Pairwise Macropixel Comparison Can Work at Least as Well as Advanced Holistic Algorithms for Face Recognition

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This paper shows by experiments the superiority of an extremely naive method over the well established popular approaches with ever increasing complexity. It stimulates us to rethink:

> *Has the current advance of computer vision research touched the underlying problem in face recognition?*

Face recognition is a special pattern recognition problem and has been a hot topic in the last thirty years, of which numerous approaches have been developed and published, but we have to confess that: *We understand very little of the real process our brains use in performing such a task.* Holistic subspace approaches (aka holistic approaches, subspace approaches) – the dimensionality techniques in face recognition research – are most popular approaches so far for face recognition; algorithms including Eigenface approach (aka Principal Component Analysis, or PCA approach), Linear Discriminant Analysis (LDA), Fisherface approach, Independent Component Analysis (IDA), Gabor feature approach, Spectral Regression Discriminant Analysis (SRDA), Spatially Smooth Subspace Learning (SSSL), Random Subspace Method (SRM), and so on, have continued to be developed and tried. New holistic subspace approaches for face recognition have been developed and published in almost every, if not every, computer vision conference in last few years.

This paper will show by extensive experiments that: If we take a few pixels together as one "big" pixel, called a macropixel, then, a method that counts matched "big" pixels, or macropixels, should work well; at least not worse than most of recently developed holistic algorithms, if not better.

Indeed, since a macropixel is still very small, consisting of only a few pixels, the simple Euclidean distance is used to decide how two macropixels are different. In our entire algorithm, no dimensionality reduction is required – actually as it is shown in our experiments, 4×4 is a typical size of a macropixel that works quite well; it is unmeaningful and there is no space left to perform any dimensionality reduction inside such a small macropixel[1]; and counting in our approach is just adding up matched pixels, where no dimensionality reduction can fit in. Therefore, our work also suggests that, it is possible that dimensionality reduction technique is unnecessary for face recognition.

Concepts

Macropixel:*Partition an image into windows of size $K \times K$ (We set K to be 4 in most of our experiments.), leaving s pixels (We let $s = 2$ in most of our experiments.), called "shift range", in each side of the image for shifting purpose. Each macropixel consists of all the $K \times K$ pixels within a window.*

A macropixel of size $K \times K$ can be represented by a K^2 dimensional vector so that Euclidean distances between macropixels can be calculated.

Distance: *The distance of two macropixels is defined as the Euclidean distance between these two macropixels after being pre-processed for reducing illumination effects.*

Corresponding Macropixel: *For a macropixel M of an image A, assume that the coordinates of its center are (x_o, y_o). To find the corresponding macropixel in image B, we first calculate the Euclidean distances between X and the macropixels with center coordinates $(x_o + s_1, y_o + s_2)$, $-s \leq s_1, s_2 \leq s$; the one with the shortest distance to M is called the "corresponding macropixel" in image B. If there is a tie, then we arbitrary choose one.*

Macropixel Counting Algorithm

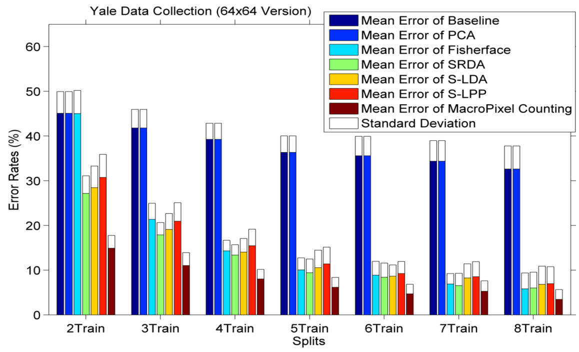
Input: face image X to be identified.

1. Set a counter for each identity in the gallery.
2. Partition X into blocks of size $K \times K$, leaving s pixels in each side for shifting purpose; a block of $K \times K$ pixels is taken to be one macropixel. (We assume both $m - 2s$ and $n - 2s$ are dividable by K, where $m \times n$ is the image size.)
3. For each macropixel P in X,
   (a) Find the corresponding macropixel of each image in the gallery and its distance to P.
   (b) Among all macropixels found in (a), find the one with shortest distance to P;
   (c) Assuming the macropixel found in (b) belongs to identity T, we increase its counter by 1.
4. Check all the counters, the one with greatest value is returned as the identity for X.

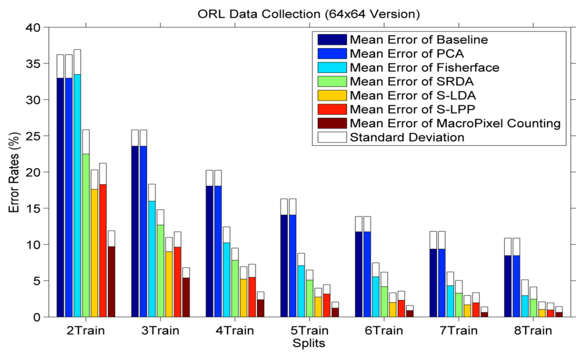
[1] It is worth noting that, in most of patch/component based approaches in face recognition, a "component" usually consists of lots of pixels, e.g. the area of an eye or nose, so that dimensionality reductions are used there.

Experimental Results

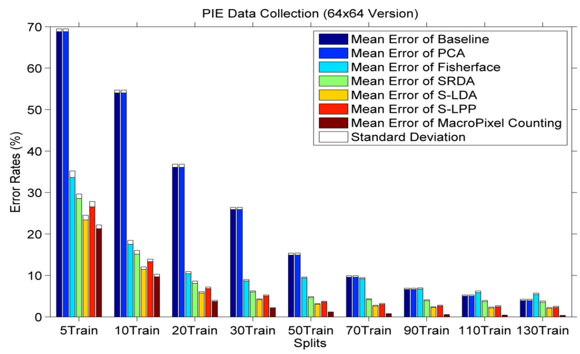
To avoid any possible bias, we use the UIUC versions of Yale, PIE and ORL face sets at `http://www.cs.uiuc.edu/homes/dengcai2/Data/data.html`[2], where all faces are already standardized. Some of the results are shown below. Here, kTrain means: k images per individual with labels are used as training images, and also as gallery images, the rest are used for testing.



(a) Yale face set (64 by 64 image version)



(b) ORL face set (64 by 64 image version)



(c) PIE face set (64 by 64 image version)

Figure 1: Average Error Recognition Rates and Standard Deviations of 5 Known Holistic Algorithms, Baseline Algorithm and Macropixel Counting Algorithm for 64 by 64 versions of Yale, ORL and PIE

[2] Also available at `http://www.zjucadcg.cn/dengcai/Data/FaceData.html`