An Ensemble of Face Recognition Algorithms for Unsupervised Expansion of Training Data

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Motivation

Security
Ability to unlock personal devices with faces

Smart Surveillance
Send alerts when unknown persons appear on premises

Deep Learning
On big data, deep learning approaches are unparalleled

Small Data
Big data is nice, but difficult to obtain

Ensemble Learners
The herd often makes better decisions than the individual
Problem

How accurate can face recognition methods be with the smallest possible training data?

Small Training

- One known face per subject given
- Many subjects possible

Goals:
- Augment training set with unlabeled faces from testing set.
- Do not introduce incorrect labels to training set

Large Testing

- Many unlabeled faces needed
- So that we can validate our method

Caveat:
- All subjects in testing must appear in training
Our Approach

We used four classical algorithms in a face recognition ensemble and created a novel voting strategy.
Common Ensemble Method

Many ensemble methods use majority voting.

- Fisherfaces
- Local Binary Pattern Histograms
- Randomized PCA
- Eigenfaces

New Face \rightarrow Trained Models \rightarrow Predictions \rightarrow Majority Vote \rightarrow Prediction

3 Votes Jeff, 1 vote Anthony -> Jeff
**Proposed Ensemble Method**

Our ensemble method take into account the confidence of each model.
**Proposed Ensemble Method**

Our ensemble method takes into account the confidence of each model.

How do we determine confidence?

- **Fisherfaces** -> Jeff
- **Local Binary Pattern Histograms** -> Jeff
- **Randomized PCA** -> Jeff
- **Eigenfaces** -> Anthony

1. Low Confident: Vote Jeff
2. Medium Confident: 2 votes Jeff
3. High Confident: Anthony

New Face | Trained Models | Predictions | Confidence Vote | Prediction
Ensemble Confidence

A novel way to combine component algorithm distance measures

- $Z_f$ - distance between testing face $X_f$ and nearest neighbor among $k$ training faces $Y$.

- Confidence: probability that a random distance is greater than the observed distance. For multiple algorithms, combine distances by summation.

- PDF $f_Z(z)$ is estimated using kernel density estimation, integral transformed and evaluated with Gaussian quadratures.

$$Z_f = \min_{i=1,2,\ldots,k} \|X_f - Y_i\|_2^2$$

$$C(z) = \Pr(Z \geq z) = \int_z^\infty f_Z(t) \, dt$$

$$C(z) = \int_0^1 f_Z \left( z + \frac{t}{1-t} \right) \frac{dt}{(1-t)^2}$$
**Ensemble Method**

Idea: Treat high confidence agreements in component algorithms as truth and retrain components.
Datasets

We used popular small-to-medium sized datasets in face recognition.

<table>
<thead>
<tr>
<th>AT&amp;T Faces</th>
<th>Extended Yale Database B</th>
</tr>
</thead>
<tbody>
<tr>
<td>40 subjects</td>
<td>38 subjects</td>
</tr>
<tr>
<td>10 faces per subject</td>
<td>Varied faces per subject (2424 total images)</td>
</tr>
<tr>
<td>112×92 pixel images</td>
<td>192x160 pixel images</td>
</tr>
<tr>
<td>Grayscale</td>
<td>Grayscale</td>
</tr>
</tbody>
</table>


Tuning the Ensemble

- Each ensemble method has a few parameters that a user must specify
- These parameters have a large impact on accuracy
- We used an evolutionary algorithm to tune these parameters
- These parameters were evolved in the ensemble method loop

- Fisherfaces
- Local Binary Pattern Histograms
- Randomized PCA
- Eigenfaces
### Accuracy of the Ensemble

<table>
<thead>
<tr>
<th>Method</th>
<th>AT&amp;T Faces</th>
<th>Yale Faces</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Best</td>
<td>Average</td>
</tr>
<tr>
<td>Eigenfaces</td>
<td>74.17%</td>
<td>69.72%</td>
</tr>
<tr>
<td>Fisherfaces</td>
<td>73.33%</td>
<td>69.33%</td>
</tr>
<tr>
<td>LBPH</td>
<td>83.61%</td>
<td>81.95%</td>
</tr>
<tr>
<td>Rand. PCA</td>
<td>74.17%</td>
<td>69.95%</td>
</tr>
<tr>
<td>MV Ensemble</td>
<td>74.44%</td>
<td>70.33%</td>
</tr>
<tr>
<td>Best Guess</td>
<td>86.39%</td>
<td>84.67%</td>
</tr>
<tr>
<td>Ensemble P0</td>
<td>76.94%</td>
<td>73.33%</td>
</tr>
<tr>
<td>Ensemble P1</td>
<td>96.39%</td>
<td>94.33%</td>
</tr>
<tr>
<td>Ensemble P2</td>
<td>98.33%</td>
<td>95.73%</td>
</tr>
<tr>
<td>Ensemble P3</td>
<td>98.61%</td>
<td>95.73%</td>
</tr>
</tbody>
</table>
Ensemble as a Face Recognition Algorithm

Evaluating the merit of the proposed ensemble in face recognition

- Each pass adds additional training samples
- These new samples are assumed to be correct, but they are never checked
- Accuracy is over 5 replicate experiments
- Points are fitted with logistic curve
- Shading is standard deviation fitted with logistic curve
Ensemble Confidence - Validation

Evaluating the merit of the proposed confidence measure

- ROC curve - false positive rate vs true positive rate varying confidence threshold

- Data points considered are agreements in ensemble.

- Can achieve over 90% true positive rate at 0% false positive (Dataset: AT&T Faces)

- Number of added faces to training is sufficient for deep learning approaches to take over.
Discussion

What do these results show?

- We have created two things:
  1. A metric for assessing the confidence of a face recognition algorithm
  2. An ensemble method that uses the confidence metric for predicting labels of new faces

- Our proposed ensemble method can be used to improve the performance of face recognition for application with the following properties:
  1. Only a few training examples are available
  2. New samples will be collecting during the testing process

- New methods can be added the ensemble as long as they provide some form of distance

- After enough new labeled (or predicted) samples are collected, a tool can switch over to a more accurate system like the Inception-ResNet deep neural network face recognizer.
Thank You

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GitHub
https://github.com/jeff-dale/face-rec-ensemble