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Gathering Geo-PointFrom User's Shared Photos Based On PNN And GLCM Method

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ABSTRACT

Therehasbeencontinuousgrowthintheareaofdetecting homelocation precisely.Thisneedcan befulfilled by thegradualhikeinthephoto community sitessuchasFlickr,Picasaalongwithmanyothersocial networkingsiteswhichenablestheusertosharetheirlocationandtheimage of thelocationimmediately.Thisfeaturewhichisdevelopedovertheyears makesitmoreeffectivetodeterminetheexactgeo-positionofauser.The paperproposesa methodwhichinvolves classifyinga givenimage as “home-type”or“non-hometype”images.Fromtheimage,onehastocollecttheclue toidentify thehiddeninformation.Thisisdonebyidentifyingandclassifying temporal, spatial andvisual cues. Forthisextractionofimage, GreyLevelCo-occurrenceMatrix(GLCM)methodisused.Thismethodhasan edgeoverthe previousmethods.Followingthisthe classificationof “home”or“non-home” imagesisdonebyPer-mutableNeuralNetwork(PNN).

KEYWORDSGeo-position, home-type, non-hometype,temporal,spatial, visual cues.

INTRODUCTION

Homeisanessentialintersectioninpeople'sactivitydetection.Thereisasoarinthe interestofpredictingexacthumanlocation.Thishelpsinunderstandingthehuman behaviorpattern.Understandingthispatternwillhelpthegovernmentandother authoritiesto improve thelivingstandardsandalsosatisfytheneedsof the civiliansin thatparticulararea.Forexample thetransportationnetwork, pollution management, populationcontroletc.Thisalsohelpsinplanningabetterurbancityplanwithfull understandingof theuser'sneed.Not alonein developmentfield,butresearchingfield alsoneedsthelocation details.Fieldsmayincludediseasepropagationandoutbreak modeling.

Existing methodsarepresent whichcandetect home locations. Theyare basedon surveys,cellularrecordsorGPSdata[5,6,8].Even thoughthese methodologies were efficient to alevel,thecollection of data arevery timeandlabour engrossed.American TimeUsesurvey(ATU)suppliesrecordof alltheactivity traces anddemographicinformation[2].Butthedrawbackinthismethodisthatthereis only alimiteddatasetwhich cannotbeusedinfurtherresearchorfollow-upresearch. Thisismainlybecause,itisalmostimpossibletocombinetheuserinformation with anyotherdatasources.Thereisamuchsimplerwaytocomeoutofthisdrawback. Theincreaseinnetworkingwebsiteshaveavastamountof geo-taggeddataavailable. Thiscan beusedasanewsourceordatabasewhichislow-cost andmoreflexible to gatherthe geopointlocationmoreefficiently.Formerly basedonuser'stweetmodels havebeenbuilttoinfertheuser'shomelocation[3].Anothermodelwasbuiltbased on the check-ins[9]also. Boththese modelshadissues.Oneof themainissueisthat these model experiencelowcoursegranularity,atcity[10]orgive risetolowlevel accuracyratewhich isonlyabout50%[3].

Themostcurrentand existing method uses photoclassificationand then detectstheusershomelocation[1].ThismethodusesConvolutionNeuralNetwork to classify imagesas"home"or"non-home".Homelocationisdetected by combining boththevisual contentofwebimagesandthespatiotemporalfeatureSVMclassifier. The accuracy rate is improved compared to the other methods, but it is time consuming.

TheproposedmethodologyusesPNNandGLCMto reducethe time-consumptionandincreasestheefficiencyinsteadoftheexistingone.

RELATEDWORK

Theactivitypattern ofbasicdaytodayis very important, whichgives us vital locationssuch ashome,workarea andothermostvisited placeslikerestaurantsand hospitalsetc.aretobepredicted.Theselocationshelpinimprovingthemobility patternandpredicthumansfeatureactivities.ToclassifylocationsbasedonATUS surveyinto differentcategories,amachinelearningalgorithmwasadvancedto make the process more efficient. This is mainly based on demographic and temporal features of user'sactivities.Then the home location is determined. This method resultedin 92%accuracy ratewhichishighestobtained,butthismethodistime consuming as wellaslaborconsuming asthree-fourthoftheworkdoneisby manual labor [2].

ThephotosfromFlickrwerecollectedwith home-relatedtagsbytheBay Area andNewYorkCity.Then physicallythephotosarefilteredouteliminatingnon-home pictures.Atotalof2167photosby192differentuserswhereminedandthentheir homelocationswasfound.Theaccuracyratewasrelativelybetterthantheother existing systems[1].

Moreandmorepeople are gettingengrossedwithsocialnetworks.This proposesanalternative methodtostable geographiclocationsinasemantically way.Chengetal [3]usedTwitterapopularsocialnetworksitetodeterminetheusers homelocation.Thiswasdonebyanalyzingtheuserstweet.Thismethodproduced 51% accuracywithin100milesofuser'sactual location.

DATA

Thissectiondescribesthedatausedintheprocessandhowtheyaretrainedand evaluatedusingthemachinelearningmodel.Insteadof usingwebimages,to train the model,firstasetof picturesaregeo-taggedmanually.Thesemanually taggedimages are

used .We select tags related "home" such as "in-home","inkitchen","familytime","familyget-together",in"bedroom".Foreach useri,werecordasequence $t.t_i$=(t_{11},t_{12})nowifjisa phototakenathomeit will be representedast_{ij}photo.A geographical tagisrelatedtoa photowhichwill provideandetailedlongitudeand latitude[11,12,13].

PROPOSEDMETHODLOGY

Thissectionpresentsthemethodwhichisusedtoacceptthephotoandpredictthe user's home location. For each user, the respective uploaded photo with the appropriategeo-taggedisreferredinordertodistinguishthelocation by userweuse (i,j) asin[1].

irepresentsthe user andjrepresentsthelocation visited bytheuseri.

FEATURE EXTRACTION

Homeisthemosthabitualvisitedplacebyauser.Forthisreasontheprocessis embarkedbyusingthe most usedlocationasaintroductoryforecastforuser'shome location.GLCMisusedforthisprocess.Itcontainsinformationaboutpositionof pixelhaving similarlygrey levelvalues. Thefollowingisthealgorithmused.

Step1:Countallpairsofpixelsinwhichfirstpixelhasvalueasianditsmatching pairisjwhichisdisplaced byadistanced, thisformsthematrix $P_d[i,j]$.

NOTE:thematrixisnotsymmetricinnature.

Step2:Theelementsof $P_d[i,j]$canbenormalizedby divingeachentry bythetotal numberofpixelpair.

Step 3:Normalized GLCMN[i,j]isgivenas

$$N\,[i,j]=\frac{P[i,j]}{\Sigma_i\,\Sigma_j\,P[i,j]}$$

which helps in finding texture that is rough, silky, bumpy etc.it also helps in extractingfeatureslike color,entropy,co-relation,varianceandprominence which givesfurther moreinformationaboutthepicture.

CLASSIFICATION

Theclassificationofpicturesto"home"or"non-home"isdonebyusingPNN.Itisa feedforwardnetwork derivedfromBayesiannetworkandstatisticalalgorithm.Ithas fourlayers: input,output,hiddenand pattern layer.

Theinputlayerrepresentsthevariableswhichisaneuron.Eachcaseconsist ofatleastoneneuronwhichwillhelpinthetrainingsetofthepatternlayer.Hidden layercomputesthetestcase.Theoutputlayercomparestheweightednodesfortarget. ThemajoradvantagesforPNNtheyarefasterthanmostofthemultilayerexisting network and are moreaccurateandinsensitive.

EXPERIMENT

Inthisexperimentweuse threebasicmodules.

PRE-PROCESSOR

Pre-processing is used for contrast enhancement of the image. For this process histogramoforientedgradient(HOG)isused.itisbasicallyafeaturedescriptorused in imageprocessingwiththemaingoalasdetectionofobjects.Thegradient of orientation iscountedin eachportionoftheimage.

PNN

It follows a neural network architecture which is slightly different from back-propagation network.it is basically feed-forward in nature. Supervised learning algorithmisused with noweightsinthehidden layer.

GLCM

Itgivesthetypicalvaluesforfeatureanalysiswhichhelpsinclassification.Itgives informationabouttthepositionofpixelshavingthesamegreylevelvalues.Thiswill bethefinalprocess wheredetection ofgeo-positiontakesplace

CONCLUSION ANDFUTURE WORK

In thispaper,anewmethodof classification with geo-taggedimagesisproposed.The efficiencyrateshowsanimprovement.Wegetanaccurateandfastoutputcompared to existingmethodology. Wealsoconsidertemporaland spatialfeatures.

Later themethodwillbeemployedtodetectotherplacelikeschool,workingplaces andvacationspots. Canalsobeusedinsocialnetworking database.

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