

Face Recognition Using Reinforcement Learning

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Abstract

Neuroscientists believe that human beings recognize faces not only by utilizing some holistic search among all learned faces, but also through a feature analysis that aimed to specify more important features of each specific face. In this paper, we propose a hierarchical classifier that uses both holistic search and per face dominant feature analysis to recognize faces. Reinforcement learning is used to find a set of dominant features for each image in a training dataset. Wavelet transform is employed as a preprocessing tool, which results in higher discrimination among classes. Simulation studies justify the better performance of the proposed method as compared to that of eigenface method.

1. Introduction

Many neuroscientists argued that face recognition in human beings is not merely a holistic search. Particularly, when a set of dominant features are presented, holistic search may not be used. Studies suggest the possibility of general descriptions as the final steps in face recognition. Feature analysis may be considered as a powerful ability for human face recognition [1].

Sirovich and Kirby used the Karhunen-Loeve transform (KLT) for face representation [2]. In 1991 Turk and Pentland introduced the eigenfaces and eigenspace for face recognition [3]. Based on this original work, a large number of algorithms are developed. The most important drawback of these algorithms is their holistic nature. By holistic nature we mean that they try to represent faces with N dimensional vectors and then classify these vectors. Gao showed that if some of the first elements of the projected vectors are removed, the Eigenface method became more robust against different expressions and lighting conditions [4].

In this paper, we utilize reinforcement learning to find out dominant features for each individual in the training data. We have used the wavelet transform (WT) as a preprocessing tool for data reduction. We called the space which is formed by principal component analysis on the transformed faces, the Wavelet Eigenspace or Weigenspace for short. We also called the eigenvectors and eigenfaces which are obtained after WT respectively the weigenvector and weigenfaces. We also develop a new hierarchical classifier which uses both general description (projected vectors in the Weigenspace) and dominant feature (which are extracted by reinforcement learning) for classification. Simulation results showed considerable improvements over the original Eigenface algorithm. The rest of this paper is organized as follows: In Section 2, we introduced the Weigenspace and its properties. In Section 3, the reinforcement learning and the model we used for dominant feature extraction are presented. The hierarchical classifier is proposed in Section 4. Simulation results and discussed in Section 5, and paper is concluded in Section 6.

2. Weigenspace

The major drawback of PCA is its poor discriminatory power. Moghaddam et al. [5] have plotted the largest three eigenvalue coefficients of each class. It is found that they overlap each other. This shows that PCA has poor discriminatory power.

Feng et al. [6] used wavelet transform to reduce the computational power and increase the discriminatory of eigenface method. The advantages of WT, such as good time and frequency localizations, have been discussed in many research articles. Feng suggested using PCA after transforming the faces into their subband images with WT.

In order to see the effect of PCA on subband images, we have compared the recognition rate of original eigenface method, bilinear and nearest neighborhood interpolation (for data reduction) and several wavelets transformed in figure 1. We have used the biorthogonal and Coiflet wavelets which are the best among the other type of wavelets from the discriminatory power aspect. We have used the ORL¹ database for this simulation. 3 first pictures of each individual are used as training data. and 2 level of decomposition are applied to wavelets. For Bilinear and nearest neighborhood the image size is reduced to a quarter of the original size so the image size after applying WT or interpolation are approximately the same. From this figure it's concluded that the discriminatory power has increased near 10% in the Weigenspace. Also this increment is not the effects of size reduction as it can see from the bilinear and nearest neighborhood curves.

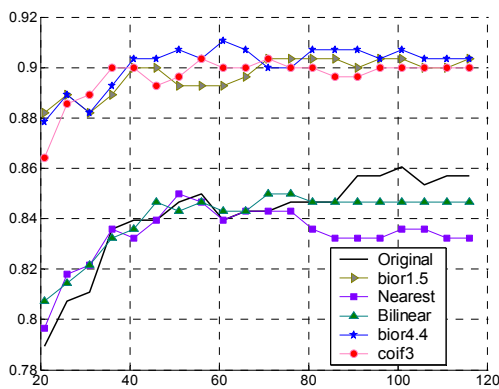


Fig. 1. Recognition rate versus number of eigenvalues for Eigenface, PCA on subband images with WT and PCA on images with reduced size using interpolations.

3. Dominant features

All the eigenface based methods for face recognition can be categorized as holistic search methods. This fact is due to their nature of classification. In these methods, first the PCA is used to extract the face representations and the resulting vectors are classified by some classification methods as shown in Fig. 2.

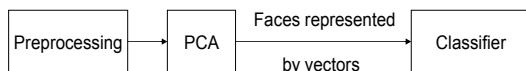


Fig. 2. General description of eigenface based methods for face recognition.

Although we have known that feature analysis is used by human for face recognition, this clue has not been used in any algorithm yet. In this paper we use reinforcement learning for finding the dominant features for each individual. These dominant features are used as the final step of our face recognizer where holistic search is used as the first step.

Reinforcement learning is learning what to do so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them [7].

Suppose we have n individual and m image from each individual in the training data. Our goal is to find the best features for each image among all the p features. For each image we construct a $p \times p$ Q table (Fig. 3). Each row of this table shows the current selected features and each column represents the next feature. The value of element (i, j) of the table shows the reward values for selecting feature number j when we have selected feature i . We also construct a 1-D array of size p for the best selected feature in the first step so the values of this array demonstrate which feature must be selected first as shown in Fig. 3. This vector is called first feature selection array or FFSA for simplicity. We have used a 1-D array of size p for memorizing which features are selected at each step of iteration of learning phase. This vector is called PATH_TRACE_FLAG. When a feature is selected in any iteration of the learning phase, the corresponding value of this vector change from zero to one. At each step of learning iteration, only those features which are not selected before could be candidates as the next feature so only those features whose corresponding values are zero in PATH_TRACE_FLAG can attend the next step of learning iteration.

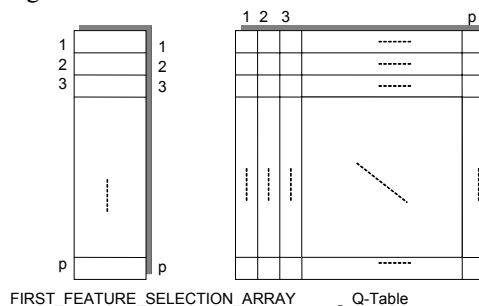


Fig. 3. Q table and first feature selection array used for RL.

Any iteration of RL for an image has maximum c steps. The policy we used for action selection is

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ϵ Greedy policy. In this policy the best action is selected with probability $1-\epsilon$ while with probability ϵ a random action can be occurred.

In learning phase we want to choose those features which decrease the distances between the current image and the other images of the same individual while increasing the distance to the images of other individuals in the Euclidean space. To achieve this goal we use K-nearest neighborhood classifier. First all the eigenvectors are multiplied by the `PATH_TRACE_FLAG` vector. This multiplication removes the effect of features which are not marked as dominant features in the Euclidean space. All the images in the train set are projected to the space spanned by these eigenvectors. Then the distances between each projected feature vector to all other feature vectors are calculated. For each projected feature vector, the K-nearest feature vectors are determined. The number of neighbors which belong to the same class is marked as n_C thus n_C is the number of feature vectors of the same individual which are in the K nearest neighborhood of current feature vector. We define the reward value function as follows,

$$reward = n_C \times R_C + (K - n_C) \times P_{NC} \quad (1)$$

Where R_C and P_{NC} are two constant correspond to reward value for correct hits and punishment value for wrong hit.

The updating relation for each cell of Q-Table is defined as

$$v(i, j) = v(i, j) + \alpha(r + \lambda \max_{l=1}^p v(i, l) - v(i, j)) \quad (2)$$

We assume that the learning can be modeled as a 1st order Markov process i.e. selecting the current feature is only affected by the previous feature. Although it seems that this simplification is not valid but the simulation results show that the learning procedure is able to find the correct features. We found out that for a good learning, 2000 iteration are needed for each image. If all the images of the same individual are found in 5 consequence steps that learning iteration are finished otherwise it takes p steps to finish. The learning algorithm can be summarized as follows,

- Select a feature vector from the training dataset.
- Initialize the corresponding Q-Table and FFSA randomly.
- *for* iteration=1 to 2000 *do*
- Initialize the `PATH_TRACE_FLAG` to zero.

- *repeat*
- Select a feature by ϵ Greedy policy.
- Change the corresponding element of `PATH_TRACE_FLAG` to 1.
- Multiply the `PATH_TRACE_FLAG` to all other feature vectors.
- Find K-nearest feature vectors to the selected vector in the training dataset.
- Find the number of correct feature vector in the K nearest neighbor.
- Update the corresponding cell of Q-Table according to equation 1 and 2
- *until* the current iteration finished (in 5 consequence steps all the images from the same individual are found or if all the elements of `PATH_TRACE_FLAG` are equal to 1).
- *endfor*

It has to be mentioned that the updating equation for the first step of any iteration is applied to the FFSA. For selecting dominant features of the trained images, we find a path inside the FFSA and the Q-table which has the highest rewards. This can be done simply by searching the maximum of the FFSA and following the position of maximum in the Q-table.

4. Hierarchical Classifier

Our proposed scheme of classification is a two step algorithm. After transforming the input image to its 2nd level lowpass subband image, the projection vector in the Weigenspace is constructed using the Weigenvectors of the training data. Then we select K candidates for the final step of recognition using a K-NN classifier. This classifier uses all the features of the projection vector and trained vectors. If more than $\frac{K}{2}$ of the neighbors belong to the same class

then there's no need for further processing and the classifier output is the label of that class.

If the K-NN classifier can not decide to which class the input image is belonged, the K found candidates are sent to the NN classifier. This classifier uses the dominant feature of the candidate images and compares them with the input vector. The nearest candidate is the winner of classification process.

5. Simulation results

For evaluating our new method, we have used the ORL database. Our proposed method is compared with Eigenface and Weigenface method in Fig. 4. For this simulation we have used the first 3 images of each individual as the training set. X axis of this figure is the number of Weigenvectors which are used in the first step of recognition. Y axis is the recognition rate for the 3 methods (Eigenspace, Weigenpace and our proposed method).

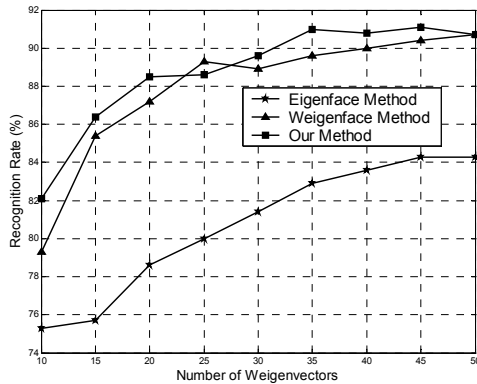


Fig. 4. Recognition rate of our proposed algorithm, eigenface and weigenface methods vs. different number of features.

The number of dominant feature used in our method is dependent to the number of Weigenvectors and tabulated in table 1. These values are found by simulation. From Fig. 4 we can see that for 35 Weigenvectors the recognition rate is 89.6% while when we use 25 dominant feature the performance increases to 91.7%. It has to be mentioned that the 25 feature are chosen from the first 35 features. If we compare the values in Fig. 4 we concluded that in most cases the proposed algorithm outperform the original Eigenface and Weigenface method. The amount of improvement of our proposed algorithm comparing to both method are more than 8% and 1.5% respectively.

Table 1. Number of dominant features for different number of weigenvectors.

Number of weigenvectors	Number of dominant feature
10	8
20	15
30	20
40	25
50	20

6. Conclusion

A new method for face recognition which uses both holistic search and feature analysis was proposed. Simulation results showed the superior performance of the proposed algorithm over the Eigenface and wavelet + PCA methods. In order to find the dominant features for each image, reinforcement learning was used, and the system was modeled as a first order Markov process. It was shown that although this assumption is not a real one, it simplifies the learning process and the feature analysis results are satisfactory. Currently, we are working on improving the learning algorithm, as well as using other classifiers in the second step of the proposed method

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