

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 On big data, deep learning approaches are unparalleled

Deep Learning



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
- $\circ~$ 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 method use majority voting



Proposed Ensemble Method

Our ensemble method take into account the confidence of each model



Proposed Ensemble Method

Our ensemble method take into account the confidence of each model



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.

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

$$e \quad C(z) = \Pr(Z \ge z) = \int_{z}^{\infty} f_{Z}(t) \, \mathrm{d}t$$

$$C(z) = \int_0^1 f_Z\left(z + \frac{t}{1-t}\right) \frac{\mathrm{d}t}{\left(1-t\right)^2}$$

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.

| AT&T Faces | | | |
|---|--|--|--|
| 40 subjects | | | |
| 10 faces per subject | | | |
| 112×92 pixel images | | | |
| o Grayscale | | | |
| | | | |
| | | | |
| F. S. Samaria and A. C. Harter, "Parameterisation of a stochastic model for human face identification," in <i>Proceedings of the Second IEEE Workshop on Applications of Computer Vision</i> . IEEE, 1994, pp. 138–142. | | | |

Extended Yale Database B

o 38 subjects

- Varied faces per subject (2424 total images)
- o 192x160 pixel images
- o Grayscale

A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, "From few to many: Illumination cone models for face recognition under variable lighting and pose," *IEEE transactions on pattern analysis and machine intelligence*, vol. 23, no. 6, pp. 643–660, 2001.

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



| | AT&T Faces | | Yale Faces | |
|-------------|------------|---------|------------|---------|
| Method | Best | Average | Best | Average |
| Eigenfaces | 74.17% | 69.72% | 13.03% | 12.05% |
| Fisherfaces | 73.33% | 69.33% | 11.78% | 11.01% |
| LBPH | 83.61% | 81.95% | 29.63% | 27.31% |
| Rand. PCA | 74.17% | 69.95% | 13.12% | 11.98% |
| MV Ensemble | 74.44% | 70.33% | 13.16% | 12.05% |
| Best Guess | 86.39% | 84.67% | 29.97% | 27.73% |
| Ensemble P0 | 76.94% | 73.33% | 16.60% | 15.40% |
| Ensemble P1 | 96.39% | 94.33% | 80.47% | 79.10% |
| Ensemble P2 | 98.33% | 95.73% | 83.32% | 82.57% |
| Ensemble P3 | 98.61% | 95.73% | 85.16% | 84.06% |

Accuracy of the Ensemble

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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

