Uncontrolled Face Recognition by Individual Stable Neural Network

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Abstract. There usually exist diversified variations in face images taken under uncontrolled conditions. Most previous works on face recognition focus on particular variations and usually assume the absence of others. Such works are called *controlled face recognition*. Instead of the 'divide and conquer' strategy adopted by controlled face recognition, this paper presents one of the first attempts directly aiming at *uncontrolled face recognition*. The solution is based on Individual Stable Neural Network (ISNN) proposed in this paper. ISNN can map a face image into the so-called Individual Stable Space (ISS), the feature space that only expresses personal characteristics, which is the only useful information for recognition. There are no restrictions for the face images fed into ISNN. Moreover, unlike many other robust face recognition methods, ISNN does not require any extra information (such as view angle) other than the personal identities during training. These advantages of ISNN make it a very practical approach for uncontrolled face recognition. In the experiments, ISNN is tested on two large face databases with vast variations and achieves the best performance compared with several popular face recognition techniques.

1 Introduction

Despite the success of many face recognition systems [1] [5] [7] [13], a lot of issues still remain to be addressed. Among those issues, perhaps the most prominent one is that most systems require the face images fed to them to satisfy certain 'rules', such as in a particular range of view angle, in homogeneous illumination and without any occlusions. We call such systems *controlled face recognition* systems. The control rules greatly restrict the commercialization of face recognition techniques because most real applications, such as intelligent surveillance, cannot satisfy such strict rules. What the real world needs are systems that can recognize any face images recognizable by human beings. We call such systems *uncontrolled face recognition* systems.

As a matter of fact, the developing history of face recognition techniques is the march from controlled conditions to more and more uncontrolled conditions. Most early algorithms [1] [5] [7] [13] can handle expression variation well but suffer from other variations. Later, a lot of methods [2] [4] [10] [11] [15] were proposed to tackle view angle and illumination variations. Recently, a few works have been emerging to remove occlusion [14] and simulate aging effect [3]. Although the treatable variations are more and more complex, most of these ingenious methods yet have to assume the absence of other possible variations. The methodology adopted by existing works appears to be 'divide and conquer', i.e. gradually reduce the restrictions through tackling possible variations one by one. However, in practice, a number of variations are often complicatedly interlaced. The combination of several algorithms each of which handles particular variations well will not necessarily result in a robust system against all variations.

Instead of 'divide and conquer', this paper presents one of the first attempts along the 'unite and conquer' strategy, i.e. directly target to uncontrolled face recognition. Since variations in uncontrolled face recognition might be too complex to be well handled by currently available mathematical tools, we avoid explicitly modeling different kinds of variations. Instead, we focus on the information which is useful for face recognition and try to filter out all other information. This is achieved by a multilayer neural network named Individual Stable Neural Network (ISNN).

The rest of this paper is organized as follows. In section 2, the extraction of personal characteristics is discussed. ISNN is proposed for uncontrolled face recognition in section 3. The experimental results are reported and analyzed in section 4. Finally in section 5, conclusions are drawn and the main future work is indicated.

2 Extraction of Personal Characteristics

The information conveyed by any face image[3] might be categorized into four kinds:

1. *Personal characteristics* (denoted by $I_{personal}$), i.e. the characteristics that make one person look different from others;
2. *Common facial characteristics* (denoted by I_{facial}), i.e. the characteristics shared by all faces;
3. *Face status* (denoted by I_{status}), i.e. any changes a particular face may undergo, such as expressions, aging effects, glasses, scars, etc.;
4. *Imaging configuration* (denoted by $I_{imaging}$), i.e. the conditions under which the face is imaged, such as illumination, view angle, etc..

Among them, $I_{personal}$ is the only useful one for recognition. Thus the key step of any face recognition methods should be the extraction of $I_{personal}$, explicitly or inexplicitly.

[3] Here the face image refers to normalized face image, i.e. only the face region is contained in the image.

The four kinds of information contained in a set of face images can be divided into two groups, i.e. *variable information* and *stable information*. Traditional research on face recognition mainly focuses on the variable information in a multi-personal face image set. In this case, I_{facial} is out of the game first. The goal is set as distinguishing the variation of $I_{personal}$ from that of I_{status} and $I_{imaging}$. Nontrivial works naturally start from the relatively easier cases when the variations of I_{status} and $I_{imaging}$ are partially restricted, i.e. the cases of controlled face recognition.

Under uncontrolled conditions, the possible variations of I_{status} and $I_{imaging}$ seem too complex to be efficiently modelled. Instead we try to 'filter out' them. I_{status} and $I_{imaging}$ are always in the group of variable information, which prompts us to shift our attention to the other group, stable information. If the face images all come from a same person, then both $I_{personal}$ and I_{facial} are stable. Noticing that I_{facial} is always stable in a face image set, we find a way to remove I_{facial} before I_{status} and $I_{imaging}$. Suppose the information contained in a multi-personal face image set is denoted by I_{multi}, then

$$I_{multi} = \underline{\underline{I_{status} + I_{imaging} + I_{personal}}} + \underline{I_{facial}}, \tag{1}$$

where the double-underlined terms are the variable information, and the single-underlined terms are the stable information. Suppose we can construct a feature space F_v that filters out the information stable in the image set, then the information contained in the projections of the image set in F_v, I^p_{multi}, will be

$$I^p_{multi} = \underline{\underline{I_{status} + I_{imaging} + I_{personal}}}, \tag{2}$$

which means that I_{facial} has been removed in F_v. If subsequently the projections are divided into subsets each of which is a single-personal set, then the information contained in each subset, I^p_{sub}, will be

$$I^p_{sub} = \underline{\underline{I_{status} + I_{imaging}}} + \underline{I_{personal}}. \tag{3}$$

Now only $I_{personal}$ is the stable information. If a second feature space F_{is} that filters out the variable information is constructed on the subset of a particular person, then the information contained in the projections in F_{is}, I^{pp}_{sub}, will be only $I_{personal}$:

$$I^{pp}_{sub} = \underline{I_{personal}}. \tag{4}$$

Such feature space F_{is} is called Individual Stable Space (ISS) of that person because of two reasons. First, since I_{status} and $I_{imaging}$ have been removed, all face images of that particular person are expected to be stable in F_{is}. Second, since I_{facial} has also been removed, if the face images from other persons are projected into F_{is}, the projections are expected to be unstable. Thus ISS can be used to design an uncontrolled face recognition system. The next section will describe how to map a face image into ISS and recognize it by the Individual Stable Neural Network (ISNN).

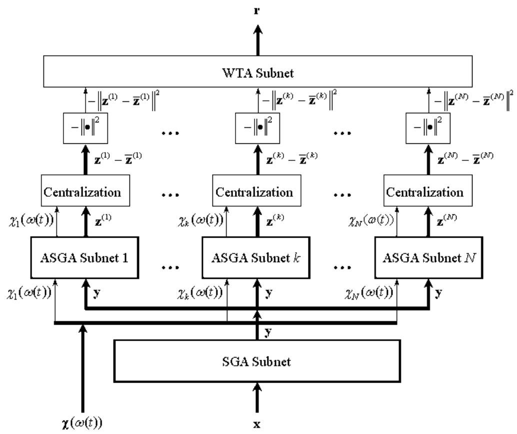

Fig. 1. The architecture of the ISNN for uncontrolled face recognition. The thick lines represent vector signals, and the thin lines represent scalar signals

3 ISNN for Uncontrolled Face Recognition

3.1 Individual Stable Neural Network

The construction of ISS involves two kinds of feature spaces. The first is the feature space that filters out the information stable in the training set (the projection from equation (1) to (2)). The second is the feature space that filters out the information variable in the training set (the projection from equation (3) to (4)). In ISNN, these two kinds of feature spaces are implemented by a pair of neural networks with opposite learning rules, namely SGA network [9] and ASGA network [16].

The architecture of ISNN, as shown in Fig. 1, is designed according to the extraction procedure of $I_{personal}$ described in section 2. The raw face image $\mathbf{x} = [x_1, x_2, \ldots, x_n]$ is first input into the SGA subnet to get its projection $\mathbf{y} = [y_1, y_2, \ldots, y_p]$ in the feature space F_v. Then $\mathbf{y}$ is input into the N (the number of different individuals) ASGA subnets together with the supervisory signal $\chi(\omega(t)) = [\chi_1(\omega(t)), \chi_2(\omega(t)), \ldots, \chi_N(\omega(t))]$. Suppose the personal ID of a particular projection $\mathbf{y}(t)$ is $\omega(t)$, then $\chi_k(\omega(t))$ is defined by

$$\chi_k(\omega(t)) = \begin{cases} 1, & \text{when } \omega(t) = k; \\ 0, & \text{when } \omega(t) \neq k. \end{cases} \tag{5}$$

The output of the k-th ASGA subnet, $\mathbf{z}^{(k)} = [z_1^{(k)}, z_2^{(k)}, \ldots, z_m^{(k)}]$, will be the projection in the ISS of person k. After centralization and negative normalization, the N scalar signals $-\left\|\mathbf{z}^{(k)} - \bar{\mathbf{z}}^{(k)}\right\|^2, k = 1 \ldots N$ are sent to a winner-take-all (WTA) subnet to choose the largest one.

The SGA network has p parallel neurons each of which is associated with a weight vector $\mathbf{w}_j$. The learning rule of the SGA network is given by

$$\Delta\mathbf{w}_j(t-1) = \alpha_1 y_j(t)[\mathbf{x}(t) - y_j(t)\mathbf{w}_j(t-1) - 2\sum_{i<j} y_i(t)\mathbf{w}_i(t-1)], \qquad (6)$$

where $y_j(t) = \mathbf{w}_j^T(t-1)\mathbf{x}(t)$ and $0 < \alpha_1 < 1$ is the learning rate. As proved by Oja [8], for $t \to \infty$, the vectors $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_p$ will converge to the principal components of the input data stream. As the first step of uncontrolled face recognition, the utility of the SGA network is to remove the common facial characteristics I_{facial} because the feature space spanned by principal components mainly reserves variable information while I_{facial} is stable information.

The ASGA network uses the opposite learning rule of the SGA network. It can be viewed as an anti-Hebbian version of SGA. Since in the second stage of the extraction of $I_{personal}$, the projections in the face space need to be divided according to personal IDs, a supervisory signal $\chi_k(\omega(t))$ should be integrated into the learning rule, which is given by

$$\begin{aligned}\Delta\mathbf{w}_j^{(k)}(t-1) = -\alpha_2\chi_k(\omega(t))z_j^{(k)}(t)[\mathbf{y}(t) - z_j^{(k)}(t)\mathbf{w}_j^{(k)}(t-1)/\left\|\mathbf{w}_j^{(k)}(t-1)\right\|^2 \\ -2\sum_{i<j} z_i^{(k)}(t)\mathbf{w}_j^{(k)}(t-1)], \qquad (7)\end{aligned}$$

where $z_j^{(k)}(t) = \mathbf{w_j^{(k)}}^T(t-1)\mathbf{y}(t)$ and $0 < \alpha_2 < 1$ is the learning rate. It was proved [17] that for $t \to \infty$, $\mathbf{w}_j^{(k)}$ will converge to the least variable components of the input data. Such components are called minor components [16]. Just as principal components retaining the information variable in the data set, minor components retain the information stable in the data set. In the subset, as shown in equation (3), only $I_{personal}$ is stable information, thus the output feature $\mathbf{z}^{(k)}$ can be viewed as the projection in ISS.

In the training phase of ISNN, all the training face images and the corresponding personal IDs are input into the initialized ISNN to update the weights. After convergence, all the training images and IDs go through the ISNN again without updating the SGA and ASGA subnets to calculate the mean vectors $\bar{\mathbf{z}}^{(k)}, k = 1, \ldots, N$. Note that in the whole training procedure of ISNN, no extra information except the personal IDs is needed. This advantage is extremely important since under uncontrolled conditions, the accurate estimation of such extra information is alone a big problem. One might ague that ISNN requires to train one network for each person, thus the training procedure is inefficient for large databases. However, ISNN adopts the so-called One-Class-One-Network (OCON) structure, which has certain advantages over the All-Class-One-Network (ACON) structure, such as less hidden units, faster convergence, and better generalization [18]. Moreover, such architecture can easily benefit from distributed computing. Thus efficiency should not be a problem for ISNN.

In the testing phase, the unknown face image $\mathbf{x}$ directly go through the ISNN. The output vector $\mathbf{r}$ indicates in which ISS the projection is most stable, and consequently $\mathbf{x}$ is recognized as from the individual associated to that ISS.

3.2 Relationship to Existing Works

The architecture of ISNN is somehow similar to the Probabilistic Decision-Based Neural Network (PDBNN) [5] because both of them adopt the OCON structure. However, the effectiveness of PDBNN relies on the ability of the mixture of Gaussians to approximate any data distribution, while the effectiveness of ISNN relies on the extraction of the only useful information for recognition, i.e. $I_{personal}$.

The Eigenface method [13] is similar to the SGA subnet in the ISNN. However, in case of uncontrolled face recognition, neither the purpose nor computation is the same. The purpose of the SGA subnet is to remove I_{facial} rather than find $I_{personal}$ in the image set. The computation is changed from eigen decomposition to recursive learning because the vast possible variations in uncontrolled conditions consequentially require a large number of training images, which makes the SVD procedure of Eigenface no longer tractable.

The idea of personalized subspace was first proposed as Face Specific Subspace (FSS) [11]. FSS is actually similar to the ASGA subnets in the ISNN. There are two main advantages of ISNN over FSS. The first is that ISNN also filters out I_{facial} while FSS doesn't. The second is that ISNN can explicitly get the projections in the ISS. This provides much more room for further improvements.

The 'unite and conquer' strategy was once adopted in controlled face recognition by the Bayesian face recognition method [6]. However, in uncontrolled face recognition, the possible cases of both extrapersonal and intrapersonal differences will exponentially grow to an unmanageable size. On the other hand, ISNN avoids directly modeling different kinds of information and instead tries to filter out all useless information.

Fisherface [1] tries to find a global feature space that maximizes the ratio of the extrapersonal difference and the intrapersonal difference. However, single linear subspace might not be powerful enough for uncontrolled face recognition. Thus ISNN uses multiple personalized subspaces to compensate the deficiency of single linear subspace.

4 Experiments

4.1 Methodology

In the experiments, ISNN is compared with those closely related methods described in section 3.2 and some of their variants by three-fold cross validation.

Two databases are used in the experiments. The first is the CMU PIE database [12]. The face images are greatly different in pose, illumination and expression. Note that although the images in this database are obtained under controlled conditions, the additional information (pose, illumination and expression) is not used to train ISNN. Thus it can be viewed as an uncontrolled face database. There are totally 38,707 images from 68 individuals used in our experiments. The normalized face image has 66×46 pixels. Some typical normalized faces are shown in Fig. 2 (a). The other data set is used to test the algorithms in another case: fewer individuals but with more variations. We have collected

Fig. 2. Typical face images from (a) the CMU PIE database, (b) the UFR face database

23,978 images from 14 individuals through a web camera to compose the UFR face database[4]. This database attempts to simulate most possible variations (pose, illumination, expression, occlusion, device noise, and inaccurate face detection) in real face recognition applications. The cropped face image has 55×42 pixels. Some typical cropped faces from this database are shown in Fig. 2 (b).

There are remarkable illumination and pose variations in both databases. Among the methods described in section 3.2, only Eigenface is not specially designed to deal with illumination variation. It has been reported that discarding the first few eigenfaces will endow Eigenface with certain ability to handle illumination variation [1]. This is tested here by discarding the first three eigenfaces, which is denoted by Eigenface-3. As for the pose variation, except for ISNN, PDBNN and FSS, none of the other methods is designed for the multi-view case. So we extend a multi-view version for each of them in a way similar to the View-based Eigenface [10] (abbreviated as V-Eigenface). The multi-view algorithms are denoted by V-Bayes, V-Fisherface and V-(Eigenface-3) respectively.

In the experiments, the parameters of PDBNN are empirically determined through several trials. When the best performance is observed, the number of Gaussians for each individual is set to 6, the learning rate for the Gaussian centers is set to 10^{-6}, the learning rate for the variance is set to 10^{-4}, the learning rate for the threshold is set to 0.05, and the penalty function for the threshold is the sigmoid function. As for the Bayes method, similar to [6], we randomly sample 1,000 intrapersonal difference images and 4,000 extrapersonal difference images as the training set. If not explicitly stated, the number of principal components p is set to 50, and the number of minor components m is set to 20. The initial weight vectors $\mathbf{w}_j(0)$ in the SGA or ASGA subnet are set to random orthogonal unit vectors. The learning rates in equation (6) and (7) are set as $\alpha_1 = \alpha_2 = 0.01$.

4.2 Results

The recognition rates from rank 1 to rank 3 on the PIE database are tabulated in Table 1. The 11 algorithms are compared in two cases: with and without pose

[4] This database will soon be publicly available.

Table 1. Recognition Rates (in %) From Rank 1 to Rank 3 on the PIE Database

Methods	Without Pose Inf.			With Pose Inf.		
	Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3
ISNN	**94.16**	**96.59**	**97.32**	**94.16**	**96.59**	**97.32**
PDBNN	81.70	88.44	91.45	81.70	88.44	91.45
FSS	89.30	92.62	94.04	89.30	92.62	94.04
Bayes	18.58	25.23	31.36	18.58	25.23	31.36
Fisherface	57.96	67.25	72.89	57.96	67.25	72.89
Eigenface	30.27	39.54	45.84	30.27	39.54	45.84
Eigenface-3	45.31	55.24	61.10	45.31	55.24	61.10
V-Bayes	N/A	N/A	N/A	48.86	61.33	68.56
V-Fisherface	N/A	N/A	N/A	89.88	93.36	94.77
V-Eigenface	N/A	N/A	N/A	65.92	72.18	75.58
V-(Eigenface-3)	N/A	N/A	N/A	85.11	88.85	90.60

information. The best performance in each case is bolded. Note that the first 7 algorithms do not use pose information, so the results in the two cases are same.

When pose information is not available, the best performance is achieved by ISNN, which is about 5% higher in rank 1 rate than the runner-up, FSS. The superiority of ISNN over FSS mainly comes from the SGA subnet of the ISNN, which removes I_{facial}. It is also worth mentioning that FSS uses a 50-dimensional subspace while ISNN only uses a 20-dimensional subspace to describe each person. Thus ISNN is much faster and requires less storage. PDBNN performs worse than both ISNN and FSS because under uncontrolled condition, the distribution of the face images is so complicated that the gradient descent learning of PDBNN will tend to fall into local optimization. The Bayes method results in poor performance, which is not surprising since the sampled difference images are only a small portion of all possible differences. Fisherface performs best among the three single-subspace methods. Just as reported in [1], Fisherface always performs better than Eigenface and its variants. Finally, Eigenface-3 performs much better than Eigenface, which is consistent to the statement in [1]. It can be found that there is a remarkable gap between the recognition rates of the best three methods (ISNN, FSS and PDBNN) and those of the others, which indicates that the personalized approach might be a suitable solution to the problem of uncontrolled face recognition.

When pose information is given, ISNN still performs the best. This is impressive because it does not use the additional information which has been exploited by the view-based algorithms. With certain ability to handle the pose variation, all the view-based variants make remarkable improvements over the corresponding original algorithms. Among them, V-Fisherface achieves the highest recognition rate, which marginally exceeds that of FSS. But in practice, the pose information is not always available, especially under uncontrolled conditions. This greatly enlarges the superiority of ISNN over V-Fisherface.

The recognition rates on the UFR database are tabulated in Table 2. With fewer classes, almost all algorithms achieve better performances than those on

Table 2. Recognition Rates (in %) From Rank 1 to Rank 3 on the UFR Database

Methods	Without Pose Inf.			With Pose Inf.		
	Rank 1	Rank 2	Rank 3	Rank 1	Rank 2	Rank 3
ISNN	**98.65**	**99.51**	**99.79**	**98.65**	**99.51**	**99.79**
PDBNN	96.84	99.04	99.54	96.84	99.04	99.54
FSS	96.79	98.52	98.99	96.79	98.52	98.99
Bayes	39.52	59.96	73.80	39.52	59.96	73.80
Fisherface	91.32	96.56	98.10	91.32	96.56	98.10
Eigenface	68.18	80.63	86.62	68.18	80.63	86.62
Eigenface-3	75.24	86.15	90.06	75.24	86.15	90.06
V-Bayes	N/A	N/A	N/A	53.71	74.76	85.78
V-Fisherface	N/A	N/A	N/A	96.41	98.56	99.26
V-Eigenface	N/A	N/A	N/A	76.01	86.05	90.26
V-(Eigenface-3)	N/A	N/A	N/A	83.56	90.60	93.06

the PIE database. The comparative results are similar with those in Table 1. When pose information is not available, ISNN is still the best one. PDBNN achieves a good performance just next to that of ISNN, and better than that of FSS. This might be because that with fewer classes, the mixture of Gaussians learned by PDBNN is enough to separate different classes. When pose information is given, there is still no other algorithm exceeds ISNN. It is noteworthy that V-(eigenface-3) is the only algorithm that performs worse on the UFR database than on the PIE database. This might be due to the diverse variations in the UFR database. When so many variations are combined together, it is almost impossible to tell which kind of variation the first three components are dominated by. Thus some useful information may be discarded in V-(eigenface-3).

5 Conclusions

This paper presents one of the first approaches toward uncontrolled face recognition. The main contributions includes: (1) The ISS is proposed as a general framework for uncontrolled face recognition; (2) ISNN is designed as a neural network implementation of the ISS; (3) The first uncontrolled face database UFR is introduced.

The implementation of ISS is not limited to ISNN. As mentioned above, the ISS-based approach can be viewed as a general framework for uncontrolled face recognition. Other novel subspace methods, including both linear and nonlinear ones, might be developed to implement ISS. This will be one of our major future work following this paper.

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