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EIGENSPACE TECHNIQUE WITH GAUSSIAN OF LAPLACIAN IMAGES FOR THE ROBUST HUMAN POSTURE RECOGNITION

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ABSTRACT

We introduce a human body-posture recognition technique, namely an eigenspace technique, in this paper overcoming the problems due to loose clothing such as wearing dresses and human body shapes. We introduce *a dress effect* due to loose clothing and *a figure effect* due to various human body shapes in this particular study. This paper is particularly introduced '*Laplacian of Gaussian (LoG)*' images and '*mean posture matrix*' in the eigenspace technique for avoiding the preceding effects. We have tested the proposed approach employing a number of human models wearing various clothes while giving consideration to their different body shapes, and significance of the method to human body-posture and/or gesture recognition has been demonstrated.

1. INTRODUCTION

There are a number of practical applications and advantages of using eigenspace [abbr. ES hereafter] technique in vision engineering due to its inexpensive mathematical computations. The appearance-based ES method was firstly proposed by Murase and Nayar [1] for recognizing 3D object's poses from 2D images. We have also seen an extensive use of the ES approach on capturing the appearances of objects and human faces under various conditions [2-5]. Besides, several models have been proposed for the underlying objectives, e.g., Bayesian rules [6], body pose detection using specialized mapping [7], and spatio-temporal correlation [8].

We have focused to employ eigenspace technique where human motion and/or gesture could be implemented for automatic air-traffic control systems. This work is one of the parts of this project. When we try to implement a conventional eigenspace technique for such an application, the eigenspace changes every time with person's change. We have investigated this problem in this paper. This study investigates that loose clothing and various body shapes have some undesirable effects on creating eigenspace. Since posture representation and recognition are the key factors for applying the ES technique in such applications, we need to overcome these problems for successful representation and recognition of human postures and/or gestures.

We propose to use *Laplacian of Gaussian* (LoG) images for eliminating the dress texture effect, and a *mean posture matrix* for overcoming the *figure effect*. Taking a mean of some selected posture sets creates the mean posture matrix. We have succesfully overcome the preceding effects by the proposed methods for human body posture recognition and tentative experimental proofs have been demonstrated.

2. PROPOSED APPROACH

2.1 Image pre-processing

As described earlier, posture representation should have generality, i.e., it should solely depend on the posture-change and not on the person or dress change. If one employs the conventional eigenspace technique [1], however, respective eigenspace is inevitably generated each time the person changes his/her dress. This is because it employs gray images for the generation of an eigenspace. We employ *Laplacian of Gaussian* images of given images to obtain a solely apperance-dependent eigenspace.

A *LoG* image $E(x,y)$ of the original image $I(x,y)$ is defined by

$$E(x,y) = D^2(G * I(x,y)) \quad (1)$$

G is the Gaussian distribution for reducing the texture effect, and the resultant image is differentiated by a Laplacian operator D^2. In the proposed technique, the *LoG* images provided by Eq.(1) are employed for generating an eigenspace.

2.2 Computing a *mean posture matrix* and basic eigenspace

Let us take a *LoG* image $E(x,y)$ and take P successive sampled images $\boldsymbol{x}_p$ (p=1,2,…,P). The sampled image $\boldsymbol{x}_p$ having $M_0 \times N_0$ pixel size is converted into a column vector of the form

$$\boldsymbol{x}_p = \left(x_{1p}, x_{2p}, ..., x_{N,p}\right)^{\mathrm{T}}. \quad (2)$$

by arranging pixels in a raster scan manner. Here $N \equiv M_0 \times N_0$. Superscript 'T' denotes transpose of a vector or a matrix.

If person h involves to make respective posture sets, a matrix X^h containing P columns and N rows can be denoted by

$$X^h = \left(\boldsymbol{x}_1^h, \boldsymbol{x}_2^h, ..., \boldsymbol{x}_P^h\right). \quad (3)$$

Here $h = 1,2,...,H$. Taking a particular posture set X^h, an ES can be produced and respective postures are represented in the produced eigenspace. For H humans, the posture curves (graphical representation of ES) corresponding to respective persons should ideally coincide with each other in the ES, which is not the case in practice. Therefore an averaged expression of the postures is taken into account.

An mean posture matrix $\overline{X}$ is defined in the following way to obtain a proposed ES;

$$\overline{X} = \frac{1}{H}\sum_{h=1}^{H} X^h = \left(\overline{\boldsymbol{x}}_1, \quad \overline{\boldsymbol{x}}_2, \quad ..., \quad \overline{\boldsymbol{x}}_P\right), \quad (4)$$

where

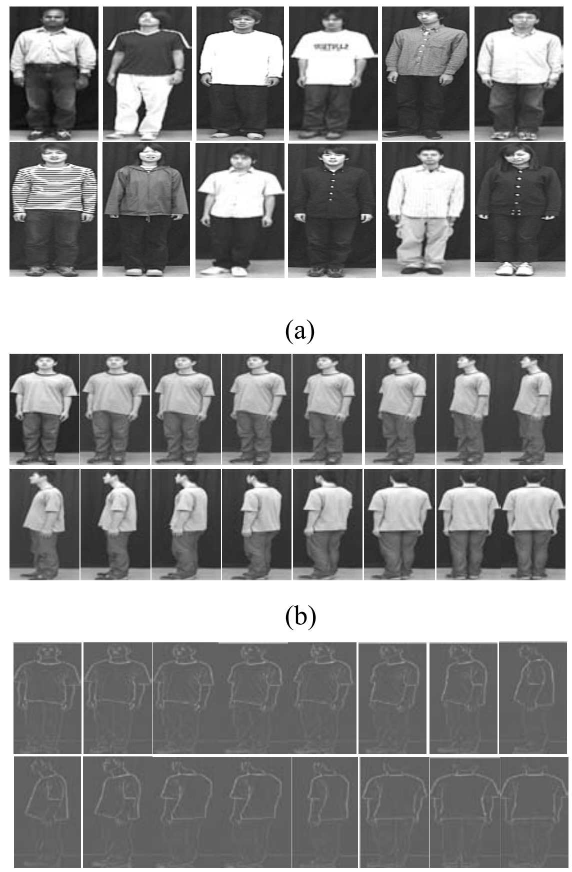
$$\overline{\boldsymbol{x}}_p = \frac{1}{H}\sum_{h=1}^{H} \boldsymbol{x}_p^h, \quad (5)$$

which is called an average image. A mean posture set $\overline{X}$ is a set of mean images.

We define a covariance matrix C as follows;

$$C = \overline{X}\overline{X}^{\mathrm{T}} \quad (6)$$

and determine eigenvalues $\boldsymbol{\lambda}_i$ with its corresponding eigenvectors $\boldsymbol{e}_i$ of the covariance matrix C using an eigen equation $C\boldsymbol{e} = \lambda \boldsymbol{e}$. The N dimensional space defined by all the eigenvectors of matrix C is reduced via PCA algorithm by choosing only k (k is an integer satisfying $k \ll N$) eigenvectors $\boldsymbol{e}_i$ (i=1,2,…,k) corresponding to the largest k eigenvalues to make an ES.



(a)

(b)

(c)

Fig. 1. Human models, postures and processed images: (a) 12 human models out of 30 used in the experiments, (b) 16 postures out of 36 of a model, and (c) blurred edge or LoG images.

Once we determine the selected eigenvectors employing the *mean postures matrix*, the successive procedures, i.e., creating eigenspace and posture recognition technique can be found in the literature [1]. The developed ES having LoG images and *mean posture matrix* is defined here as the proposed or basic ES.

3. EXPERIMENTAL RESULTS

3.1 Effect of the employment of LoG images

In the performed experiment, a setup is conducted using a camera and 30 different human models (H=30) with their clothes and body-shape's variations. Each and every person is asked to stand in front of a fixed video camera, and to make a slow turn in order to take his or her video of turning body-motion. The video motion is sampled approximately every 10 degrees yielding 36 (=P) images of different postures. The original sampled image is reduced to a 32×32 pixels image for the sake of memory efficiency. Considerations of occlusion and background issues are out of scope in this particular study. **Fig. 1a** shows 12 human models out of 30 employed in the experiment, and 16 (out of 36) body postures of a particular person are also shown in Fig. 1b. These images are submitted to the proposed image processing according to Eq. 1. The result of *LoG* images is also shown in Fig. 1c.

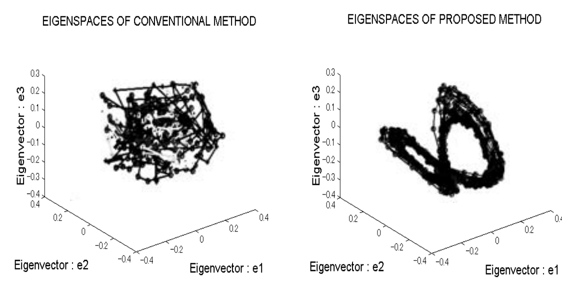
We have generated 30 individual posture curves (single person) as shown in **Fig. 2**. A posture curve refers a single eigenspace made from a particular person's posture frames. These posture curves are obtained from the individual models and placed on a same axis dimension in order to compare the effect of proposed image processing graphically. It should be noted that these posture curves have generated using *LoG* images and this is just separate eigenspaces from the respective models. Therefore, we avoid to taking the mean for this issue, i.e., covariance matrix $C = X^h {X^h}^{\mathrm{T}}$. This performance is just for highlighting the effect of proposed image processing. The posture curves obtained from the conventional method are illustrated in Fig.2a, whereas those derived from the proposed method are depicted in Fig.2b. It is obvious that the dress effect has made the posture curves completely different with each other by the conventional method, though the models' postures are similar. On the other hand, the dress effect has been successfully overcome in the proposed approach as shown in Fig.2b. Since the eigenspaces have not been changed with even changing dresses, it is assumed that the dress effect has been eliminated successfully.

3.2 Recognizing human postures employing the proposed eigenspace

We divide all data sets randomly (taking equal number) into three sets, i.e., LS , $\mathrm{TS_A}$ and $\mathrm{TS_B}$ where LS denotes learning samples and TS denotes testing samples. We employ a k-fold cross validation method for choosing the learning samples for making the basic ES so that all data sets can be used either for training and/or testing. Therefore, when we use LS for generating a basic ES, $\mathrm{TS_A}$ and $\mathrm{TS_B}$ data sets remain for testing. Similarly, if we choose $\mathrm{TS_A}$ as learning samples, LS and $\mathrm{TS_B}$ are used for testing purposes, and vice versa. **Table 1** shows the distribution of data set for generating the proposed ES and the samples for testing. The average recognition results of each test are also shown in this table. We have projected unknown postures onto the basic eigenspace, and calculated the recognition rates by the ratio between the successful hits and the total postures projected. Employing a learning sample, we calculate a mean data set by Eq.(5) and generate the basic eigenspace from it. **Fig. 3** shows a basic ES of the data set LS.

Table 1. Data distribution for the proposed ES and recognition results.

Test	S 1-10	S 11-20	S 21-30	Recog. rate(avg.)	Avg. (all data)
(i)	LS	TS_A	TS_B	86.2%	
(ii)	TS_A	LS	TS_A	83.4%	85.6%
(iii)	TS_B	TS_B	LS	87.2%	



(a) (b)

Fig. 2. Individual posture curves obtained from (a) the conventional method and (b) the proposed method.

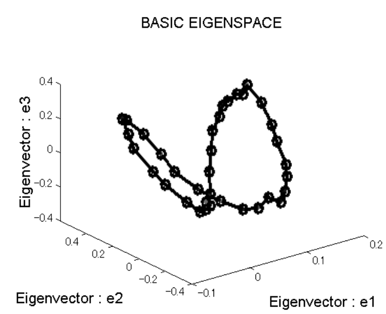


Fig. 3. A basic eigenspace created from the mean posture set.

Table 2. Classification results between conventional and proposed methods.

Methods	Recog. rate	Test sets	Eigen dimn.
Method [1]	40.05%	29	8
Method [8]	71.29%	29	8
Proposed ES	85.6%	20	6

This basic ES is used for recognizing image data contained in TS_A and TS_B. Moreover, the k-fold cross validation method can also be arranged the data sets such a way that each time 29 data sets will be used for learning, and single data set will be employed for testing. In this case, we have obtained an average of 88.6%. However, if we use more data set at a time, the CPU time will be a bit higher.

We have obtained an average recognition rate of 71.66% (not shown in the tables) using the LoG images where only one set was used for learning and 29 sets were for testing. We have also obtained the recognition rates of two other conventional methods for highlighting the robustness of the proposed approach. Classification results between two conventional and the proposed methods are also shown in Table 2. According to the papers of Murase & Nayar [1] and Murase & Sakai [8], we have used the original gray images and silhouette images, respectively, for their input images. In these cases, a best-search method has applied for selecting an appropriate learning sample while other data sets are used for testing (i.e., total of 29 data sets) purposes. It is also noted that these comparisons may not appropriately be same but similar with their concepts. Obtained higher recognition rates have proved the robustness of the proposed method. In case of time efficiency, we need only 1.5 Sec. (CPU time) using 1 G Htz PC and Matlab implementation software.

4. CONCLUDING REMARKS

This paper is an experimental analysis on an eigenspace technique in order to employ it for human body posture and/or gesture recognition. We have found that the eigenspace varies with changing human dresses and body shapes, and, therefore, the conventional eigenspace technique is not suitable for non-rigid object's detection such as human posture. To overcome the limitations, the proposed eigenspace technique has considered LoG images and a *mean posture matrix* for developing a basic eigenspace which is finally be used for human posture recognition. We have conducted various experimental activities on these issues and the robustness of the proposed approach has been demonstrated experimentally. We have also applied this technique for marshalling an aircraft that is experimentally shown in the paper [9]. However, we need some further work for implementing this technique in a practical use.

5. REFERENCES

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