

**Face detection**

**using**

**image discrimnant**

**BACHELOR OF TECHNOLOGY**

**In**

**COMPUTER SCIENCE AND ENGINEERING**

BY

**Group : 7**

Section - K18HA



**School of Computer Science and Engineering**

Lovely professional University

Phagwara, Punjab (India)

Contributions:

Abhinav Kumar 11813122 53(Leader)(Python codes)

Ramnandan mishra 55(Python code)

Ashwani Sharma 11807530(Report)

Mayank Kalal 11813116(Report)

**ABSTRACT**

iLinear iDiscriminant iAnalysis i(LDA) ihas ibeen isuccessfully iapplied ito iface irecognition iwhich iis ibased ion ia ilinear iprojection ifrom ithe iimage ispace ito ia ilow idimensional ispace iby imaximizing ithe ibetween iclass iscatter iand iminimizing ithe iwithin-class iscatter. iLDA iallows iobjective ievaluation iof ithe isignificance iof ivisual iinformation iin idifferent ifeatures iof ithe iface ifor iidentifying ithe ihuman iface. iThe iLDA ialso iprovides ius iwith ia ismall iset iof ifeatures ithat icarry ithe imost irelevant iinformation ifor iclassification ipurposes. iLDA imethod iovercomes ithe ilimitation iof iPrinciple iComponent iAnalysis imethod iby iapplying ithe ilinear idiscriminant icriterion. iThis icriterion itries ito imaximize ithe iratio iof ideterminant iof ithe ibetween-class iscatter imatrix iof ithe iprojected isamples ito ithe ideterminant iof ithe iwithin-class iscatter imatrix iof ithe iprojected isamples. iLinear idiscriminant igroups ithe iimages iof ithe isame iclass iand iseparate iimages iof idifferent iclasses. iHere ito iidentify ian iinput itest iimage, ithe iprojected itest iimage iis icompared ito ieach iprojected itraining, iand ithe itest iimage iis iidentified ias ithe iclosest itraining iimage. iThe iexperiments iin ithis ipaper iwe ipresent ito iuse iLDA ifor iface irecognition. iThe iexperiments iin ithis ipaper iare iperformed iwith ithe iORL iface idatabase. iThe iexperimental iresults ishow ithat ithe icorrect irecognition irate iof ithis imethod iis ihigher ithan ithat iof iprevious itechniques.

**Introduction**

iFace irecognition isystem iis ia icomputer iapplication ifor iautomatically iidentify ior iverifying ia iperson ifrom ia idigital iimage ior ivideo iframe ifrom ia ivideo isource. iFacial irecognition isystem itypically iused iin isecurity isystem. iIn ithis isystem iautomatically isearching iof ifaces ifrom ithe iface idatabases, itypically iresulting iin ia igroup iof ifacial iimages iranked iby icomputer ievaluated isimilarity. iSome ifacial irecognition ialgorithm iidentifies ifaces iby iextracting ilandmarks, ior ifeatures ifrom ian iimage iof ithe isubject iface. iFor iexample, iface irecognition ialgorithm imay ianalyze ithe irelative iposition, isize, ishape iof ithe ieyes, inose icheekbones iand ijaw ito irecognize ifaces. i

Linear iDiscriminant ianalysis iexplicitly iattempts ito imodel ithe idifference ibetween ithe iclasses iof idata. iLDA iis ia ipowerful iface irecognition itechnique ithat iovercomes ithe ilimitation iof iPrinciple icomponent ianalysis itechnique iby iapplying ithe ilinear idiscriminant icriterion. iThis icriterion itries ito imaximize ithe iratio iof ithe ideterminant iof ithe ibetween-class iscatter imatrix iof ithe iprojected isamples ito ithe ideterminant iof ithe iwithin iclass iscatter imatrix iof ithe iprojected isamples. iLinear idiscriminant igroup iimages iof ithe isame iclass iand iseparates iimages iof idifferent iclasses iof ithe iimages.

Discriminant ianalysis ican ibe iused ionly ifor iclassification inot ifor iregression. iThe itarget ivariable imay ihave itwo ior imore icategories. iImages iare iprojected ifrom itwo idimensional ispaces ito ic idimensional ispace, iwhere ic iis ithe inumber iof iclasses iof ithe iimages. iTo iidentify ian iinput itest iimage, ithe iprojected itest iimage iis icompared ito ieach iprojected itraining iimage, iand ithe itest iimage iis iidentified ias ithe iclosest itraining iimage. iThe iLDA imethod itries ito ifind ithe isubspace ithat idiscriminates idifferent iface iclasses. iThe iwithin-class iscatter imatrix iis ialso icalled iintrapersonal imeans ivariation iin iappearance iof ithe isame iindividual idue ito idifferent ilighting iand iface iexpression. iThe ibetween-class iscatter imatrix ialso icalled ithe iextra ipersonal irepresents ivariation iin iappearance idue ito idifference iin iidentity. iLinear idiscriminant imethods igroup iimages iof ithe isame iclasses iand iseparates iimages iof ithe idifferent iclasses. iTo iidentify ian iinput itest iimage, ithe iprojected itest iimage iis icompared ito ieach iprojected itraining iimage, iand ithe itest iimage iis iidentified ias ithe iclosest itraining iimage.

To iexplain idiscriminant ianalysis, ihere iwe iconsider ia iclassification iinvolving itwo itarget icategories iand itwo ipredictor ivariables.

**Literature ireview**

As ihighly istructured itwo-dimensional ipatterns, ihuman iface iimages ican ibe ianalyzed iin ithe ispatial iand ithe ifre-quency idomains. iThese ipatterns iare icomposed iof icompo-nents ithat iare ieasily irecognized iat ihigh ilevels ibut iare iloosely ide®ned iat ilow ilevels iof iour ivisual isystem. iEach iof ithe ifacial icomponents i(features) ihas ia idifferent idiscrimination ipower ifor iidentifying ia iperson ior ithe iper-son's igender, irace, iand iage. iThere ihave ibeen imany istud-ies iof ithe isigni®cance iof isuch ifeatures ithat iused isubjec-tive ipsychovisual iexperiments.

Using iobjective imeasures, iin ithis isection iwe ipropose ia icomputational ischeme ifor ievaluating ithe isigni®cance iof idifferent ifacial iattributes iin iterms iof itheir idiscrimination ipotential. iThe iresults iof ithis ianalysis ican ibe isupported iby isubjective ipsychovisual i®ndings. iTo ianalyze iany ireprentation.

Proposed imethodology

**ALGORITHM iUSED iIN iLDA**: iIn iLinear idiscriminant ianalysis iwe iprovide ithe ifollowing isteps ito idiscriminant ithe iinput iimages: i

Step-1 iWe ineed ia itraining iset icomposed iof ia irelatively ilarge igroup iof isubjects iwith idiverse ifacial icharacteristics. iThe iappropriate iselection iof ithe itraining iset idirectly idetermines ithe ivalidity iof ithe ifinal iresults. iThe idatabase ishould icontain iseveral iexamples iof iface iimages ifor ieach isubject iin ithe itraining iset iand iat ileast ione iexample iin ithe itest iset. iThese iexamples ishould irepresent idifferent ifrontal iviews iof isubjects iwith iminor ivariations iin iview iangle. iThey ishould ialso iinclude idifferent ifacial iexpressions, idifferent ilighting iand ibackground iconditions, iand iexamples iwith iand iwithout iglasses. iIt iis iassumed ithat iall iimages iare ialready inormalized ito im i× in iarrays iand ithat ithey icontain ionly ithe iface iregions iand inot imuch iof ithe isubjects’ ibodies. i

iStep-2 iFor ieach iimage iand isub iimage, istarting iwith ithe itwo idimensional im i× in iarray iof iintensity ivalues iI(x, iy), iwe iconstruct ithe ivector iexpansion iΦ iR im× in. iThis ivector icorresponds ito ithe iinitial irepresentation iof ithe iface. iThus ithe iset iof iall ifaces iin ithe ifeature ispace iis itreated ias ia ihigh-dimensional ivector ispace. i

Step-3 iBy idefining iall iinstances iof ithe isame iperson’s iface ias ibeing iin ione iclass iand ithe ifaces iof idifferent isubjects ias ibeing iin idifferent iclasses ifor iall isubjects iin ithe itraining iset, iwe iestablish ia iframework ifor iperforming ia icluster iseparation ianalysis iin ithe ifeature ispace. iAlso, ihaving ilabeled iall iinstances iin ithe itraining iset iand ihaving idefined iall ithe iclasses, iwe icompute ithe iwithin-class iand ibetween-class iscatter imatrices. i

iNow iwith-in iclass iscatter imatrix i‘Sw’ iand ithe ibetween iclass iscatter imatrix i‘Sb’ iare idefined ias ifollows: i i iSw i=∑ iC i∑N ij i i( iГi ij i- i iµj i)( iГij i i- i iµj)T i i------ i(1) i i i i i i i i i i i i i i ij=1 i i i ii=1 i

iWhere i, iГi ij i, ithe iith isamples iof iclass ij, iµj i iis ithe imean iof iclass ij, ic iis ithe inumber iof iclasses, iNj iis ithe inumber iof isamples iin iclass ij. i i

Face iimages ishould ibe idistributed iclosely iwith-in iclasses iand ishould ibe iseparated ibetween iclasses, ias imuch ias ipossible. iIn iother iwords, ithese idiscriminant ivectors iminimize ithe idenominator iand imaximize ithe inumerator iin iequation i(3). iW ican itherefore ibe iconstructed iby ithe ieigen ivectors iof iSw-1 iSb. iPCA itries ito igeneralize ithe iinput idata ito iextract ithe ifeatures.

**CONCLUSION**

Linear iDiscriminant iAnalysis imethod ihas ibeen isuccessfully iapplied ito iface irecognition iwhich iis ibased ion ia ilinear iprojection ifrom ithe iimage ispace ito ia ilow idimensional ispace. iBut ithe imajor idrawback iof iapplying iLDA iis ithat iit imay iencounter ithe ismall isample isize iproblem. iWhen ithe ismall isample isize iproblem ioccurs, ithe iwithin-class iscatter imatrix ibecomes isingular. iSince ithe iwithin-class iscatter iof iall ithe isamples iis izero iin ithe inull ispace iof iSw, ithe iprojection ivector ithat ican isatisfy ithe iobjective iof ian iLDA iprocess iis ithe ione ithat ican imaximize ithe ibetween-class iscatter. i

But iface iimage idata idistribution iin ipractice iis ihighly icomplex ibecause iof iillumination, ifacial iexpression iand ipose ivariation. iThe ikernel itechnique iis iused ito iproject ithe iinput idata iinto ian iimplicit ispace icalled ifeature ispace iby inonlinear ikernel imapping. iTherefore ikernel itrick iis iused itaking iinput ispace iand iafter ithat iLDA iperformed iin ithis ifeature ispace, ithus ia inon ilinear idiscriminant ican ibe iyielded iin ithe iinput idata.

**REFERENCES**

i[1] i iR. iChellappa, iC. iWilson, iand iS. iSirohey, iHuman iand iMachine iRecognition iof iFaces: iA iSurvey, i i i i iProc. iIEEE, ivol. i83, ino. i5, ipp. i705- i740, i1995. i

i[2] i iP.N.Belhumeur iand iD.J. iKriegman, i“What iis ithe iSet iof iImages iof ian iObject iunder iall iPossible iLighting iConditions”, iIEEE iProc. iConf. iComputer iVision iand iPattern iRecognition, i1996. i

[3] i iK.Etemad iand iR. iChellappa i,"Discriminant ianalysis ifor iface irecognition iof ihuman iface iimages" iJournal iof iOptical isociety iof iAmerica iA/Volume i14,pp i1724- i1733 i,Aug1997. i

i[4] i iP.N.Belhumeur i,J.P.Hespanha iand iD.J. iKriegman,"Eigenfaces iVs iFisherfaces i: iRecognition iusing iClass ispecic ilinear iprojection" iIEEE iTrans. iPattern iAnal i. iMachine iIntell, iVol i19, ipp i711-720,July1997 i

i[5] i iJuwei iLu,Kostantinos iN. iPlataniotis iand iAnastasios iN. iVenet isanopoulos, i"Face iRecognition iUsing iLDA- iBased iAlgorithms" iIEEE iTransactions iin iNeural iNetwork,Vol.14 iNo.1,January i2003. i

i[6] i iORL iface idatabase: i iAT i&T iLaboratories, iCambridge,U.K..[Online]. iAvailable: ihttp://www. icam-orl. ico. iuk i/ ifacedatabse.html. i

[7] i iAleix iM.Matinez iand iAvinash iC. iKak," iPCA iversus iLDA"IEEE iTransactions ion iPattern iAnalysis iand iMachine iIntelligence,Vol.23,No. i2, iFebruary i2001. i

i[8] i iM. iTurk iand iA. iPentland, i“Face iRecognition iUsing iEigenfaces,” iProc. iIEEE iConf ion iComputer iVision iand iPattern iRecognition i, i1991, ipp. i586 i– i591. i