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Smile, You're Recognized: Applications of Face Recognition in Marketing

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Abstract
The technique of classifying a face as recognized or unknown in computer vision is known as face recognition. The procedure follows a pipeline that includes steps for data collection, detection,pre-processing,and recognition.The research focuses on with the assumption that photos have already been processed at the end of the pipeline pre-processed and gathered Face recognition software in the past has relied on the full face.Their algorithms take a face picture as input.The study has proposed a new method in which the individual facial segments,such as the left, are sent into the recognition algorithm.The four components that make up the face are the left eye,the right eye, the nose, and the mouth.After that, the output of each algorithm is labelled, and it is categorized as belonging to right feature class.According to the findings of our research,the granularity of information gathered for each subdivision class has the potential to be utilized in order to create a higher accuracy rate than can be achieved by using the complete face technique.

Keywords: *Face Recognition; Algorithm; Face detection; Distribution, Individual facial segments method,*

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I. Introduction

Over the course of the last several decades, research into facial recognition has been more popular.Computer vision was first thought of as a subset of artificial intelligence that was intended to provide robots with visual perception,but over time, it has developed into a discipline that is more general and comprehensive.Computer vision programmers are able to analyses images from a broad variety of different parts of the electromagnetic spectrum.X-rays are a kind of imaging technology that may be used in the field of medicine in place of more invasive surgical procedures.In magnetic resonance imaging, often known as MRI, gamma rays and radio waves are combined to produce images of very thin sections of the human body.These images may then be used to diagnose and treat a variety of medical conditions[2].In the automotive industry,X-rays are used to inspect materials that are difficult to detect with the naked eye. One example of this is the wheel rim casting,which is inspected for fractures,cracks,and cavities in the form of bubbles and other typesof flawdefects produced by insufficient fusing of materials X-rays and gamma rays are employed in the food sector for a variety of purposes range of applications,each serving a specific function. Their items are inspected, safe, and of high quality.The finding of extraterrestrial objects is one illustration of this.Pollutants in food products, such as fish bones in Fish,and packaged food items,such as fish bones in fish Quality check whether based on water content or pitting in citrus fruits,as well as bug infestations in citrus fruits.[3] distribution the electromagnetic Face recognition applications, in contrast to computer vision, are limited to the visible light spectrum, within which only certain kinds of biometric identification and surveillance may be carried out.[4]The term "biometrics" is used to refer to Indicators of human nature include fingerprints, iris patterns, and hand shapes. This measure used to identify individuals who are being monitored and to restrict their access to certain areas.[5]. The natural statement of identification provided by a person's face, along with its non-intrusive nature, has made it the preferred measure over existing biometrics. In a fingerprinting system, for instance, the subject must place a finger on a reader, and the findings must be checked by a specialist. Using the subject's face as a measure, on the other hand, eliminates the need for any outside involvement and may be independently checked by anybody.

II. Literature Review

Detecting a face in a picture without first identifying it is known as "facial detection.". The research conducted by Viola-Jones in 2001 and titled "Rapid Object Detection using a Boosted Cascade of Simple Features" was a significant advance in the field of face detection. [6]-[7]. In contrast to earlier face recognition algorithms that relied on pixel analysis, Viola- Jones made use of properties similar to those of Haar.The Haar classifier is a technique of object recognition that is taught by machine learning both positive and negative examples of images. To ensure proper operation of the classifier, the dimensions of both the training picture and the object detection input image must be same.For recognition purposes,appearance-based algorithms take into account all of the informationcontained inside a picture's pixels.Eigenface,Fisher-face, and Direct Correlation are some of the methods that belong to this category.The picture pixels of two different people's faces are compared directly in direct correlation, which produces a result.[9]-[10] a rating of similarity Algorithms based on Eigen-face and Fisher-face compress image to most discriminating factor and compare photos picture space with decreased dimensions[11],[12]. This is in contrast to direct correlation technique, which uses the original image space for facial photographs.Principal component analysis was used by Coots et al.[13] in order to discover visual landmarks. Landmarks play an important role in the process of learning model parameters and training image displacement. In order to get a good match, the model's residual error is evaluated against the expected changes to the model parameters. [14].Statistics about shape and texture are taken into consideration by the algorithms that make up the Alive Model. Discovering visual landmarks required the use of principal component analysis by Coots et al.[13],who conducted the study. In the process of learning model parameters and training picture displacement,landmarks are an essential component due to the vital function they play.In order to get a satisfactory match, the model error with residuals is compared to the predicted changes to the.The coupling of a prior distribution with an unknown is the core of the Bayesian modelling approach.The approaches provided by the Bayesian Model provide a probability-based similarity index that is created from collection of data points.The Bayesian analysis is used to determine the similarities and differences between two face photographs.The Bayes method generates a similarity score by using the differences in the brightness of the images found in two different data set to construct probability functions. This score may then be used to show who you are categorization.[16].Information is processed by neural networks in a manner similar to that of the brain.Their example- learning capabilities,fault tolerance,and resilience are some of their characteristics. They are capable of identifying a wide variety of face photographs with very little adjustments to the algorithm.In [17],Lawrence walks the reader through the process of training a neural network image classifier. By separating a face into numerous parts, Textual information is extracted by algorithms that analyses texture.Characteristics from facial photos. Binary Pattern Isolated to a Small Area (LBP) texture-based method that extracts characteristics of weighted LBP create vector.The weighted Chi-squared distance metric is used to match two

LBP feature vectors [18]. These algorithms take pictures of faces, extract group of geometrical properties as well as distances to those pictures,and then use those measurements as basis for comparisons between picture.One example of this kind of method is feature-based approach,such as the Local Feature Analysis[19].

III. Research Methodology

31. Bayesian Modeling

The coupling of a prior distribution with an unknown is the core of the Bayesian modelling approach. The approaches provided by the Bayesian Model provide a probability-based similarity index that is created from collection of data points.

3.2 Data Collection

The AT&T data collection served as the foundation for each and every one of our conclusions [1].Open to the general public, this data collection is one that is often used in the field of face recognition research and development. The data set comprises four hundred photographs depicting 10 diverse poses for each of forty unique individuals.These are images consisting of a single exposure that were captured under the usual lighting conditions.The photographs used for several of the themes were taken over the course of a number of years. The photographs capture a variety of face expressions,including both smiling and unsmiling versions of the subject, as well as open and closed eyelids.The subject was captured on camera in a frontal, upright position against a uniformly dark background,with their face rotated up to 20 degrees in some of the shots.The pictures are all in grayscale, and their dimensions are 92 by 112 pixels each.

3.2 Eigen-Face

Face recognition measures a fresh face's resemblance to the training set. Distance betweenphotosdeterminessimilarity. Whenthechangeismodest,thenewfaceiscomparabletooneof the training set photographs and is identified. In the event that the considerable, the freshlookwillbelabelledIgnoredornotacknowledged. Assume a look can be depicted in 2 pixels, as well as the practice set comprises 4 suchpictures,a1,a2,b1,andb2. Image 4 exhibits photos pixel values for a1, a2, b1, and b2, and 1 x 2 transposed vectors.Figure right displays each image's transposed vector on a plane. Image map with vectors,pictures with close pixel values are transferred into the same plane. New picture point ona flat surface may be labelled "a", "b", or neither by determining its How far away "a" or "b"isinEuclidean space Euclideandistance betweenxandyisfound using Equation1. An image with only two pixels may be transferred to

$$distance = \sqrt{(delta\,x)^2 + (delta\,y)^2} \qquad \text{Equation 1}$$

a space that has just two dimensions,knownastheplane,justaseasilyaslarger pictureswithmorepixels.Animagewithdimensionsof 50by 50may beconvertedintoa single pointwith sizeof 2500.Each pixelvaluecorresponds to a different dimension, and the components that make up a vector in the spaceare those that match the pixel values of the image. Images that are the same but of a greaterdimension are clustered together, whilst images that are different are farther apart. Whenworking with bigdimensions,calculating Euclidean distance requires performing a numberof subtraction operations. If each of thesevariations adds to noise (which is defined asanything that makes a sound), has an effect on the final acknowledgement, then the total levelthe level of noise will be rather high. When all squared differences are added together, morenoise is produced in comparison to information that is significant. Calculating the differenceinpixelvaluesinahigherdimensionisnotsignificant.aviableendeavorduetothenoiseintheimage.

IV. Results and Discussions

4.1 Subspace

Because it is a one-dimensional object that exists inside a two-dimensional plane, the "bestlinefit"isconsideredtobe a subspaceofa space thatconsistsoftwo dimensions. The angle at which the line slopes Identify the direction in which the points are most widelydispersedapartfromoneanother. A new reference frame may be created by relocating the origin of a coordinate system to anypoint along the line. In x-y space, a subspace is created by the line that has the equation y =mx + b. The new reference frame draws attention to the direction in which the data areseparated[21]. The first key aspect to consider is the path that leads to the greatest distance. A line that isperpendicularto the firstmaincomponentisthesecond primary component. Thefiguredemonstrates thatthepointdistributionisnotrandomandthatthevaluesof xandyareconnectedinalinearfashion. When the X value is high, the Y value also tend to be x-axisImage6.Distributionbased-frameofreference. Image 7 a representation of a new frame of reference based independent of any othercoordinatesystem,horizontal axisservingasfirstprimary componentandvertical axisservingas secondmaincomponent.

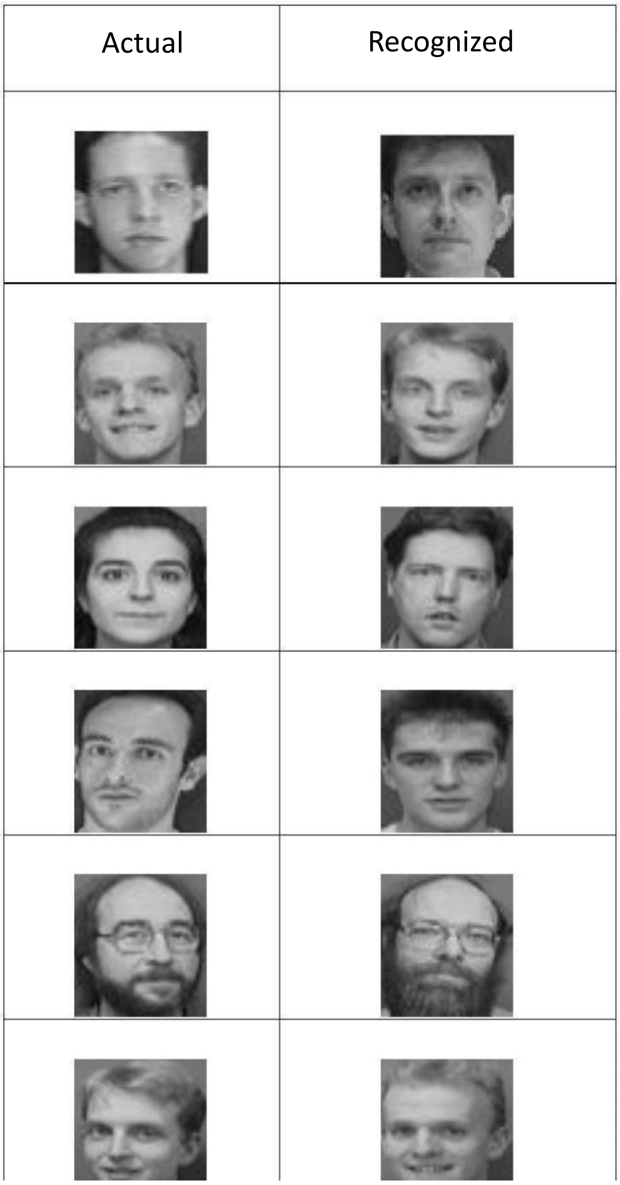


Figure.1. Eigen-facefailedrecognitiononimages fromtheAT&Tdatabase[1].

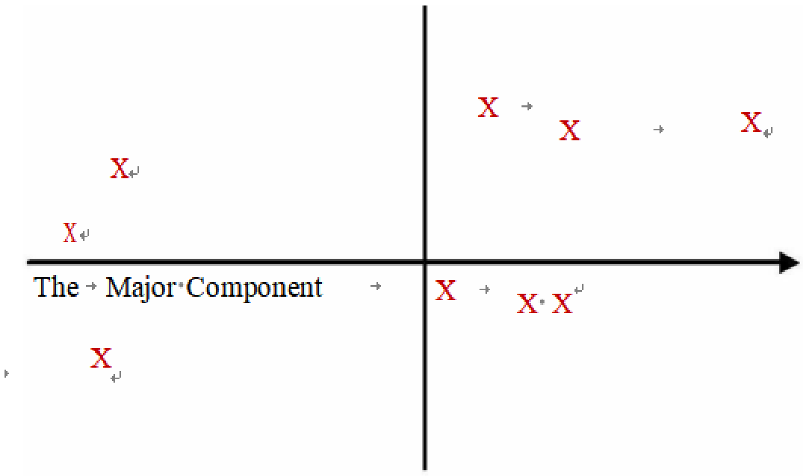


Figure.2.CoordinatesofthePrincipalComponent

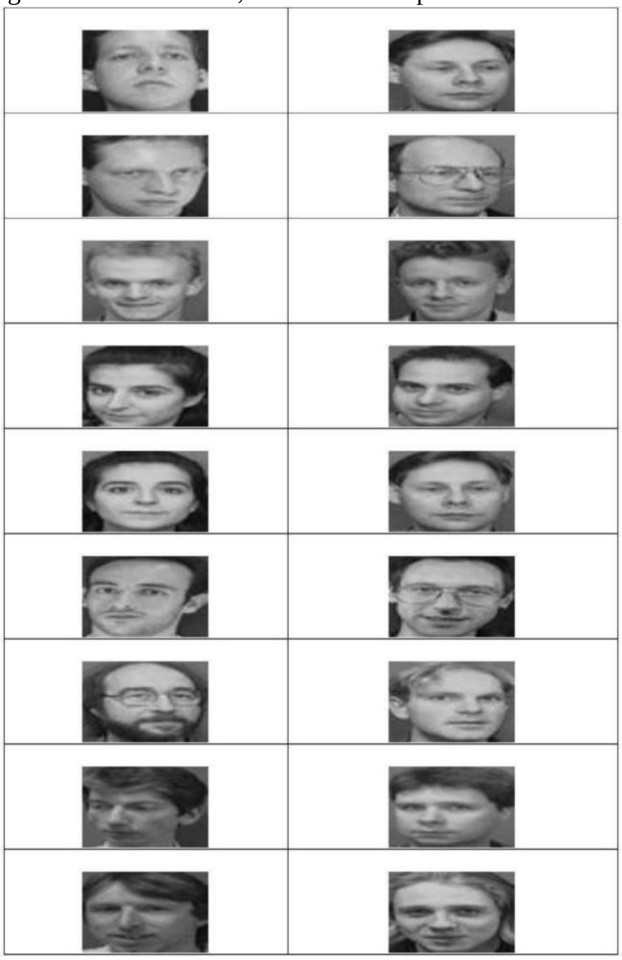
As may be seen from figure, the 1st component varies across rather the 2ndcomponent,however, fluctuates across large range of points. relatively small number of points. Extrapoints along the 1st and 2nd axes that aren't included in the variant principal components arelacksarepresentationintheprimary component's coordinate system because they are not significant and do not contribute to thevariation along those components. When an image is subspace from high dimension to lowdimension, extraneous data points are removed, and what is left are just the data points thatare essential to producing the final product. Variations in the data points that define facialtraitsareessentialforcomparisonpurposes;however,othervariationsinthedata, such as light and illumination, are not considered to be variables in contrast, thesefactorsdonotaffectthe accuracyoftheidentificationprocess.

4.2 LBP Method

The LBP method works by regionalizing a picture and then utilizing its statistical distributiontorepresentlocaltexture.Thealgorithm,infurtherdetail,collectsandtrainsvisualcharacteristics before summarizing their distribution.Determine the LBP of all the areas in the photo, taking into account an acceptable threshold.Although thresholds are often set manually to ensure optimal performance in a particularcircumstance, they may also be set to automatically adapt to changes in the surroundingenvironment based on factors like the mean and standard deviation of the local population[30].

4.2 Segmentation of Face Features

Geometryandtheirrelativelocationtooneanothermaybeusedtoidentifyfacialcharacteristics. To identify its placement, one may measure the thickness of the brow and its relative positionto the eye, for example. Brunelli and Poggio [32] describe a geometrical face recognitionsystem. They locate a feature using a template matching strategy, then utilize what they knowaboutthe normalface structuretonarrow downtheremainingcharacteristics.Following the recognition of all of the traits, a dimensional vector is created to representthe face.Afterthat,therecognitionisdoneusingthenearestneighborclassifier.Thisresearch takes a different approach. Unlike Brunelli and Poggio, no effort will be made tomeasure the characteristics of the face. Instead, the image's face traits are segmented andremoved,thenstoredina separatedatacollection.



Although pre-processing methods such as those discussed in section 1.8 mayincrease the accuracy ofthe findings, it was decided to disregard this stage and its influence on the output of the face recognition method.

Featureanddatasets

Figures 12-14 show that the distribution of recognized features varied depending on theidentification technique utilized, but remained mostly within 1-3 degrees of recognition. Theage groupings are 18- 20, 23-25, and 30-35. The pictures' horizontal axis is set to a standardscaleforsubjects1 through40,butthevertical axisshowshowaparticulargroup ofindividualsdid.Thedata is disseminated.

Lefteyedistribution

The dispersion of the left eye is seen in Figures 12, 13, and 14. The Eigen-face and Fisher-facehave arange of2-3recognitionlevels,whileLBPhas a rangeof1-2.

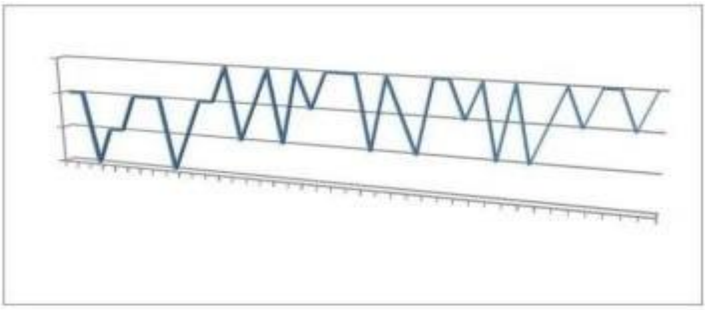


fig5.1:Eigen-facemethodlefteyerecognitiondistribution.

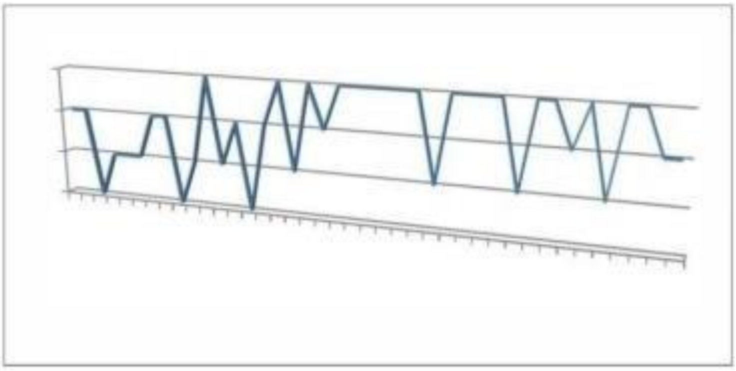


Fig5.2:Fisher-facealgorithmlefteyerecognitiondistribution.

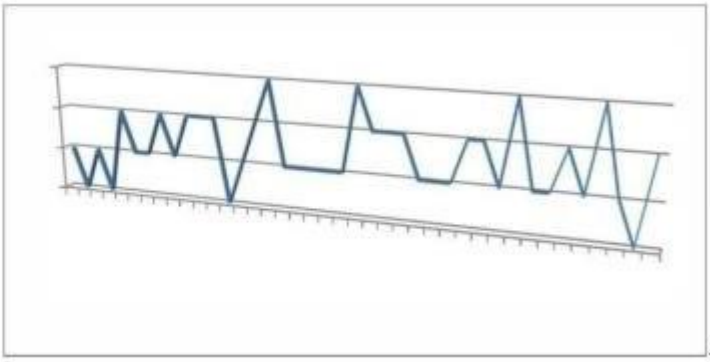


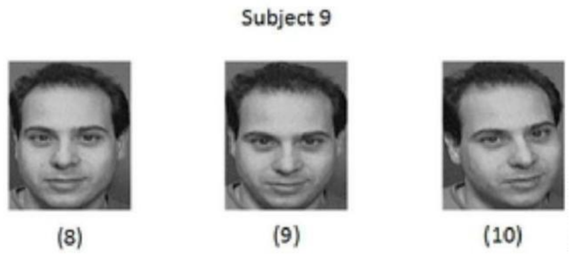
Fig5.3:LBPalgorithm'slefteyerecognitiondistribution.

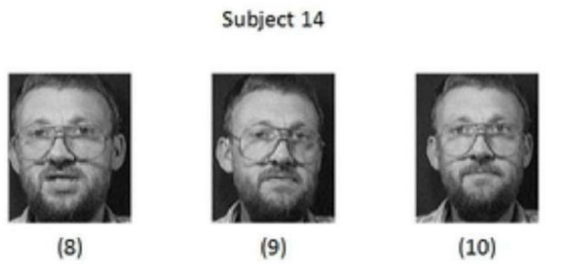
Table5-2showsa failuretorecognizethelefteye.

Algorithm	Subjectlefteye
Eigenface	3,9
Fisherface	3,9,15

Both the Eigen-face and Fisher-face methods are relatively comparable, with the exception ofthe mannerin which they do image analysisin a space with decreased dimensions.,asdetailed in Chapters 2 and 3. Subjects 3 and 9 were failed by both methods, however Subject14 was also failed by the Fisher-face algorithm. Figures 15, 16, and 17 depict test participants3,9,and14.

Peson 3 in the left eye recognition test (fig. 15). The picture for Subject 3 comes from AT&Tdatabase [1].





Person 14 in the left eye recognition test (fig. 17).

The picture for Subject 14 comes from theAT&Tdatabase [1]. Person 14 (8) (9) (10) is wearing spectacles in above photographs, Person3 (8) is looking down, andPerson 9's There are ten eyeballs that are not facing the camera inthe correct position. Table 8 demonstrates that the Eigen- face approach outperformed boththeFisher-facialand theLBP algorithmswhenitcameto identifying thelefteye.

5.1 Righteyedistribution

Images 18,19,and20indicate thatEigen-facial andFisher-faceareoften between 2-3recognitionlevels,whileLBPistypicallywithin1-2recognitionlevels.Fisher-faceisalsotypicallywithin2-3recognitionlevels.
ThisisbecauseLBPrequiresmoreregionsforitsgridcalculationthanourrighteyesegmentation's27x27pixelsize.

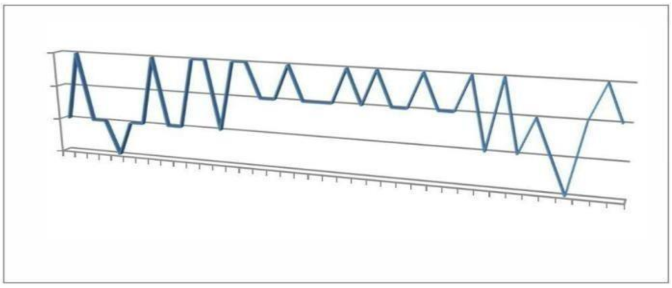


Fig5.4:Eigen-face methodrighteyerecognitiondistribution.

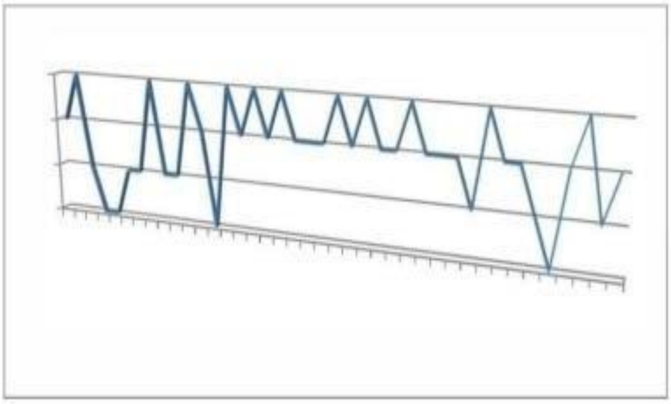


Fig5.5:Fisher-face methodforthe distributionofrighteyerecognition

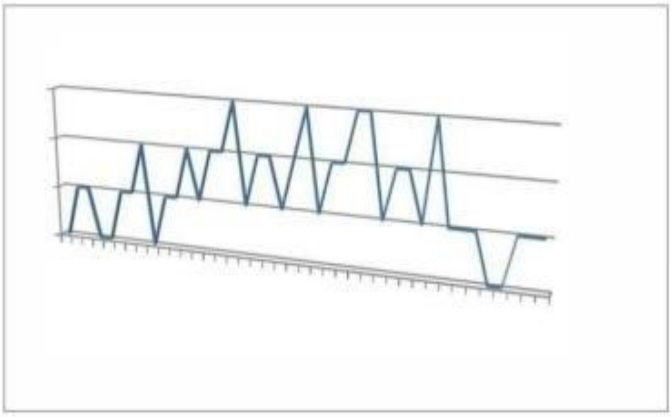


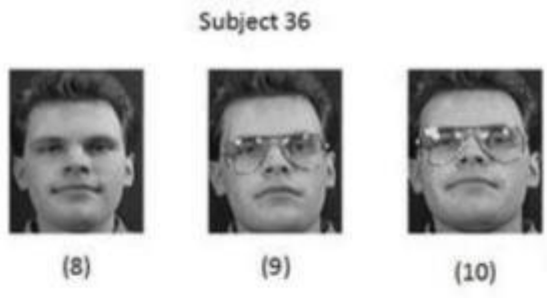
Fig5.6: LBPalgorithm'srighteyerecognitiondistribution.

Table5-3summarizestheinabilityofthethreealgorithmstorecognizetherighteye.

Algorthm	Subjectrighteye
EgenfaceFisherface	1,4,2,9,36,37
Fisherface	5,36

Forrighteyeidentification According to theresults shown in Table 9,Eigen-face wasvictorious over both the Fisher-face and the LBP algorithms. As can be seen in Figures 21and22,noneofthethreealgorithmsweresuccessfulwhenappliedtoSubjects5and36,respectively.

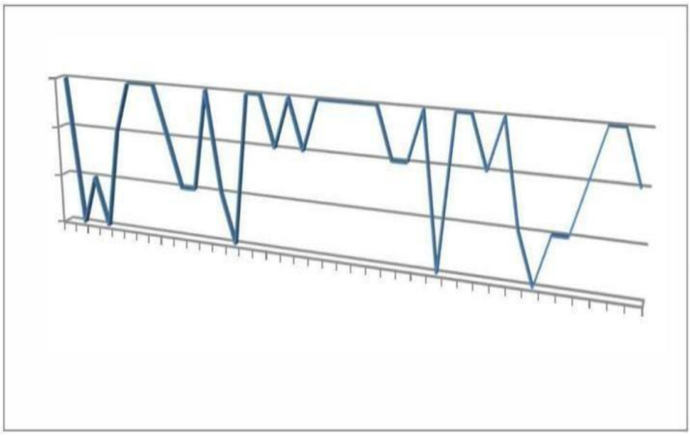
Subject5inaright-eyeidentificationtest(Figure21).



ThepictureforSubject5comesfromAT&Tdatabase

Person 36 in a right-eye recognition test (Figure 22). The picture of Subject 36 comes fromAT&Tdatabase [1]. Person 36's training set included seven photos, all of which were notwearing glasses, but if you look closely at Figure 36, you'll see that two of the test photosinclude people who are wearing glasses. As was covered in Chapter 1, partially obscuring aface may have an effect on the accuracy of recognition algorithms; hence, this might be thereason why the right eye did not work well in this case. One potential solution to this problemis to make use of a classifier that was created specifically for the purpose of locating andidentifying eyeglasses. In spite of the fact that such a classifier was available, it was not usedin order to maintain the highest possible level of objectivity in the results. It is important topoint out that not a single one of the algorithms was unable to identify Subject 36's left eye;yet, they were all unable of identifying his right eye. In a complete face recognition scenario,an image that is unable to be recognised has no option for further processing, as was shown inchapters 2, 3, and 4. On the other hand, the segmentation approach takes into account anumber of different elements of a full face; each of these aspects contributes to an increasedlikelihoodofasuccessfulrecognition.

5.2 Distributionofbotheye



5.7DistributionofBothEyes

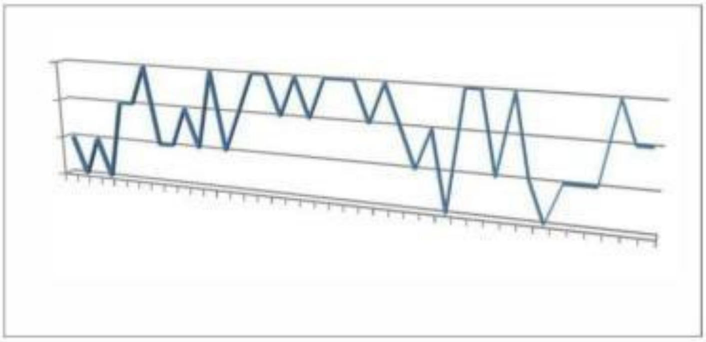


Fig5.8:Fisher's methodforfaceidentificationusingbotheyes distribution.

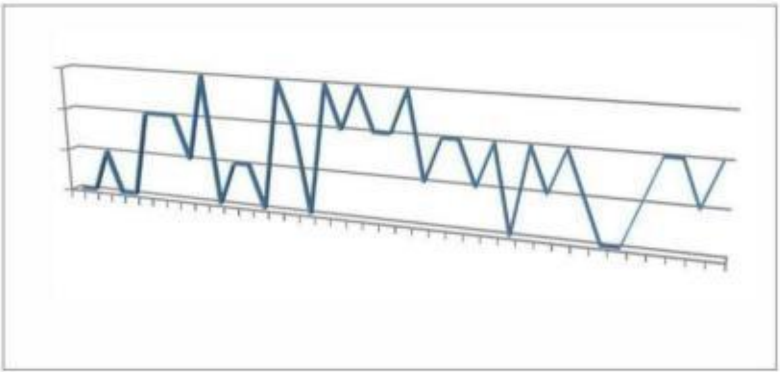


Fig5.9: LBPalgorithmboth-eyerecognitiondistribution

VI. Conclusion

Radiowavesandgammaraysarebothusedbycomputervision.Onlyvisiblelightisnecessary for the process of face recognition, which is a subfield of computer vision. Theintensity of visible light has an effect on recognition algorithms. This effect may be mitigatedby using histogram equalisation, which spreads the light uniformly over the image. BothEigen-face and Fisher-face use the data contained inside a picture's pixels in order to performrecognition.Comparison of images in a space with less dimensions is accomplished by bothmethods via the use of subspace projection. Eigen-face minimizes the number of dimensionsby using PCA and Fisher-face LDA.A smaller size results in less noise and an improvedability to identify.Textures are used by the local binary pattern. It does this by regionalizingthe image in such a way that the threshold for each region is determined by a pixel in thecenter of the image. A histogram of all regions is shown by the LBP image.Face recognition accuracy scores of 98percent, 96 percent, and 95 percentwere obtained on the same data setand algorithmsutilizing the facial feature segmentation technique.Because identification is based on a rangeof facial features, such as the left eye, right eye, nose, and mouth, the increase in accuracymay be attributed to greater data granularity. In a holistic approach, there is no backup planfor a failed recognition, but in face segmentation, feature sets provide extra possibilities for apositive recognition result.Despite the fact that image pre-processing may increase the accuracy of face recognition systems, no effort was made to pre-process images in order to maintain results that were not affected by image pre- processing.

References

[1]. C. H. Chen, Computer Vision in Medical Imaging. vol. 2, University of Massachusetts,2014.
[2]. ComputerVisionTechnologyforFoodQualityEvaluation,Dec2007[Online].Available:http://www.researchandmarkets.com/reports/1758859
[3]. Electromagneticspectrum,(n.d.)[Online].Available:http://www.darvill.clara.net/emag/
[4]. Biometrics,(n.d.)[Online].Available:http://en.wikipedia.org/wiki/Biometrics
[5]. P. Viola and M.J. Jones, “Rapid object detection using a boosted cascade of simpleFeatures,” IEEE Transactions on Computer Vision and Pattern Recognition, vol. 1, pp. 511-518,2001.
[6]. R.LienhartandJ.Maydt,“Anextendedsetofhaar-likefeaturesforrapidobjectdetection,” IEEE Transactions on International Conference on Image Processing, vol. 1, pp.900-903,2002.
[7]. YaleFacedatabase(n.d.)[Online].http://vision.ucsd.edu/content/yale-face-database

[8]. R.BrunelliandT.Poggio,“Facerecognitionfeaturesvstemplates,”IEEETransactionsonPatternAnalysisandMachine Intelligence,vol.15,no.10,pp1042-1053Oct1993.
[9]. A.V. Nefian.“Statistical approaches to face recognition.” PhD Thesis,Georgia InstituteofTechnology.Dec1996.
[10]. M. Turk and A. Pentland, “Face recognition using eigenfaces,” IEEE Conference onComputerVisionandPatternRecognition,pp.586-591,Jun1991.
[11]. R.N.Belhumeur,J.P.HespanhaandD.J.Kriegman,“eigenfacesvsfisherfacesRecognition using class specific linear projection,” IEEE Transactions Pattern Analysis andMachine Intelligence,vol.19,no.7,pp.711-720,July1997.
[12]. T. F. Cootes, K. Walker and C. J. Taylor, “View based active appearance models,” IEEEInternational Conference on Automatic Face and Gesture Recognition, Grenoble, France, pp.227-23,Mar2000.
[13]. W.Zhao,R.Chellappa,A.RosenfeldandP.J.Phillips,“Facerecognitiona literaturesurvey,”ACMComputingSurveys,vol.35,no.4,pp.399-458,Dec 2003
[14]. G. Guo, S. Z. Li and K. Chan, “Face recognition by support vector machines,” IEEEInternational Conference on Automatic Face and Gesture Recognition, pp. 196-201, Mar2000.
[15]. B.Moghaddam,T.Jebara andA.Pentland,“Baysian face recognition,”in PatternRecognition,vol.33,no.11,pp.1771-1782,Nov2000.
[16]. S. Lawrence, C. L. Giles, A. C. Tsoi and A. D. Back, “Face recognition: a convolutionalneural network approach,” IEEE Transactions on Neural Network, vol. 8, no. 1, pp. 98-113,Jan1997.
[17]. T. Ahonen, A. Hadid and M. Pietikanen, “Face description with local binary patterns:applicationtofacerecognition,”IEEETransactionsonPatternAnalysisandMachineIntelligence,vol.28,no.12,pp.2037-2041,Dec 2006.
[18]. P. Penev and J. Atick, “Local feature analysis: a general statistical theory for objectrepresentation,” in Network: Computation in Neural Systems, vol. 7, no. 3, pp. 477-500, Oct1996.
[19]. W. S. Yambor. “Analysis of PCA-based and fisher discriminant-based imagerecognition algorithms.” M.S. Thesis, Technical Report CS-00-103, Computer ScienceDepartment,ColoradoState University,July2000.