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FACERECOGNITIONTECHNOLOGY

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ABSTRACT

In a world where security issues have been gaining growing importance, face recognitionsystemshaveattractedincreasingattentioninmultipleapplicationareas,rangingfrom forensicsandsurveillancetocommerceandentertainment.Oneobviousapplicationforfacerecog nitiontechnology(FRT)islaw-enforcement.Incommercialapplications,facerecognitionhasbeenemployed for automatic exposure/focus in digital cameras, which will automatically detect the facewithin a fraction of seconds. Finally, image searching techniques, including those based on facialimageanalysis,havebeenthelatesttrendintheboominginternetsearchindustry.Inthisrevie w,thevarious applications of face recognition and the different techniques employed in face recognitionwillbe analysed

Introduction

Face recognition is one of the most used applications in the area of computer vision, where acomputer automatically identifies a person by means of digital images of his/her face. Facerecognitionsystemsareusedtoaccesstoapplicationsonmobiledevicessearchforsuspectsinair ports or controlling access to restricted areas. Therefore, since face recognition systems aremainlyusedinsecurityrelatedtasks,theymustberobust,whichisanalyzedinseveralsurveysoftec hniques.Theimage-basedfacerecognitionsystemshavereachedahighlevelofmaturity,the methods show quickly their limitations when applied in real applications. Most methodsprove to be highly sensitive to various changes in the illumination conditions, face poses,occlusionsor low resolution.

1.1 Literaturesurvey

Changxing Ding **[1]** In this paper, we present a novel software-based fake detection methodthat can be used in multiple biometric systems to detect different types of fraudulent accessattempts**.** We have considered a feature space of 25 complementary image quality measureswhich we have combined with simple classifiers to detect real and fake access attempts. Thenovel protection method has been evaluated on three largely deployed biometric modalitiessuch as the iris, the fingerprint and 2D face, using publicly available databases with well-definedassociated protocols.

Sebastien Marcel **[2]** This paper proposes a novel face identification framework capable ofhandling the full Range of pose variations within ±90° of yaw**.** PBPR-MtFTL frameworkeffectively utilizes all the unoccluded face texture and the correlation between differentposes, very encouraging results for face identification in all three popular multi-posedatabases are achieved. We also slightly modify the proposed approach to tackle theunconstrained face verification problem, and achieve top level performance on thechallengingLFWdatabase.

Changxing Ding, **[3]** In this paper, we propose a comprehensive framework based onConvolutional Neural Networks (CNN) to overcome challenges in video-based facerecognition(VFR)**.**Weproposeanovel deepmetric learningapproach namedMDR-TL, which outperforms the widely adopted triplet loss by a considerable margin. Extensiveexperiments have been conducted for S2V, V2S, and V2V tasks. Since the proposed TBE-CNNapproacheffectivelyhandlesimageblur,occlusion,andposevariations,itshowsclearadvantages compared with state-of-the-art VFR methods on three popular video facedatabases.

Dihong Gong and Zhifeng Li, **[4]** In this paper, we propose a new feature descriptor calledcommon encoding model for heterogeneous face recognition, which is able to capturecommon discriminant information. The basic idea of our approach is to reduce the modalitygap at the feature extraction stage by converting the original face images pixel by pixel into acommon encoded representation, and then infer the person's identity information forenhancedrecognition performance.

Hao Yang and Xiaofeng Han, **[5]** In this paper, a simple and fully automatic panoramicimage-based pose-invariant face recognition method is proposed to present excellentaccuracy with low complexity**.** The students who completed the attendance sign-in systemquickly completed the tasks, got rid of the complicated sign of roll call, and soon realized thesign of operation and function. The future system time and the form of attendance systemconversion have made tremendous innovations, greatly improving the attendance rate and thereliabilityof facerecognition technology

Francisco Pizarro, **[6]** In this paper we analyse the problems produced by temporal variationsof infrared face images when used in face recognition systems**.** A comparative study wasperformed on five current face recognition methods and a classic appearance based method toanalyze the capability of each in overcoming the temporal variation problem in thermal facerecognition, specifically the problem due to environmental variations and metabolic changesintheindividuals at themoment of the imageacquisition.

Jianshu Li and Junliang Xing **[7]** A Dual-Agent Generative Adversarial Network (DA-GAN)modelisproposed,whichcanimprovetherealismofafacesimulator'soutputusingunlabelledrealfaces whilepreserving theidentity information during therealismrefinement**.**

Weihong Deng, [**8]** in this paper, we propose a new face alignment method for pose-invariantface recognition, called adaptive pose alignment (APA) which can greatly reduce the intra-classdifferenceandcorrectthenoisecausedbythetraditionalmethodinthealignmentprocess,especiallyin unconstrained settings.

Jie Cao, Lingxiao Song,**[9]** This paper models high-resolution heterogeneous face synthesisas a complementary combination of two components: a texture inpainting component and apose correction component. We have shown that our approach not only outperforms thepopular face feature descriptors but also outperforms the state-of the-art approaches in bothsketch-photoand NIR-VIS scenarios.

Hao Yang and Xiaofeng Han, **[10]** This article mainly sets four directions to consider theproblems: the accuracy rate of the face recognition system in the actual check-in, the stabilityof the face recognition attendance system with real-time video processing, the truancy rate ofthe face recognition attendance system with real-time video processing and the interfacesettingsof thefacerecognition attendancesystemusingreal-time video processing**.**

F. Schroff and D. Kalenichenko**[11]** In this paper, we have proposed a new architecture

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forNIRVISfaceimagesynthesis,wemodeltheheterogenoussynthesis.Usingtwocomplementarycomponents:atextureinpaintingcomponentandaposecorrectioncomponent.Thesynthesisproblemissimplifiedintotwolearningproblems,facilitatingone-to-onesupervisedtexturecompletion**.**

Dongfeng Luo **[12]** We proposed a novel Dual-Agent Generative Adversarial Network (DA-GAN) for photorealistic and identity-preserving profile face synthesis. DA-GAN combinesprior knowledge from data distribution (adversarial training) and domain knowledge of faces(poseandidentityperceptionloss)toexactlyrecovertheinformationlostinherentlyinprojectinga3D faceinto the 2Dimagespace**.**

R. Jayaswal, **[13]** In this paper, the use of FRT, like any technology, has its share of privacyand ethical concerns, particularly when it comes to health care. While the Health InsurancePortability and Accountability Act (HIPAA) provides a framework for protecting patientprivacy,FRT,likeanypatient data,canalways be reidentified evenonceanonymized.

A.J. Goldstein, **[14]** In this paper, we have proposed a context-aware local binary featurelearning(CA-LBFL)methodforfacerecognition.Inordertoexploitmorespecificinformationfrom different scales, we have presented a context-aware local binary multi-scale featurelearning(CA-LBMFL)method.Moreover,wehaveappliedtheabovetwomethodstoheterogeneousfacematching bycoupledlearningmethods(C-CA-LBFLandC-CA-LBMFL).Ourmethods achievebetteror very competitive recognition performance**.**

A.J.GoldsteinandL.D.Harmon**[15]**Inthispaper,weproposedemergingtrendsandapplicationsthey arerecognizingafacebytaking areferencefromavideo-basedimageso wecan easily identify the person through this video recognition and another application is 3Drecognition. This method is more accurate than 2D recognition and there are low-cost 3Dsensors.Wealsofacedsomedifficultiesinrecognizingafaceinthesituationsofaging,plasticsurgery,cosmetics,etc**.**

1.2 ImportanceofFaceRecognitionTechnology

At present, face detection and recognition technology is one of the most popular technologies.Face detection and face recognition are also important research works [26,27]. Because CNN-basedfacedetectorsareinefficientinhandlingfacesofdiversescales.SoHaoetal.[22]proposeScale-awareFace Detection (SAFD) to handle scale explicitly using CNN. Because these faces will be roughly thesamesizeafterscaling,evenCNN,whichismuchsmaller,candetectthemaccurately.AndThismethodcanachieve betterperformance with lesscomputationalcost.

-CLASSIFICATIONOFFACERECOGNITIONTECHNOLOGIES

1.3 METHODSOFFACERECOGNITION

1.3.1. POSE-INVARIANTFACERECOGNITION

Itisclassifiedinto2types.Therearefaceimagesynthesisandsynthesis-freemethods.Faceimagesynthesiscanbeaccomplishedwith2Dor3Dtechniques.Nowadays3DmodelingisknownasGENERICELASTICMODELS(GEM).GEMcanonlyestimatethe3Dshapeforfrontalfaces. This method can handlewithin $+45^0$to -45^0ofyaw.

1.3.2. MULTI-TASKINGLEARNING(MTL)

MTL has been widely applied to computer vision taskset: -Visual tasking, actionrecognition,andfacerecognition. MTLisusedforfeaturetransformationsfordifferentposes.MTLimplicitlyincreasesthesamplesizeandimprovesthegeneralizationabilityforeachtask;hence, it is especially beneficial when the training data for the tasks is small. MTL provides aprincipledwayforustomodelthecorrelationbetweenposesifweviewthelearningoffeaturetransformationforeachposeasatask.MTLapproachthatjointlylearnsfeaturetransformationsfordifferentposesandisshowntoprofitfromthelatentinter-posecorrelations.

1.3.3. FACERECOGNITIONFORPOSEPROBLEM

HereweusePBPRfacerepresentationscheme,whichisrelatedtotheposeoftheface.Thereare3stepstheyare:-Faceposenormalization,Unocculdedfacialtexturedetection,patchwise feature extractions. This hypothesis does not hold for a profile face where there is severe self-occlusion. In this section, we propose the flexible PBPR face representation scheme, where thelengthoffacerepresentationisrelatedtotheposeoftheface;forexample,afrontalfaceimagewillhavelarger facerepresentation than aprofilefaceimage.

1.3.3.1. FACEPOSENORMALISATION

Here 3D method is used for face pose normalization. The 5 most facial feature pointsare the centers of 2 eyes, tip of the nose, the two mouth corners by using ORTHOGRAPHICPROJECTIONMODEL.Thedetectedfivefacialfeaturepoints,a3Dgenericshapemodelis alignedtothe2Dfaceimage.1The2Dfaceimageisthenback-projectedtothe3Dmodel,andafrontal faceimageis rendered with thetextured3D model.

1.3.3.2. UNOCCLUDEDFACIALTEXTUREDETECTION

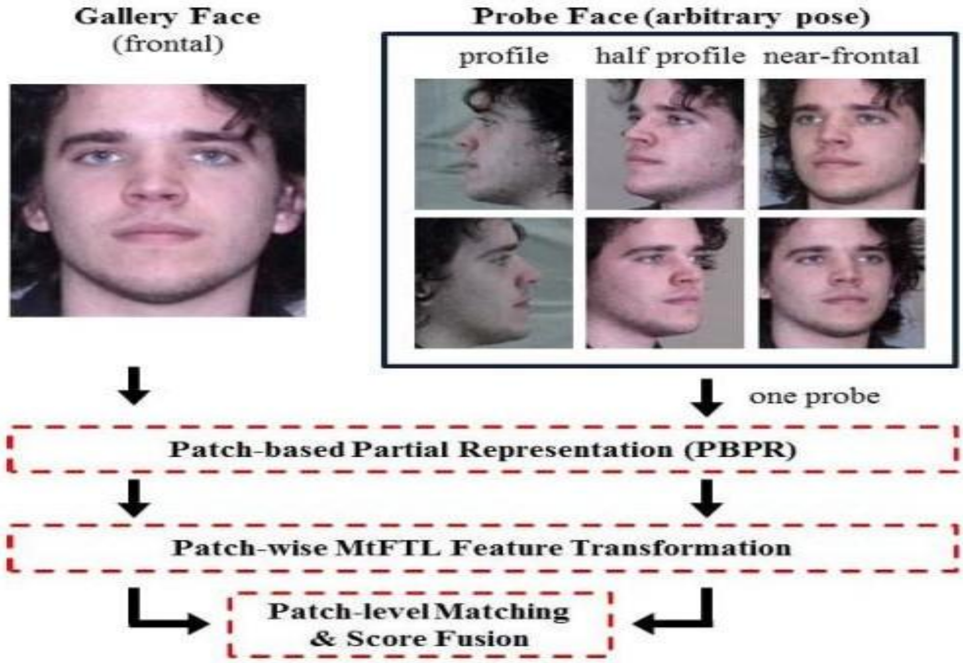
The edge points are then detected in this region by the Canny operator. The facialcontourisobtainedbyapointsetsregistrationalgorithmcalledCOHERENTPOINTDRIFT[CPD]. Pose normalization corrects the deformation of facial texture resulting frompose variations, but it cannot recover the texture lost by occlusion. Rather than trying tosynthesize the occluded texture to obtain a complete frontal face [4], we propose to make fulluse of the unoccluded texture only. This is inspired by the observation that human beings caneasily recognize profile faces without the need to recover the whole frontal face. Therefore,facialcontour detection isthe key toidentifying the occluded facial texture.

1.3.3.3. PATCHWISEFEATUREEXTRACTIONS

This is a valuable property because we do not need to apply different algorithms tofrontal and non-frontal faces. If more than 80% of pixels in one patch fall into the unoccludedregion, then it is designated as an unoccluded patch. Each unoccluded patches is split into J*Jcells.Astate-of-the-artlocaldescriptorcalledDUALCROSSPATTERNS[DCP]isemployed.Theareaoftheunoccludedfacialtextureintherenderedfrontalviewvarieswithposechange,withdemonstrablefluctuationintheamountofeffectiveinformationavailableforfacerecognition.Inlightofthisobservation,avariable-lengthfacerepresentationmethodisproposed.

1.3.3.4. PBPR-MtFTLMETHOD

PBPR-MtFTL framework effectively utilizes all the unoccluded face texture and thecorrelationbetweendifferentposes,veryencouragingresultsforfaceidentificationinallthreepopular multi-pose databases are achieved. We also slightly modify the proposed approach totackletheunconstrainedfaceverificationproblem,andachievetoplevelperformance.Although the adopted matching scheme is simple compared to existing methods , it is stillexpectedthattheproposedPBPR-MtFTLframeworkwillachievestrongerperformance,sincethe recognition ability of PBPR-MtFTL has been enhanced by exploiting the correlationbetweenposes.

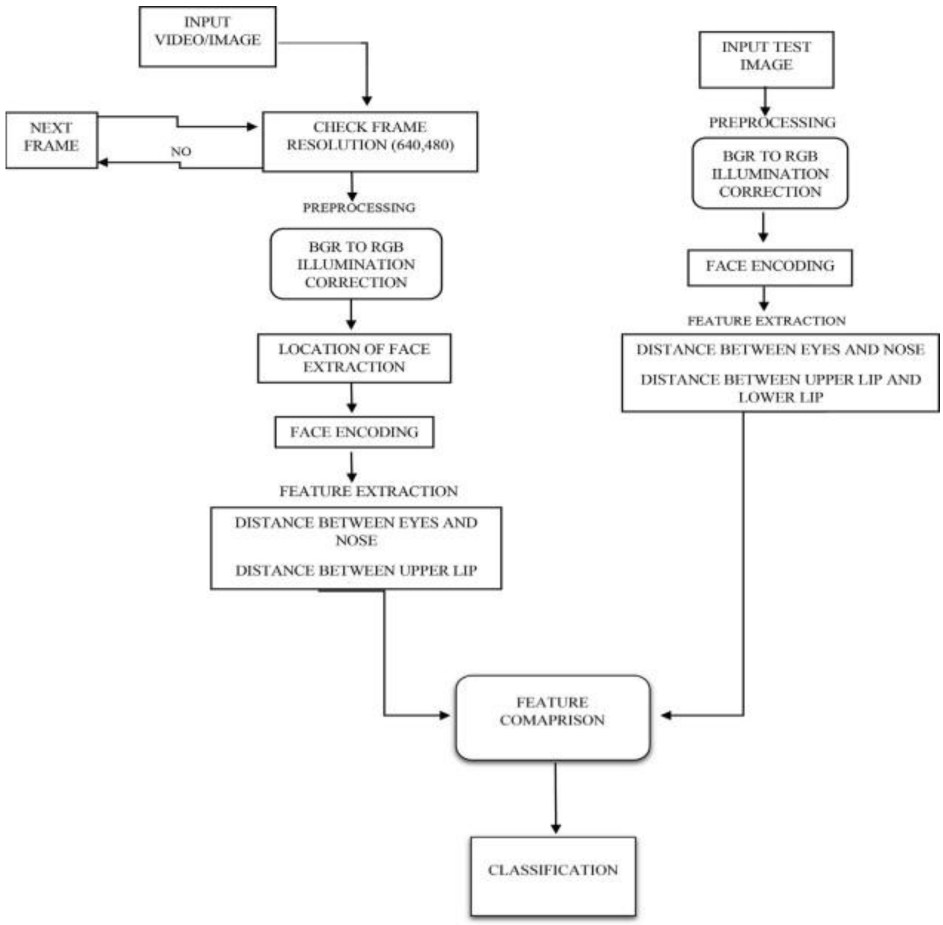


2.2.1Facerecognitionusingfacialfeatures

Inthismethod,weanalysed(I)Crimedetection,(ii)faceverification,and(iii)humantracking. The features selected are Euclidean distance between eyes, the structure of the nose,lip to lip distance. This process helps reduce the dimensionality of the data by extracting themaincomponents of the3D data.

For recognition of face from a given input image or video frame (I) Computing thefaciallandmarks(ii)Detectingfacesfromtheimageusingthefaciallandmarks(iii)Recognizeface from the input image/video ramification methods. The result shows that it has a goodrecognition rate. Detection of facial landmarks involves Machine learning techniques thatsurfaceofour face,ourmouth,nose,jaws,and eyescanbeidentifiedand whenwetriangulatethepoints, wewill beable to build a3D mesh.

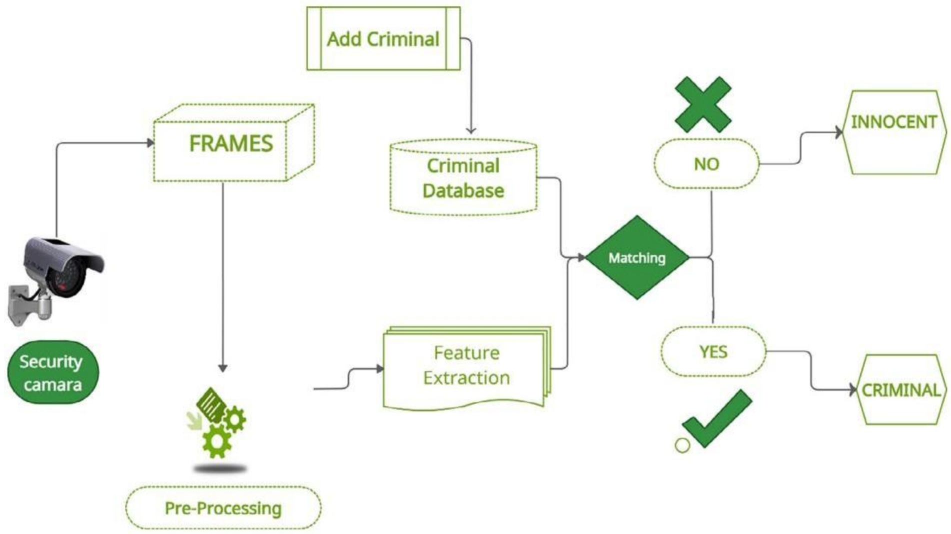
The system proposed will help to identify a person from a video clip or in real-timefromacamerausingfacetandlandmarkestimationalgorithmsandhencecanbeusedinmanyaspects, such as law enforcement, biometric identification, monitoring the students duringonlineexams, and trafficmonitoring, etc.



2.3.1.Multi-TaskCascadeNeuralNetwork(MTCNN)

MTCNNmethodisusefulforpoliceforidentifyingcriminals.Inresponsetoincreasinganxietiesaboutcrimeanditsthreattosecurityandsafety,theutilizationofsubstantialnumbersof the closed-circuit television system (CCTV) in both public and private spaces has beenconsideredanecessity.

The existing system cannot detect faces in an environment where there is low lightintensity,substantialposefluctuations,severelighting.Thefirststepofimplementingface detection as the criminal face with id, name, age, state, and crime committed is registered tothedatabase.Thefacialimageiscroppedandisresizedatalesserpixelvalue.Differentfacialfeatures are extracted using different mtcnn classifiers. Grayscale images from this step wereusedforidentification ofthe criminal and trainingthemodel.



The criminal database with 50 records is collected and trained. The accuracy achieved is86%.Thesystemconsidersthresholdparametersthatcanbeadjustedaccordingtoourrequirements. The model can be utilized in any situation where wrongdoings are bound tooccur. Rather than looking through the whole data set to analyze the faces, model executioncanbeimprovedbyconsidering differentqualities liketheageandsex of anindividual.

2.4.1. ATTENDENCESYSTEMUSINGFACERECOGNITION

Face recognition is divided into two parts: face detection and face recognitionmatching. Face recognition technology belongs to biometric recognition technology, whichmainly includes four parts: face image collection, face image pre-processing, face imagefeatureextraction,matchingandcombininghardrecognition,combinedwithhardwarecameras.Themain methods of facerecognition are:-

2.4.1.1. Geometricfeaturemethod

Itsadvantageistheuseofsimplegeometricinformation,sothetimecostofstoragespace and classification is small, and it can still be used when the image recognition rateis low; it is not sensitive to changes in lighting. Its disadvantage is that it is difficult toextract stable features from the image, it is greatly affected by changes in posture andexpression,and the stability is nothigh.

2.4.1.2. Subspaceanalysismethod

Different subspace analysis methods use different criteria, and different subspacescanbeobtained.Commonsubspaceanalysismethodsforfacerecognitioninclude:pri ncipal component analysis, linear discriminant analysis, independent element analysis,etc.

2.4.1.3. Neuralnetworkmethod

Neuralnetworkshavesomeadvantagesinfacerecognition,theyalsohaveconsiderable defects. The structure of neural networks is huge and complex, and theirtrainingrequiresahugesamplelibrary.Thetrainingtimeoftentakesdaysorevenmonths.Th e speed is not fast enough. Therefore, neural networks are not commonly used in theactualapplication offacerecognition.

2.4.1.4. SupportVectorMachine(SVM)method

Supportvectormachineswanthigh-dimensionalspaceprojection,whichrequiresthesupport ofkernel functions,but choosing kernelfunctions isindeed alotof trouble.

2.4.1.5. Videoimagerecognitionsystem

The video image recognition system is mainly composed of four parts: loginmodule,recognitionmodule,check-inmoduleandbackgroundmanagementmodule.ExampleSCHOOLSYSTEM.Theloginmoduleis wherethelecturerorbackgroundadministratorlogsin with an account and password to view attendance information. The main function of therecognition module is to receive a face picture, call the system application programminginterface(API).Thecheck-inmodulereceivestheidentificationcodeobtainedinthe identification module and compares the database the student by quering the current time andtheschedule information indatabase, thecurrent courseinformation is obtained.

The accuracy rate of the face recognition system in the actual check-in, thestability of the face recognition attendance system with real-time video processing, and thetruancyrateofthefacerecognitionattendancesystemwithreal-timevideoprocessing.Compared with the control group, the efficiency is greatly improved, which can preventstudentsfrom leaving early and skipping classes.

2.5.1. FACERECOGNITIONINMOBLIEACCESSORIES

In recent years, fingerprint identification and face recognition technologies have set offa huge tide in the identification and authentication of mobile terminals. In recent years,fingerprint identification and face recognition technologies have set off a huge tide in theidentificationand authentication ofmobile terminals.

2.5.1.1. Dynamicpasswordauthentication

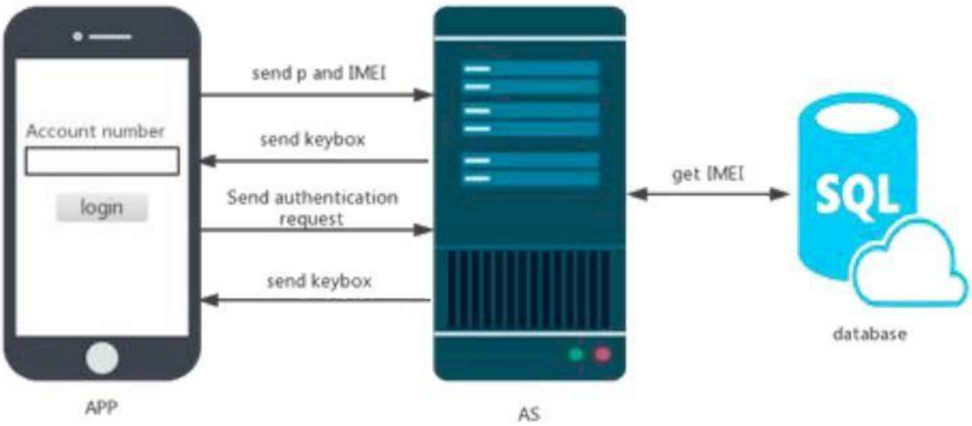
SMS verification code is one of the most common dynamic password techniques ofidentity authentication used in mobile terminals. The disadvantage of an SMS authenticationcodeisthatthemessageissentusingcleartextbecauseitcanbeinterceptedbymanykin dsofcommunicationstricks to hack the data.

2.5.1.2. Biometricauthenticationmethod

Each person has unique biological characteristics, biometrics cannot be falsified easilyfor a long time, so biometrics authentication can be used as a reliable means of identityauthentication. At present, biometrics authentication and identification security systems havebeenimproved,butcomparedwithotherauthenticationtechnologies,theresearchanddevelop ment cost is relatively high. In addition, because biometrics authentication is uniqueandnon-modifiable, it is generallyconsidered highly secure.

2.5.1.3. IMEI(InternationalMobileEquipmentIdentity)

IMEI consists of 15 digits "electronic serial number", which is marked as an IMEInumberon the backof themobilephonefuselage,andstored in themobilephonememory.



2.5.1.4. Blowfishalgorithm

Blowfish algorithm is very fast, the encrypted data is reversible and it is free for anyonetouseanddoesnotneedtopayanycharges,whichgreatlymeetourneeds.Blowfishalgorithmi s very fast, the encrypted data is reversible and it is free for anyone to use and does not needtopay any charges, which greatly meet our needs.

Theaspectsofthespeed,security,anduserexperience,theauthorshavedesignedanewidentity authenticationschemebasedontheBlowfishalgorithm,whichovercomestheweaknesses of the traditional authentication methods. The scheme does not use any password,verificationcode,verificationmail,butadoptsthebackgroundautomaticidentificationpr ocessto authenticate the user. The scheme was analysed in terms of efficiency, security,

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userexperience.

2.6.1. CHALLENGES

- There have been great achievements and progress in this particular field of study buttherearemanychallenges left to overcome.
- Still today, low accuracy is one of the main drawback of face recognitionthat thistechnology can be applied in several importantareas is making it an appropriatetechnologyto develop.
- The purpose of this project is to create a face recognition system that can recognizefacesin manipulated images.
- The final step is to determine real face from the face candidate using a multilayerclassificationscheme.

2.7.1.APPLICATIONS

- Facerecognitionisalsousefulinhumancomputerinteraction,virtualreality,informationsecurity andso on.
- Face recognition is widely used in unlocking mechanism in mobiles like android andIphone.
- Facerecognitioncanbeusedtofindmissingchildrenandvictimsofhumantrafficking.
- Facerecognitionsystemcanaidinvestigationbyautomaticallyrecognizingindividualandsecurephotos.

-DISCUSSIONANDCONCLUSION

3.1. VARIOUSASPECTSOFFACERECOGNITION

S.NO	ASPECT	METHOD	CONTENT

1	Methods of facetechnology	PBPR-MtFTL	PBPR-MtFTL framework effectivelyutilizesalltheunoccludedfacetextureandthecorrelation between differentposes,veryencouragingresults for face identificationinallthreepopularmulti-posedatabasesareachieved.Wealsoslightlymodifytheproposed approach to tackletheunconstrainedfaceverificationproblem,andachieve top levelperformance.
2	Recognizing facial Features	MachineLearning	Forrecognitionoffacefromagiveninputimageor video frame (I) Computingthefaciallandmarks(ii)Detectingfacesfromtheimageusingthefaciallandmarks(iii)Recognizefacefromtheinputimage/videoramificationmethods.Theresultshowsthat it has a good recognitionrate. Detection of facial landmarksinvolvesMachine

			learningtechniquesthatsurfaceofourface,ourmouth, nose, jaws, and eyescanbeidentifiedandwhen wetriangulatethepoints,wewil lbeableto build a3D mesh.
3	Identifyingcriminals	MTCNN	Thefirststepofimplementing face detectionas the criminal face with id,name,age,state,andcrimecommitted is registered to thedatabase. The facial image iscroppedandisresizedatalesserpixelvalue.Differentfacialfeaturesareextractedusingdifferentmtcnnclassifiers. Grayscale imagesfrom this step were used foridentification of the criminalandtraining the model.
4	Attendancesystem	Video Image Recognition	Thevideoimagerecognitionsystemismainlycomposedoffour parts: login module,recognitionmodule,check-inmodule and backgroundmanagement module.ExampleSCHOOLSYSTEM. The loginmoduleiswherethelecturer or background administratorlogsinwithan

			accountandpasswordtoviewattendanceinformation.Themainfunctionoftherecognitionmoduleistoreceiveafacepicture,callthesystem application programminginterface(API). Thecheck-inmodulereceivestheidentificationcodeobtained in the identificationmoduleandcomparesthedatabasethestudentby querying the current time andthescheduleinformationin database,thecurrentcourseinformationis obtained.

CONCLUSION

From this study, we can conclude that the face recognition has been one of the mostactive research topics in computer vision for more thandecades. With years of effort,promising results have been achieved for automatic face recognition, in both controlled anduncontrolled environments. However, face recognition remains significantly affected by thewide variations of pose, illumination, and expression often encountered in real-world images.By using PBPR-MtFTL method we can easily recognize the face of the person. By usingMTCNN method we detect the real or fake image of a criminal which is very useful for thepolice to identify the criminals in a group of people. Video image recognition method is usedforthestudentstogettheaccurateattendance.Thissystemreducesthechanceofescapingfromthe class and percentage of attendance level will also increasing. In mobile accessories facerecognitionisusedwhichovercomestheweaknessesofthetraditionalauthenticationmethods. The scheme does not use any password, verification code, verification mail, but adopts thebackgroundautomaticidentificationprocesstoauthenticatetheuser.Theschemewasanalysedin terms of efficiency, security, user experience. Blowfish algorithm is used in this methodwhichisvery fast,theencrypteddataisreversibleanditisfreeforanyonetouseanddoesnotneedto pay anycharges,which greatlymeet our needs.

Thus,facerecognitiontechnologyisusedinmanyaspectssuchassecuritypurpose,attendancepurpose, identifying criminals, etc. And the future is completely going to depend on the facerecognitiontechnologyin theseaspects.

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