding remark is placed in Section 4.

2 Eigenwindow Method

First, we review the eigenspace technique [1] and discuss the limitations of the technique under apperance-change due to occlusion and shape-destruction. The eigen window method [2] is also discussed and it's contradiction with the basic concept of traditional eigenspace technique is identified. Then, a mean eigenwindow method is proposed. This method is designed to overcome the preceding problems, which follows the basic eigenspace analysis [1] with simplifying the eigenwindow method [2].

2.1 Eigenspace Technique

Let *M* be the number of the images in a training set of a particular object. Each image is converted into a column vector z_i of length *N*:

$$[z_1, z_2, \ldots, z_M] \tag{1}$$

By subtracting the average image of the all images, we obtain the training matrix,

$$Z = [z_1 - c, z_2 - c, \ldots, z_M - c] \tag{2}$$

where c is the average image, and the size of the matrix Z is $N \times M$. The sample covariance matrix $\boldsymbol{Q}$, $N \times N$, is obtained from

$$\mathbf{Q} = \boldsymbol{Z}\boldsymbol{Z}^T \tag{3}$$

This sample covariance matrix provides a series of eigenvalues λ_i and eigenvectors $\boldsymbol{e}_i (i = 1, 2, \ldots, N)$ where each corresponding eigenvalue and eigenvector pair satisfies:

$$\lambda_i \boldsymbol{e}_i = Q\boldsymbol{e}_i \tag{4}$$

That is, matrix **Q** can be decomposed into *N* orthonormal components, of which the eigenvalues are λ_i. Thus, each image set can be described by a set of eigenvectors with associated weight factors, i.e., eigenvalues. If the number of images *M* is much smaller than the number of pixels *N*, the implicit sample covariance matrix can be used instead of the sample covariance matrix $\boldsymbol{Q}$ to calculate the first *k* eigenvectors.

For the sake of memory efficiency, we will ignore small eigenvalues and their corresponding eigenvectors using a threshold value, *T*:

$$W_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{N} \lambda_i} \geq T \tag{5}$$

where *k* is sufficiently smaller than the original dimension *N*.

From this reduced set of eigenvectors, the matrix is constructed to project an image, z_i (dimension *N*) into the eigenspace as an eigen point, g_i (dimension *k*).

$$\boldsymbol{g}_i = \boldsymbol{E}^T (z_i - c) \tag{6}$$

This eigenspace method can drastically reduce the dimension of the images (*N*) to the eigenspace dimension (*k*) while keeping several of the most effective features that summarize the original images.

2.2 Limitations of the Eigenspace Technique

The eigenspace representation, a collection of image poses or points in the eigenspace, is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination-change. As an effort to reduce these disturbance effects in the eigenspace, we have seen various studies using the eigenspace technique [2-4, 9]. However, the literatures do not provide such convenient clues for avoiding occlusion and destruction of objects in a particular environment. There are a number of expected practical applications, e.g., robotic rescue for estimating a disaster or collecting goods from the debris, industrial application for monitoring inventories, car navigation for obstacle identification, etc. As described, Ohba and K. Ikeuchi [2] proposed an eigen window method for such applications. However, their proposal contradicts with the concept of basic eigenspace technique. Moreover, it is so complicated to collect similar parts (edges) of objects in a window and to use matching algorithm. Thus, we propose rather very simple technique that merges an eigenspace and an eigen window method.

2.3 Mean Eigenwindow

We have investigated that pattern of eigenspaces change with changing the object's shape due to disturbance effects. The rate of pattern changes depends on the disturbance appeared in the object's shapes. This paper is, as a primary step, focuses on a defined partial disturbance due to occlusion or destruction. To reduce the disturbance effects, we propose to apply a mean eigen window where similar disturbed or non-disturbed appearances/image views are collected in a particular window, called the *eigen window*, and mean of each eigen window is taken for obtaining a generalized form of the appearances/views called the *mean eigenwindow*. We refer to this method as the "*mean eigenwindow*" technique.

2.3.1 Training Eigen Windows

The training set of eigen windows is given as:

$$F^s = [F_1^1, ..., F_M^1; F_1^2, ..., F_M^2; F_1^s, ..., F_M^S] \tag{7}$$

Let us consider F_i^j the collection of similar appearances or shapes with respect to the object S and image M where F_i refers an eigenwindow from the ith training image. Each F_i has the form

$$F_i = [f_1, f_2, ..., f_s] \tag{8}$$

A mean eigen window can be obtained as:

$$\overline{F} = \frac{1}{S} \sum_{i=1}^{s} f_i \tag{9}$$

Therefore, the training eigen windows of Eq. (7) reform as:

$$F_{mean} \equiv [\overline{F}_1, \overline{F}_2, ..., \overline{F}_M] \tag{10}$$

If we calculate an eigen space using this mean eigen window, Eq. (6) can be reformed as:

$$\boldsymbol{g}_M = \boldsymbol{E}^T (\overline{F}_M - m) \tag{11}$$

where m is the average eigen window across the all eigen windows.

2.3.2 Matching Operation

Since we have obtained a mean eigenwindow which is similar to a simple eigenspace made from a set of image sequences, the system is prepared to accept the minimum description length principle that uses the L1-norm. From an input unfamiliar/unknown image including partially occluded or destroyed shapes, a sub-window image is obtained. The similarity between a training eigenwindow and an input eigen window is evaluated by calculating their distance in the eigenspace. The minimum distance

$$d_{M^*} \equiv \min_{M} \left\| \boldsymbol{g} - \boldsymbol{g}_M \right\| \tag{12}$$

is calculated to find the nearest learned point in the mean eigenwindow or eigenspace. For a certain threshold $\varepsilon(>0)$, if $d_{M^*} < \varepsilon$ holds, we conclude that the unknown posture M' is similar to the one represented by the point $\boldsymbol{g}_{M^*}$. It is noted that the unknown image point is denoted by $\boldsymbol{g}$.

3 Experimental Results

In our study, we have considered that shapes of objects do not change ambiguously and object disturbance should not be more than 20% of the total shape of objects. Our study is limited to partially occluded or destroyed object's representation and

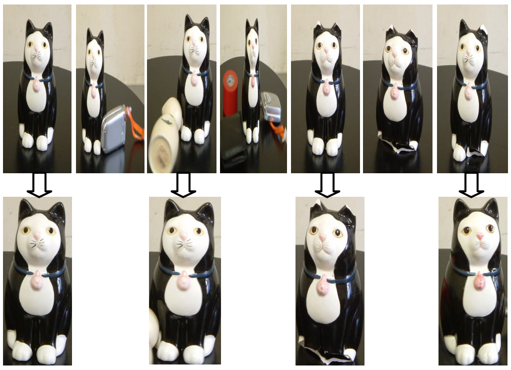


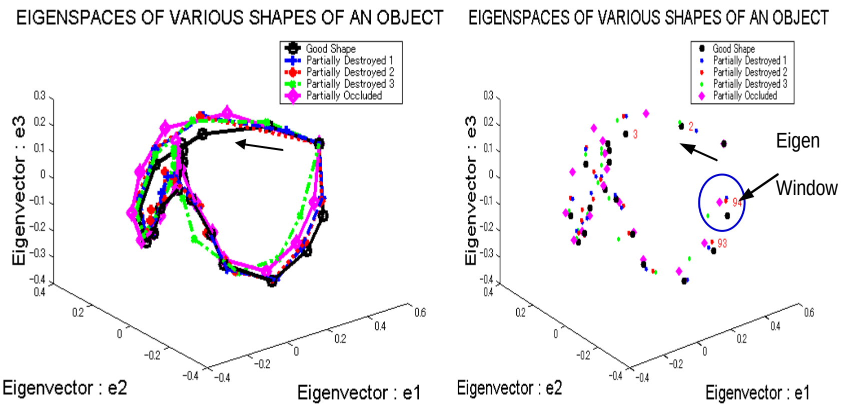
Figure 2. Some of object's situations and image sampling used in the experiment.

recognition. The definition of occlusion refers that an object is disturbed by some other objects and some parts of the objects cannot be viewed properly. Similarly, partial destruction refers that some portions of a particular object are lost by any means and a complete shape of object is not available.

In the experiment, we have taken a particular object with various disturbed and non-disturbed image situations that give us 9(=*S*) sets of image sequences. A turntable is taken to obtain 18 various poses via a digital camera in 20-degree rotation of each object's situation. Therefore, we have obtained a total of 162(=*M*) training image samples, which are used for generating the eigen windows. Some of object's situations such as non-disturbed situation, partially occluded and destroyed situations, etc. are shown in **Figure 2**. Figure 2 also shows some of image sampling from their original images. Image sampling eliminates some occlusion and we include the rest of disturbances in generating eigenspace. It should be noted that we have not extracted or segmented any part of the objects even they are occluded. One may choose to extract the occluded parts for making eigenspace. However, it makes partial segmentation of the objects that contradicts to the conventional method and it is also computationally expensive. Once we have prepared the image sets, we generate eigen window by Eq. 7

and then make a mean eigenwindow by Eq. 9. Finally, the eigenspace is obtained by Eq. 11.

Therefore, we have obtained a mean eigenwindow which contains 18 (= F_{mean}) mean appearance-points (or mean window) in the eigenspace. **Figure 3a** shows eigen



(a) (b)

Figure 3. Eigenspaces of various shapes of a particular object. (a) Five different eigenspaces from 5 situations and (b) magnification of eigen windows.

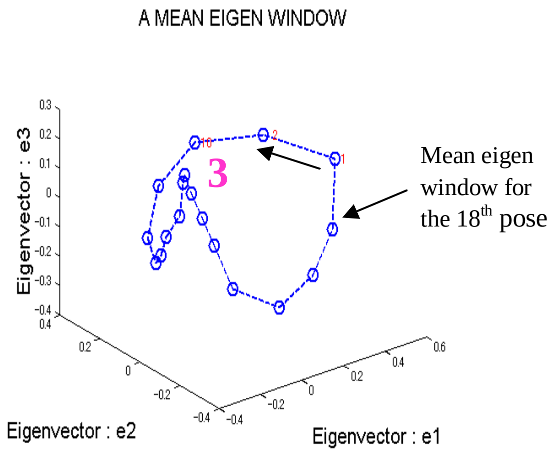


Figure 4. A mean eigenwindow used for further recognition purposes.

windows created from 5 sets of training images. A magnified eigen window is also shown in Figure 3b. A mean eigenwindow is also placed in **Figure 4**. This mean eigenwindow has been created from all of training samples, i.e., 9 sets of images.

In case of matching operation, we have also taken the similar number of images (S=9 and M=162) for testing purposes. It should be noted that these testing samples also include disturbed and non-disturbed object's shapes. We have projected each set of objects onto the mean eigenwindow to verify the performance of the proposed technique. Therefore, we have obtained total 9 sets of recognition rates from the testing samples. **Table 1** shows experimental activities including the obtained recognition rates. We have obtained an average of 91.66% recognition rates where mean square error was 0.0021. We have also calculated the recognition rates based on conventional method [1] in order to compare the performance and we have obtained 53.66% of recognition rates.

Table 1: Images used in the experiment and recognition rate.

Samples	Non-disturbed shape	Occluded shape	Destroyed shape	Total pose	Recognition rates (Avg.)
Training	1	4	4	$18 \times 9 = 162$	91.66%
Testing	1	4	4	$18 \times 9 = 162$	

4 Conclusions

This paper describes a novel method, referred to as the *mean eigenwindow* method, to extend the standard eigenspace method and to simplify the eigen window technique which is able to recognize partially occluded/destroyed objects in a common eigenspace. We have overcome the limitations occurred in the eigen window technique and the eigenspace technique has been extended for tracking objects in the occluded or data-loss environments. The proposed approach can be applicable to various industrial and military applications such as object picking, automatic target recognition and surveillance and monitoring, etc.

The limitations of the *mean eigenwindow* method may be recognition under large occlusion and/or destruction and under various illumination conditions. Future work will concentrate on recognizing objects considering these issues.

References

1. Murase H., Nayar S. K.: "Visual Learning and Recognition of 3D Objects from Appearance," *Int'l J. Computer Vision*, Vol. 14, No. 1, pp. 5-24 (1995).
2. Ohba K., Ikeuchi, K.: “Detectability, Uniqueless and Reliability of Eigen Windows for Stable Verifications of Partially Occluded Objects,” *IEEE Trans. on Pat. Anal. Machine Intell.*, Vol. 9, pp. 1043-1047 (1997).
3. Leonardis A., Bischof H.: “Robust Recognition Using Eigenimages”, *Computer Vision and Image Understanding*, Vol.78, pp.99-118 (2000).
4. Borotschnig, H. et. al.: “Appearance-Based Active Object Recognition”**,** *Image and Vision Computing*, Vol. 18, No. 9, pp. 715-727(2000).
5. Turk, M. A., Pentland, A. "Face Recognition Using Eigenfaces," *Proc. CVPR 1991*, pp. 586-591, 1991.
6. Pentland, P.A., Horowitz, B: "Recovery of Non-rigid Motion and Structure," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 13, No. 7, pp. 730-742 (1991).
7. Rahman, M. M., Ishikawa, S.: “Representing Human Motions by an Eigenspace”, *Journal of Biomedical Soft Computing and Human Sciences*, Vol. 9, No. 1, pp.27-33 (2003).
8. Moghaddam, B., Pentland, A. P.: "Probabilistic Visual Learning for Object Detection," *Proc. 5th Int'l Conf. Computer Vision*, CD-ROM (1995).
9. Ohba, K., Ikeuchi, K.: "Recognition of the Multi Specularity Objects Using the Eigen Window," *Proc. Int'l Conf. Pattern Recognition*, CD-ROM (1996).