Gender Classification from Facial Images

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Problem Statement

Identification of Gender from facial images of people is done using 5 different methods of classification. These methods are :

1. kMeans method
2. FisherFaces Method
3. EigenFaces Method
4. HOG feature Extraction and SVM
5. GDA with PCA

Introduction

A gender classification method has many potential applications such as human identification, smart computer-human interface, computer vision approach for monitoring people, passive demographic data collection, etc. The methods chosen here deal with frontal facial images with inherent variations in the image formation process.

Some challenges faced will be the variations in the dataset taken like illumination, change in camera angle, head pose, expressions, facial hair, background etc.

Each method has its own set of challenges. The database used in this project is the Gender Database from University of Nevada, Reno which consists of 500 male and 500 female images. 317 male images and 317 female images were used for training. 172 male and 172 female images were used for testing.

Method 1 : Using kMeans

The steps to apply this method are as follows :

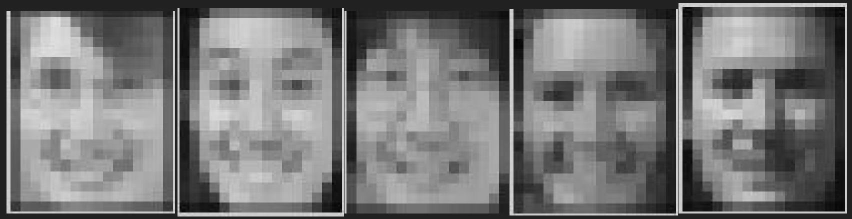
- Applying kMeans Clustering to male and female images seperately. We take 10 cluster from male images and 10 from female images.
- The Means of the images in each cluster is obtained. These mean faces are considered as the 'Representative Faces' and there will be 10 female and 10 male.
- Then kNN classifier is applied on the test images with respect to these representative faces.
- By experimental analysis, k was chosen to be 5.
- This way, each test image is plotted in the D dimensions space and the euclidean distance is calculated from the meanfaces.

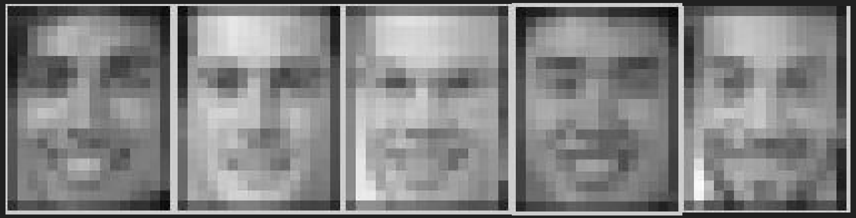
- The 5 Meanfaces with the least distance are considered and if the majority is female, then the test image is female and vice versa

Challenges faced :

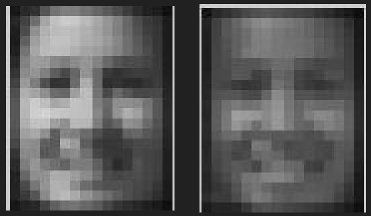
- K needs to be decided experimentally and most probably is variable with the kind of dataset considered.
- Computation cost is quite high and hence the dataset needs to be small for instantaneous results. Though, some indexing can help overcome this.

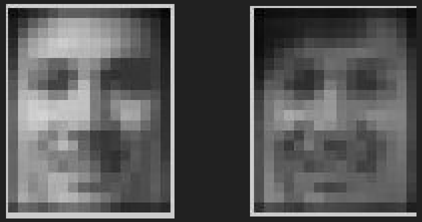
Training Faces





Representative Faces





Results

Gender	No of images used for testing	No. of correct classifications	Accuracy
Male	172	157	91.2%
Female	172	152	88.3%

Method 2 : Fisherfaces

The steps to apply this method are as follows :

- Assume that in absence of all other information, the probability of encountering a male and a female image is the same. (i.e 0.5)
- The data in each class(male and female) is normalised using the respective MeanFaces.
- The covariance matrix for each class is calculated and it is weighted.
- Now for each test image, a 'score' is calculated with respect to each class with the following formula.

$$d_i(\mathbf{x})=(\mathbf{x}-\mu_i)T\Sigma^{-1}_i(\mathbf{x}-\mu_i)+\ln|\Sigma_i|-2\ln P_i$$

- The scores are compared and if the score with respect to female class is higher, then the image is classified as female and vice versa.

Challenges faced :

- Doesn’t work properly for a small sample set.
- Fails if Scatter matrices are singular.

Results

Gender	No of images used for testing	No. of correct classifications	Accuracy
Male	172	163	94.7%
Female	172	156	90.6%

Method 3 : EigenFaces

The steps to apply this are as follows :

- The training data is loaded and normalised with the MeanFace. It should be noted that each image has been linearised.
- A single matrix is formed by making all linearised images as the columns.
- The eigen values and the eigen vectors of the covariance matrix of the above data matrix are calculated.
- Another matrix consisting of EigenFaces is calculated by the following -

$$\mathbf{U}=\mathbf{AV}\Lambda^{-1/2} \text{ , where } \mathbf{U}=\{\mathbf{u}_i\} \text{ is the collection of eigenfaces.}$$

- Using heuristics, we ignore the first 3 Eigenfaces are ignored due to lighting variations.

- The next 50 are considered as relevant Eigenfaces.
- On these EigenFaces, kMeans clustering is done to form 10 female and 10 male clusters.
- On these cluster means, kNN classifier is applied to classify between male and female with K = 5.

Challenges faced :

- This method is extremely sensitive to lighting variations and positioning of the faces.
- Accuracy is slightly poorer.

Results

Gender	No of images used for testing	No. of correct classifications	Accuracy
Male	172	141	82.1%
Female	172	133	77.6%

Method 4 : HOG Feature Extraction and SVM

The steps to apply this method are as follows :

- The training data is loaded and for each image HOG features are extracted.
- The HOG feature vector is 768 dimensional. The whole extraction process gives us an output as a .txt file in which the information is in the form of {0:value[0] 1:value[1] 2:value[2]…. 768:value[768]} where ‘value’ is the HOG value at that dimension.
- These .txt files are given as input to an SVM for training.
- This SVM will be an SVM with kernelization with RBF as the kernel function.

- After the training of the SVM, HOG features are extracted from each test image and converted into a .txt file as stated before.
- This .txt file is sent to the SVM to predict the class of the image(if it is female or male).

Challenges faced

- This method has very low false-positive rate but computational complexity will be high.
- There is a lack of transperency in the results because output is non-parametrc.

Results

Gender	No of images used for testing	No. of correct classifications	Accuracy
Male	172	169	98.2%
Female	172	167	97.1%

Method 5 : GDA with PCA

The steps to apply this method are as follows :

- The training data is loaded and dimensions are reduced by applying PCA as in the former methods.
- Let x_i be the i^{th} training sample. Max(x) is the maximum value in our dataset and Min(x) is the smallest.
- Normalisation of the data is done by

$$x_i = \frac{x_i - max(x)}{max(x) - min(x)}$$

- So, now for the margin, y = mx + c, the error function J(θ) is as follows,

$$J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x_i) - y_i)^2$$

- To minimise the error, we keep iterating over the data in such a way that,

$$\{ \theta j \leftarrow \theta_j - \alpha\, \partial J(\theta)/\partial\theta_j \}$$

- Repeat till convergence and we shall have the optimised margin, y=mx+c.

Challenges faced :

- Computationally, time taking but gives optimal results.

Result

Gender	No of images used for testing	No. of correct classifications	Accuracy
Male	172	157	91.5%
Female	172	154	89.3%

Bibliography

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