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Rapid and Brief communication

Low resolution face recognition based on support vector data description

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Abstract

In the face recognition process, it is important to deal with a facial image of low-resolution. For low-resolution face recognition, we propose a new method of extending the SVDD, which is one of the most well-known support vector learning methods for the one-class problem. The proposed method can recognize a person even with a low-resolution image.

Keywords: Support vector data description (SVDD); Face recognition; Low resolution; Image enhancement

1. Introduction

Recently, with the rapid progress made in CCTV technology, the requirements of face recognition have dramatically increased. However, the facial images captured by CCTV are of low-resolution and suffer from degradation. Many attempts in the world have been made to solve this problem. Dedeoglu et al. tried to recognize faces in low-resolution images using the super-resolution method [1] and Zhou et al. proposed a video-based face recognition approach [2]. These approaches need several frames which include the face. Park et al. proposed the stepwise reconstruction of a high-resolution facial image based on the extended morphable face model. However, this method suffers from the difficulty of finding the corresponding pixels and dividing the shape and texture [3]. In this paper, we propose a new method of low-resolution face recognition using the SVDD (support vector data description).

2. Face recognition using SVDD

2.1. Overview

One of the most well-known support vector learning methods for the one-class problem is the SVDD. In the SVDD, balls are used to express the region used for the normal class. Since balls in the input domain can express only limited class of regions, the SVDD generally enhances its expressing power by utilizing balls in the feature space rather than in the input domain. In this paper, we apply and extend the main idea of the SVDD to the problem of low-resolution face recognition. Utilizing the projection onto the spherical decision boundary of the SVDD, and a method of solving the pre-image problem, we propose a new method of recognizing faces in low-resolution images.

As shown in Fig. 1, the proposed method consists of the following steps: first, we solve the SVDD problem for the data belonging to the given prototype facial images, and model the data region for the normal faces as the ball resulting from the SVDD problem. Next, for each degraded input facial image, we project its feature vector onto the spherical decision boundary in the feature space. Finally, we recognize the facial image in the input domain by obtaining the pre-image of the projection using the strategy described in Ref. [4] and then performing the popular correlation method.

2.2. Support vector data description

The SVDD method, which approximates the support of objects belonging to the normal class, is derived as follows [5]: consider a ball, B, with center, $a \in \Re^d$, and radius, R, and the training data set, D, consisting of objects,

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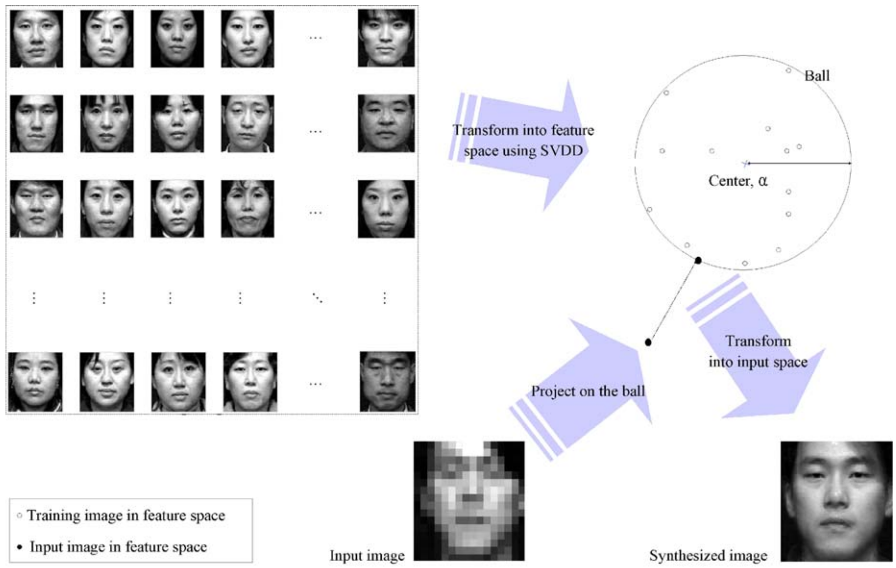

Fig. 1. Central idea of the proposed method.

$x_i \in \Re^d$, $i = 1, \ldots, N$. Since the training data may be prone to degradation, some parts of it could be abnormal objects. The main idea of the SVDD is to find a ball that can achieve two conflicting goals simultaneously. Firstly, it should be as small as possible and secondly, but with equal importance, it should contain as many training data as possible. Balls satisfying these objectives can be obtained by solving the following optimization problem:

$$\begin{aligned} \min \quad & L_0(R^2, a, \xi) = R^2 + C \sum_{i=1}^{N} \xi_i \\ \text{s.t.} \quad & \|x_i - a\|^2 \leqslant R^2 + \xi_i, \quad \xi_i \geqslant 0, \quad i = 1, \ldots, N. \end{aligned} \tag{1}$$

Here, the slack variable, ξ_i, represents the penalty associated with the deviation of the ith training pattern outside the ball. The objective function of (1) consists of two conflicting terms, i.e., the square of the radius, R^2, and the total penalty, $\sum_{i=1}^{N} \xi_i$. The constant, C, controls the relative importance of each term and is thus called the trade-off constant. Note that the dual problem of (1) is

$$\begin{aligned} \max_{\alpha} \quad & \sum_{i=1}^{N} \alpha \langle x_i, x_i \rangle - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j \langle x_i, x_j \rangle \\ \text{s.t.} \quad & \sum_{i=1}^{N} \alpha_i = 1, \quad \alpha_i \in [0, C], \quad \forall_i. \end{aligned} \tag{2}$$

From the Kuhn–Tucker condition, the center of the SVDD ball can be expressed as $a = \sum_{i=1}^{N} \alpha_i x_i$, and the radius, R, can be computed by utilizing the distance between a and any support vector, x_i, on the ball boundary. After the training phase is over, one may decide whether a given test point, $x_i \in \Re^d$, belongs to the normal class by utilizing the following criterion: $f(x) \cong R^2 - \|x - a\|^2 \geqslant 0$. In order to express more complex decision regions in $\Re^d$, one can use the so-called feature map, $\phi\colon \Re^d \to F$, and balls defined on the feature space, F. By proceeding in a similar manner to that described above and utilizing the kernel trick, $\langle \phi(x), \phi(z) \rangle = k(x, z)$, one can find the corresponding feature-space SVDD ball, B_F. If the Gaussian function, $K(x, z) = \exp(-\|x - z\|^2/\sigma^2)$, is chosen for the kernel, K, one has $K(x, x) = 1$ for each $x \in \Re^d$, and this is assumed throughout this paper. Finally, note that in this case, the SVDD formulation is equivalent to

$$\begin{aligned} \min_{\alpha} \quad & \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j K(x_i, x_j) \\ \text{s.t.} \quad & \sum_{i=1}^{N} \alpha_i = 1, \quad \alpha_i \in [0, C], \quad \forall_i, \end{aligned} \tag{3}$$

and the resulting criterion for normality is represented by

$$\begin{aligned} f_F(x) &\cong R_F^2 - \|\phi(x) - a_F\|^2 \\ &= R_F^2 - 1 + 2 \sum_{i=1}^{N} \alpha_i k(x_i, x) \\ &\quad - \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j k(x_i, x_j) \geqslant 0. \end{aligned} \tag{4}$$

2.3. Low-resolution face recognition using SVDD

In the SVDD, the objective is to find the support of the normal objects, while anything outside the support is viewed as abnormal. In the feature space, the support is expressed by a reasonably small ball containing a reasonably large portion of $\phi(x_i)$.

Fig. 2. Examples of reconstructed images: (a) synthesized image of a face, which is not in the training set and (b) synthesized image of a face, which is in the training set.

A central idea of this paper is to utilize the ball-shaped support in the feature space for the purpose of recognizing input facial images degraded by CCTV. More precisely, when the trade-off constant C is set appropriately,[1] we can find a region in which the facial image data belongs to the normal facial images of high resolution. When a facial image is given as a test input, x, in low-resolution form, the network resulting from the SVDD is supposed to judge that the x of low-resolution does not belong to the normal class. The SVDD has played a conventional role up to this point, and the problem of recognizing low-resolution facial images might be thought to be beyond the scope of the SVDD.

However, herein we observe that since the decision region of the SVDD is a simple ball, B_F, it is quite easy to let the feature vector, $\phi(x)$, of the low-resolution image move toward the center, a_F, of the SVDD ball, B_F until it reaches the decision boundary, so that it can be tailored enough to be considered as normal. Of course, since the movement starts from the feature, $\phi(x_i)$, there are plenty of reasons to believe that the tailored feature, $P\phi(x_i)$, still contains essential information about the facial image. Thus, we affirm that it is possible to perform better recognition with $P\phi(x_i)$ than with $\phi(x_i)$. The above arguments together with additional steps used to find the pre-image of $P\phi(x_i)$ and the application of the general correlation method comprise the essence of our method for low-resolution face recognition.

[1] In out experiments. $C = 1/(N \times 0.2)$ was used.

3. Experimental results

In order to illustrate the proposed method, we used two-dimensional images of Korean faces contained in the Asian Face Database [6]. For the experiments, we extracted faces using the ground truth information and normalized them based on the distance between the eyes. The resolutions of these images were 128 by 128 pixels, and the color images were converted to 8-bit gray level images. The 100 facial images were used for the SVDD training set. For the test data set, we prepared three different data sets from 100 training images. First, all training images were resized to 16 by 16 pixels by nearest neighbor resampling and were resized again to 128 by 128 pixels without interpolation. Second, the same images were resized to 16 by 16 pixels by the same resampling and were resized again to 128 by 128 pixels with bicubic interpolation. Finally, the images in first data set were projected on the boundary of the ball and were synthesized by solving the pre-image problem.

In Fig. 2, the first column shows the test images (in the first data SET), the second column shows the images interpolated by the bicubic method (in the second data set), the third column shows the images synthesized using the proposed method, $P\phi(x_i)$, and the last column shows the original high-resolution images. In the case of the images contained in the training set, the synthesized results are plausible. However, in the case of images which do not exist in the training set, the performance was decreased.

We also performed face recognition experiments with these data sets and the results are summarized in Table 1.

Table 1
The results of face recognition

	Avg. of face recognition rates (%)	Avg. of correlation values
Low-resolution images (16×16)	84	0.79
Low-resolution images (32×32)	86	0.82
Interpolated images from 16×16	70	0.75
Interpolated images from 32×32	76	0.78
$P\phi(x_i)$ from 16×16	93	0.92
$P\phi(x_i)$ from 32×32	96	0.93

In these experiments, we used the general correlation method. In Table 1, the proposed method shows better performance than others.

4. Conclusions

In this paper, we addressed the problem of recognizing low-resolution facial images. The proposed method depends on the SVDD-based learning technique, which makes use of the projection onto the SVDD balls in the feature space, and a method of finding the pre-image of the projection. The experimental results showed that the facial images synthesized using the proposed method were quite similar to the high-resolution facial images, thus making it possible to recognize a person from a low-resolution image.

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