ResearchonEndtoEndControlAutonomousDrivingSystemBasedonDeepLearning

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Abstract

Deep learning machine algorithm is successfully used in automatically driving of a toy car. Firstly, the car was controlled by the system wirelessly to move along the designated route, and the frame sample data and simultaneously records of the car direction operation were collected using a camera to make the training data and label separately. Secondly, the ResNet convolutional neural network was established by using the frame sample data to predict the operation direction of the car. Thirdly, the loss value calculated from the predicted action was compared with the value from actual operation, and reduced by implementing the gradient descent algorithm. After a series of experimental processes, the predicted value of the system can be equivalent to the value obtained from actual driving action. The experimental results show that the processing rate can effectively reach more than 30 fps with a high accuracy.

Keywords: Autopilot, Deep Learning, Neural Networks, Gradient Descent, Prediction

1.Introduction

Withthecontinuousdevelopmentofartificialintelligence,moreandmoreattentionhasbeenpaidontheresearchof autonomousdriverlesscars.Thesystemusedinsmartcarisahighlycomputer-basedandcomplexlyintegrated,whichiscomposedofenvironmentalawareness,planninganddecisionmaking,andmulti-levelassisteddriving.Itis wellknownthatthetransportationmodeinthefuturewill besignificantlychanged,andprobablyreplacedbydriverlesscars.Theresearchonself-drivingstartedbyGoogle andthenattractednumerousattentionsfromallovertheworld.In2009,Googlebegantotestitsownself-drivingcar,whichhasbeentestedfor2.89millionkmuntillJuly2016[1].However,highaccuracyoflanedetection,obstacledetectionandtrafficidentificationofself-drivingcarcannot beachievedwithoutthedeeplearningalgorithm[2-7].

Nowadays,therearethreemainmethodstorealizeautomaticdrivingbasedoncomputervision,i.e.,indirectperception,directperceptionandend-to-endcontrol.Indirectperceptionsystemisatraditionalauto-drivingsystem,includingfoursub-modulesoftargettracking,targetdetection,cameramodelandcalibration,and3dreconstruction[9].Thismethodisrealizedtointegratethedetectionresultsfromtheabovemodulestoestablishacompleteenvironmentrepresentation.Researchesonthissystemisveryabundant,resultingintheimprovementoftechnologiesinself-drivingcars.However,thesystemhasobviousdisadvantageswithhighcomplexityandredundancy,andhighcostforcommercialapplication.

Directperceptionsystemisasystemimprovedbasedont heindirectperceptionsystem[10].Thelearningartificiali ndicatorsareusedtodescribethetrafficscenewithoutthe dependenceoneachsub-module.Forexample,whenthe auto-vehicleisdetectingthedistancebetweenitselfando thernearbyvehiclesontheroad,forthetraditionalindirec tperceptionsystem,thetargetvehicleshouldbedetected bystandardfirst,andthenconvertedintodistancethroug hthecameramodelcalculation,whilethedirectperceptio nsystemistolearnthevehiclesdistancebyneuralnetwor k,leadingtoalowersystemcomplexity.However,thisme thodisrelativelyweakinadaptabilityandhighinspecifici ty,andspecifictrafficscenesareneededtomaximizeitsad vantagesItmayalsobedifficulttomigratetootherscenes .

Theautomaticdrivingsystemusingend-to-endcontrols ystemdirectlyusestheneuralnetworktraininglearning methodtolearnthedrivingaction,whichdoesnotdividet hesystemintomultiplesub-modulestoperceivethedrivi ngenvironment[11].Thevisualimageisinputinthesyste maccordingtothetrainedneuralnetwork,andthenthesys temwilljudgethecurrentcorrespondingleft-turn,right-t urnorstraight-linedrivingactionsaccordingtothepredic tedresultsofthenetworkoutput,whichcanbeattributedt otheimageclassification.Asthenumberoflayersofneur alnetworkincreases,theabstractionlayeroffeaturebeco meshigher,andtheapproximationeffectofthesystemfu nctionbecomesbetter.Thissystemhasalowcomplexity, andeasytoobtaindata,andmoresuitableforsmallscenari os.Pomerleau[12]successfullyestablishedasetofautono mouslandvehicleinaneuralnetwork(ALVINN)in1989, whichprovedthefeasibilityofend-to-endtrainingneural networkmodelforauto-driving.

Atthealgorithmlevel,theautomaticdrivingsystemalsor eliesheavilyonresearchlevelofdeeplearningandcompu tervisiontechnologies.Inrecentyears,deeplearningand computervisiontechnologieshavedevelopedrapidly,b utitstilltakesalongtimetorealizeautomaticdrivinginan ycomplexenvironment.Amongthethreecommonauto maticdrivingmethods,theindirectperceptionmethodis moretraditionalwithhighsystemcomplexity,alargeam ountofcomputingresourcesandoftenhighinvestmentc ost.However,theresearchoftheothertwosystemmethod sisstillintheearlystage,andtheextensibilityandstability stillneedtobeverifiedbylong-termtheoreticalresearch. Themethoddescribedinthisresearchbelongstotheend-t o-endcontrolmethod,whichissignificantlyimportantfo rthesystemdevelopment.

2.AnOverviewofConvolutionalNeuralNetworkOr ganizationoftheText

Convolutionalneuralnetwork(CNN)belongstothecate goryofartificialneuralnetwork[13].Becauseitsnetwork modelisusuallycomposedofmultiplelayers,itisalsocall eddeepconvolutionalneuralnetwork.Itisoneofthetypic almodelsofdeeplearning.Comparedwiththetraditional artificialneuralnetwork,convolutionalneuralnetworki slocallinkandweightsharing,whichreducesnotonlythe weightnumberofthenetworkbutalsothecomplexityoft henetworkmodel.Therefore,thenetworkissuitablefort askswithabundantinformationandlargeamountofinput data,e.g.,imagerecognition.Thisisalsothereasonwhyth isresearchchoosesconvolutionalneuralnetworkastheb asicnetworkmodel.Aconvolutionalneuralnetworkgen erallyincludesfivelayersneuralnetworkstructures,i.e.,i nputlayer,convolutionallayer,poolinglayer,fullconnec tionlayer,andSoftmaxlayer,asshowninFig.1.
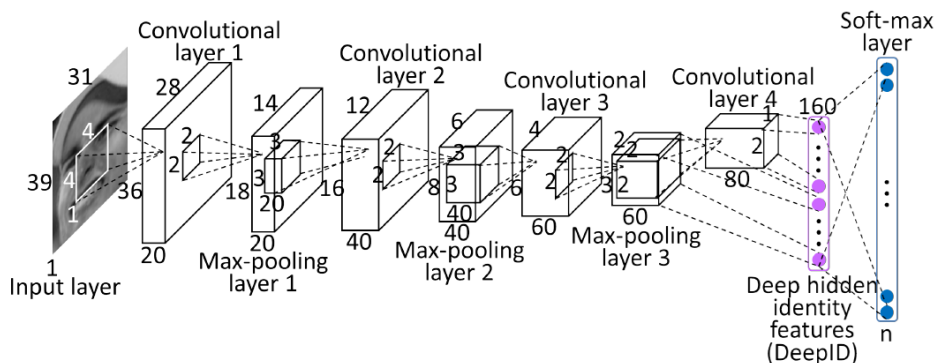
Fig.1.StructureofConvolutionalNeuralNetwork

2.1ConvolutionalLayer

Theconvolutionlayer,calledasfilter,isthemainpartoftheconvolutionalneuralnetworkstructure[14].Thefilterisusedtoextractthecharacteristicinformationoftheinputdatabyperformingconvolutioncalculationinthelocalsensingdomain.Differentfilterscanextractdifferentfeatures,suchasshadows,outlinesandsoon.Withthecharacteristicofweightsharing,itcangreatlyreducethetrainingparametersonneuralnetwork.Theconvolutionoperationistheinnerproductoperation(elementmultiplicationandthensummation)betweentheimagelocalwindowdataandthefilteringmatrix,asshowninFig.2.Theleftsiderepresentstheoriginalinputdata,themiddlepartisthefilteringmatrix,andtherightsideisthetwo-dimensionaldataobtainedaftertheconvolutionoperation.
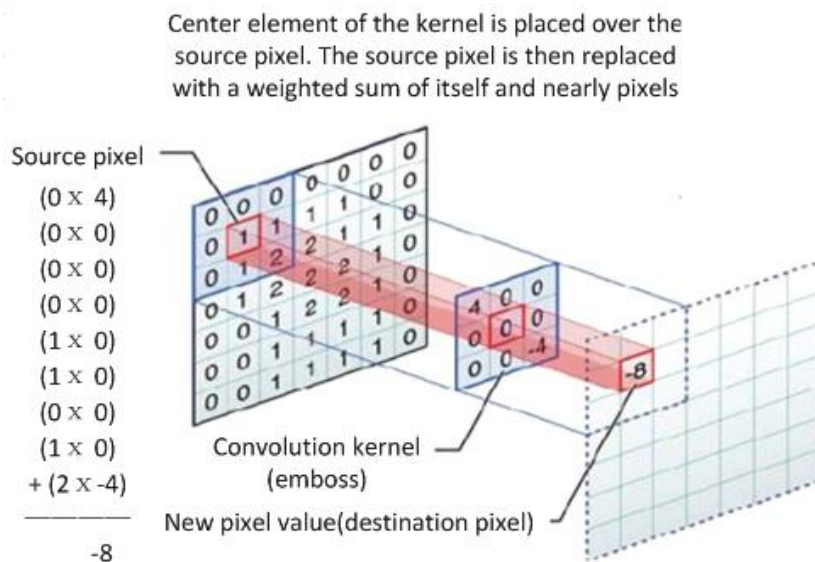

Fig.2.ConvolutionProcedure

IntheprocessofCNNtraining,multipleconvolutioncoresareoftenusedforconvolutionoftheinputdata[15].Afterthedatawindowconvolutionoperationiscompleted,thedatawindowwillbeshiftedandmoveduntilalldataistraversed,andthenthenextconvolutionoperationwillbeprocessed.Eachconvolutionkernelgeneratesalayerfeaturegraph.ThemathematicalexpressionoftheaboveprocessisshowninEq.1.

$$a_{i,j} = f\left(\sum_{d=0}^{D-1}\sum_{m=0}^{F-1}\sum_{n=0}^{F-1} w_{d,m,n} x_{d,i+m,j+n} + w_b\right) (1)$$

Where, $x_{d,i+m,j+n}$ representstheelementoftheinputimageinthe*i*throwand *j*thcolumnofthe*d*thlayer, $w_{d,m,n}$ representstheweightvalueoftheconvolutionkernelinth e*m*throwand*n*thcolumnofthe*d*thlayer,drepresentsthed epth.Frepresentsthewidthandheightinformationofthec onvolutionkernel, w_b representsthepartialtermoftheconvolutionkernel, $a_{i,j}$ representstheelementofthefeaturegraphinthe*i*throwan d*j*thcolumn,and*f*()representstheactivationfunction.

2.2PoolingLayer

Thepoolinglayerisinsertedbetweentwosuccessivecon volutionlayers.Poolinglayeriscommonlyrecognizedas theconversionofoneimagewithhighresolutionintoanot herimagewithlowresolution.Itisusedtoreducesamplin g,thespatialsizeofdatablocksinthenetworkgradually,a ndthenumberofparametersinthenetwork,whileitimpro vestheiterationrateofmodellearning,andovercomeove rfitting[16].

Similartotheconvolutionlayer,theforwardpropagation processofthepoolinglayerisalsoperformedbymovingt hestructureofsimilarfilters.However,thecalculationoft hepoolinglayerfilterisnottheweightedsumofnodes,but simplythemaximumvalue.Thepoolinglayerthatusesth emaximumoperationiscalledthemaximumpoolinglay er,andthepoolinglayerofthisstructureisusedfrequently ,asshowninFig.3.Thefiltersizeis2x2,andthepooledste psizeis2,whichmeansthattheinputdataof4x4sizeischa ngedto2x2throughthepoolinglayer.
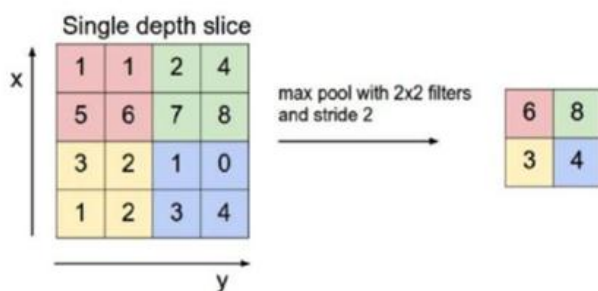
Fig.3. MaximumPoolingLayerAlgorithm

2.3LossFunction

Crossentropyisoneofthecommonlyusedlossfunctionst oevaluatethegapbetweenpredictedvalueandexpectedv alue.ThespecificformulaofcrossentropyisshowninEq. 2,wherepandqarerespectivelytheprobabilitydistributi onsofpredictionandexpectation.

$$H(p,q) = -\sum_x p(x)\log q(x) \qquad (2)$$

Accordingtotheaboveformula,crossentropydescribest hedifferencebetweentheprobabilitydistributionofpred ictionandexpectation,butinfact,theoutputofneuralnet workisnotnecessarytotheprobabilitydistribution,whic hdescribestheprobabilityofdifferentevents.Theprobab ilityofanyeventhasaprobabilitybetween0and1,andther ewillalwaysbeaneventtohappen.Tosolvetheproblemo fturningtheoutputofneuralnetworkintoaprobabilitydis tribution,Softmaxregressionmethodisused.Supposeth attheoutputpredictionvectorsoftheneuralnetworkarey $_1$,y$_2$,...,y$_n$,thentheoutputafterusingSoftmaxregression methodis:

$$soft\max(y)_i = y'_i = \frac{e^{yi}}{\sum_{j=1}^n e^{yj}} \qquad (3)$$

Accordingtotheaboveformula,theoutputoftheoriginal neuralnetworkisusedasconfidencetogeneratenewoutp ut,whichmeetsallrequirementsofprobabilitydistributi on.Inthisway,theoutputoftheneuralnetworkisturnedint oaprobabilitydistribution,sothatthedistancebetweenth epredictedprobabilitydistributionandtheactualprobab ilitydistributionoftherealanswercanbecalculatedbycro ssentropy.

Inthisresearch,theprobabilitydistributionofleft-turn,ri ght-turnandstraight-linedrivingactionspredictedbyC NNisamulti-classificationproblem,sothelossfunction usescrossentropy.

2.4NeuralNetworkOptimizationAlgorithm

Thefunctionoftheoptimizationalgorithmistominimize (ormaximize)thelossfunctionJ(x)byimprovingthetrai ningmethod.Someparametersinthemodelareusedtocal culatethedeviationbetweentherealandpredictedvalues ofthetargetvalueYinthetestset.Basedontheseparamete rs,thelossfunctionJ(x)isformed.Forexample,weight(

W)anddeviation(b)areinternalparameterscommonlyu sedtocalculateoutputvaluesandplayamajorroleintraini ngneuralnetworkmodels.Theinternalparametersofthe modelplayanimportantroleineffectivelytrainingthemo delandproducingaccurateresults.Thisisthereasonwhy variousoptimizationstrategiesandalgorithmsareusedt oupdateandcalculatenetworkparametersthataffectmo deltrainingandoutputtomakethemclosetoorreachtheo ptimalvalue.

Reversepropagationalgorithmandgradientdescentalg orithmarethecoreoptimizationalgorithmsofneuralnet work.Gradientdescentalgorithmistooptimizethesingle parameterinthenetworktoreducethelossfunction.Ther eversepropagationalgorithmperformsgradientdescent onallparametersoftheentireneuralnetwork,optimizesa llparametersonthedefinedlossfunction,andmakestheo veralllossfunctionoftheneuralnetworkreachasmallval ue.

Adamalgorithmisanadaptivetimeestimationmethod,w hichcanfurtheroptimizegradientdescentandhasagooda ccelerationeffectondeepnetworktraining.Thealgorith mcancalculatetheadaptivelearningrateofeachparamet er,whichnotonlystorestheexponentialdecaymeanofthe previoussquaregradientofAdaDelta,butalsoretainsthe exponentialdecaymeanofthepreviousgradientm_t.

$m_t$isthemeanvalueatthefirstmomentofthegradient,and $v_t$isthenon-centralvariancevalueatthesecondmomento fthegradient.

$$\hat{m}_t = \frac{m_t}{1-\beta_2^t}$$
$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

(4)

Then,thefinalformulaforparameterupdateis:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon}\hat{m}_t$$

(5)

Where,$\beta_1$issetto0.9,$\beta_2$issetto0.9999,andϵissetto10^{-8}.

Inpracticalapplication,Adamalgorithmworkswell.Co mparedwithotheradaptivelearningratealgorithms,Ada malgorithmismoreeffectiveanditsconvergencespeedis faster.Inaddition,someproblemsinotheroptimizationte chniquescanbecorrected,suchastooslowconvergences

peed,disappearanceoflearningrateorparameterupdate withhighvariance,sothatthelossfunctionfluctuatesgre atly.

3.StructureDesignofConvolutionNetworkModel

Therearemanykindsofneuralnetworkmodelsthatcanbe obtainedbycombiningthefivenetworkstructuresofinp utlayer,convolutionallayer,poolinglayer,fullconnectio nlayerandSoftmaxlayer,amongwhichmanyexcellentcl assicalconvolutionalnetworkmodelsareproposedtosol veimageprocessingproblemswithbettereffects,suchas VGGNetandResNet.Indeepnetworktraining,ResNeth asmoreobviousadvantages.Accordingtothelatestreco mmendationrankingofdeeplearningnetworkmodel,Re sNethasbecomeoneofthemostrecognizedefficientneur alnetworkmodels.Theproposeddeeplearningalgorith madoptstheResNetnetworkmodeltocontrolthetrainin gnetworkofthecarinthisresearch.

ResNet'smethodaimsatsolvingtheproblemofdeepneur alnetworkdegradation.Asthedepthoftheneuralnetwor kincreases,theaccuracycontinuestoriseuntilitreachess aturation.Ifthedepthcontinuestoincrease,theaccuracy willdecrease.Thissituationisnotcausedbyover-fitting, butbecauseintheprocessofneuralnetworktraining,noto nlytheerroroftestsetincreases,butalsotheerroroftrainin gsetincreases.Assumingthatthenetworkhasreachedthe accuracyofsaturation,apairofy=xcompletemappingla yersareaddedlater,andtheerrorwillnotrise,thatis,thepu rposeisachievedbyaddingresidualnetworkblocks,assh owninFigure4.Deeperneuralnetworksshouldnotleadt oincreasederror.Thefullmappinglayeradditionprincipl ementionedjustnowisthesourceofinspirationforResN et.Itworthsmentioningthat,ResNetwontheILSVRcha mpionshipin2015andreachedthetop5errorrateof3.57 %.

Fig.4.ResNetResidualNetworkBlock
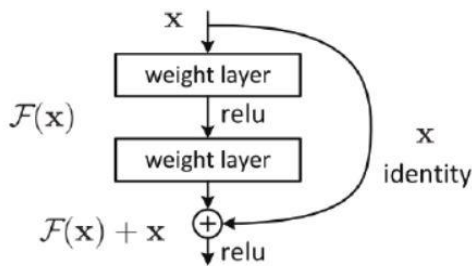

Fig.5.ResNet-50IncompleteBlock

Afterfurthertheoreticalresearchverificationanddevelopment,ResNetgenerallyhas18layers,34layers,50layers,101layers,and152layersdepthsofthesuperiorstructure.ResNet-50andResNet-101areparticularlycommonlyused.TheResNet-50convolutionalneuralnetworkmodelisadoptedinthisresearch.AsshowninFig.5.,theResNetmoduleisapartialincompleteblockofResNet-50(includingthree-layerconvolutionalnetwork),whichisknownasthe"buildingblock".Accordingtomanyrelevantresearches,theResNet-50networkisgenerallydividedintofiveparts,namelyconv1,conv2_x,conv3_x,conv4_xandconv5_x.Eachpartcontainsmultiple"buildingblocks",andthenetworkinall"buildingblocks"has50layersintotal.Finally,imageclassificationisprocessedthroughthefullconnectionlayerandSoftmaxlayer.TheResNet-50convolutionalneuralnetworkmodelisimplementedinTensorFlowframework.TensorFlowisamainstreamdeeplearningframeworkofGooglecompanyopensource,supportsavarietyofdeeplearningalgorithms,andcanautomaticallycompletecalculusandothercomplexcalculations.Inaddition,TensorFlowprovidestheinterfacetosupportC++andPythonlanguage,atthesametimecross-platformoperation.TensorFlowusesdataflowdiagramtodescribethecalculationprocess,andconvertseachcalculationintoanodeonthecalculationdiagram,andthelinesbetweennodesrepresenttheconnectionsbetweencalculations.
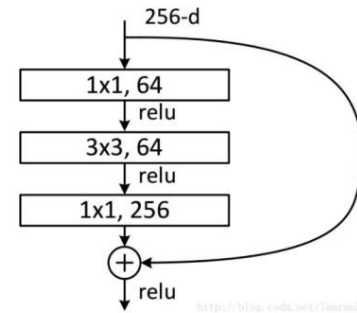
4.SystemDesignandImplementation

ThisdesignadoptsthetoycarcarryingRaspberriespieasexperimentplatform,andthecarwasdrivenbyusinganUSBcameraanddrivemotor.TheimagedatacollectedbythecamerawastransmittedbyusingtheRaspberrypietotheremotehostviawirelessnetwork,andthenthedrivingpredictionresultswasreturnedbytheremotehosttotheRaspberrypieforexecution.ThisdesignisimplementedbyTensorFlowGoogledeeplearningframework.The320*240resolutionimagedatacollectedbythecarinrealtimeweretakenastheinputofconvolutionalneuralnetwork,andthedrivingactionofthesametimestampwastakenasthedatalabel,thatis,eachtrainingdatashouldcontainthefirstvisualimageofthecarandtheappropriatedrivingdirectioncorrespondingtotheimage.Thefirstvisualimageofthecarandthecorrespondingdrivingactionwereallmanuallyselected.Therefore,thisalgorithmwasthesupervisedlearningalgorithmandthesamplecollectorwasthesupervisor.Inaddition,inordertoensuretherepresentativenessandadaptabilityoftrainingsamples,datawascollectedunderdifferentlightintensityandenvironmentalsites.Andtheconsistencyofthedataacquisitionstrategygreatlyaffectedtheentirenetworkstudyeffect.Thecardataacquisitionwasfocusedonthefirstrepresentativeofvisualimages,suchasthecarinfrontofbarrier-freewaskeptdrivingdirection,whenclosetotheobstaclebegantoadjuststeering,whichismoreconducivetoimageclassification.Thedataacquisitionshouldalsotrytoreducetheoccurrenceofbaddata,topreventtheoverfittingcausedbynoisedata.Thesampledatawasdividedinto80%trainingsetand20%testset,andthetrainingsetwasdividedintosmallbatchsetagain,whichwastrainedbyAdamadaptivelearningrateopti

mizationalgorithm.Thenetworkoutputtheprobabilitydistributionofforward,theleftandright,andcrossentropywasusedasthelossfunction.Bycontinuouslyreducingthelossfunctionandupdatingtheweightofnetworktrainingparameters,theoptimalvaluesofalltrainingparameterswereachieved.Incontrast,anoptimalabstractfeaturesamplerwastrainedintheconvolutionlayer.Afteroneiterationoftraining,thetestsetwasusedforverificationtocalculatethetestsetaccuracy.Accordingtothehightestsetaccuracy,aneuralnetworkmodelwithgoodeffectwasfinallyobtained.

4.1HardwareDesign

Accordingtothefunctionalrequirementsoftheautomaticdrivingsystembasedonend-to-endcontrol,thehardwarewasmainlydividedintofourparts:motordrivedesign,cameradesign,Raspberrypihardwareplatform,andremotehostPCterminalinteraction.TheoveralldesignframeworkisshowninFig.6.

DCmotordriverchipL298N:receiveRaspberrypieandsendPWMsignaltocontrolmotorrotation.

Raspberrypi3Bmaincontrol:collectcameradataandsendframedatatoPCthroughwirelesswifi;AcceptthePCterminaldrivingactioninstructionstodrivethemotor.

USBcamera:collectreal-timeimagedatawhenthecarismoving.

Remotehost:receivetheframedataofRaspberrypieandcalculatethepredictionresultofconvolutionalneuralnetworkmodel,returnthedrivingcommandtoRaspberrypie.
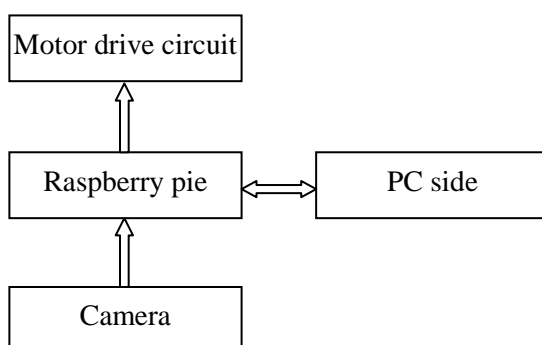
4.2SoftwareDesign

Firstly,systemloggedinRaspberrypieremotelythroughnetworkprotocolSSH.Then,makesurethatthetimezoneandtimesynchronizationbetweenRaspberrypieandPCbeforedatasamplecollectionbegan.Itthencalledthecamerain theRaspberrypieusingtheffmpegtoolandstoredthevideobufferstream.Itstartedtheprogramscripttoreceivethedrivingcommandofthecar,andcreatedanewcommandreceiverwebapplicationserviceintheRaspberrypie,whichisresponsibleforreceivingandexecutingthedrivingactiononthewirelessnetworkatanytime.

ThePCsidereadtheimageframedatafromffmpegserverserviceportofRaspberrypieinrealtime,andusedOpenCVtoopenthevideostreamonthePCside.Whileobtainingthecameraangleof Raspberrypie,theaccesscommandreceivedthewebservice.RaspberrypiereceivedthePCkeyboardkeyvaluefromtheport.Accordingtotheanalysisofkeyvalues,itistofindthecorrespondingdrivingcommandandtoachievethecomputerremotesynchronouscontrolofthecar.Fig.7.andFig.8.respectivelyshowtheflowchartofPCandRaspberrypie.
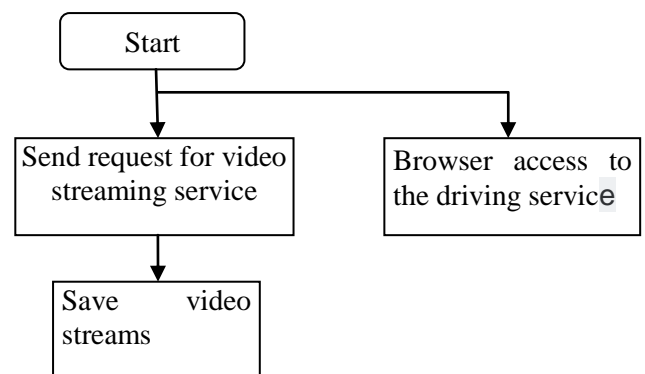

Fig.7.SampleDataCollectionSoftwareDesignFrameworkofPC
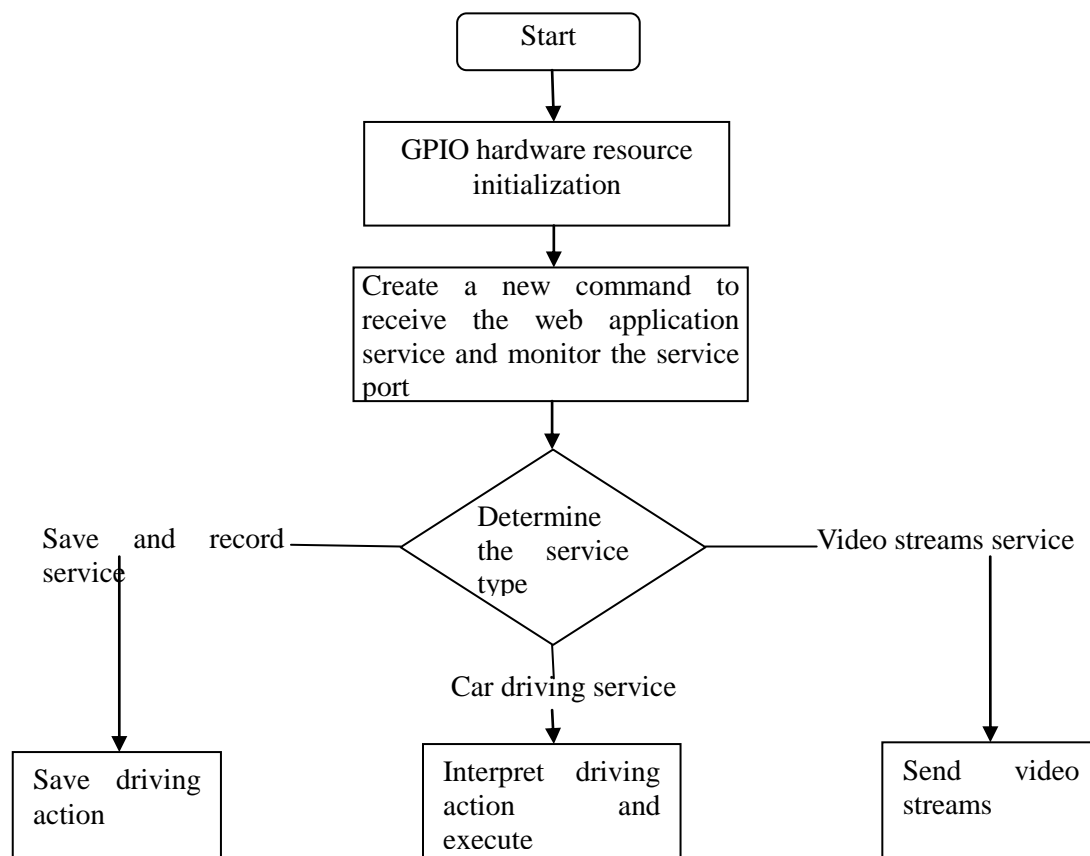

Fig.6.HardwareDesignBlockDiagram

Fig.8.SampleDataCollectionSoftwareDesignFrameworkofRaspberryPie

4.3SystemTest

Thesiteofthesoftwarecollectionwasinroom04010,zhonghailoulaboratory,GuangdongOceanUniversity.Firstly,thebackgroundwebservicereleasedbyRaspberryPI wasaccessedontheremotehostterminal,andthenthekeyboardkeyvaluewastransmittedthroughthewirelessnetworktocontrolthecarmovementandrecordthetimestampofthedrivingaction.Meanwhile,theRaspberryPIinthecarsentthecameradatatothehostforvideostreamingdatastorage.Finally,thetimestampsofthevideostreamanddrivingoperationswerematchedandpackagedintosampledata.Fig.9showsdataacquisitionprocess.

Fig.9.DataCollectionProcess
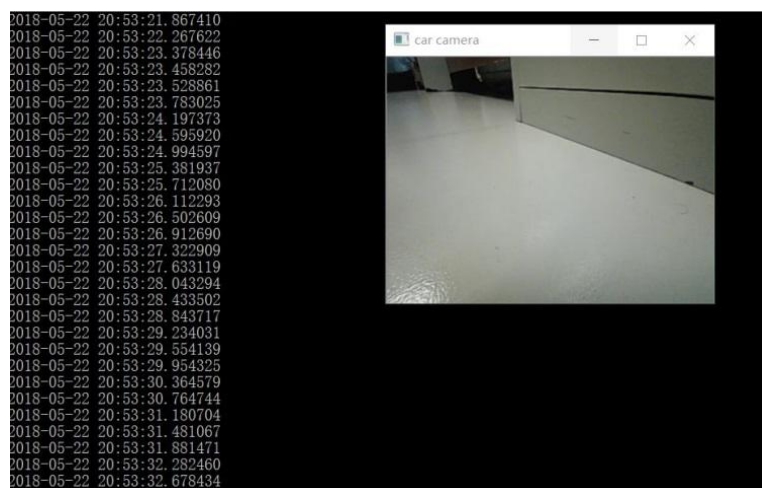
TheframeworktoolofTensorFlowwasusedtotrainRes Net-50neuralnetworkmodel,inwhichthesystemselecte dthegraphicscardplatformNVIDIAGTX1050,collecte dabout2GBimagedatavolume,anditeratedtrainingfor1 00timesintheconvolutionalneuralnetwork,andtheGP Uconsumedabout30hoursintraining.Aftertheinputofs ampledata,thenetworkmodelkeptlearningandtraining. Withtheincreaseofthenumberofiterations,theaccuracy becamehigherandhigher,upto89%.Theexperimentalre sultsshowthattheframeratecanreachabove30fpswithhi ghaccuracy.Fig.10showsthetrainingpartialresultsofth econvolutionalneuralnetwork.


```
epoch: 0, training accuracy: 0.3499999940395355, validation accuracy: 0.44999998807907104
epoch: 1, training accuracy: 0.5, validation accuracy: 0.5249999761581421
epoch: 2, training accuracy: 0.5, validation accuracy: 0.4749999940395355
epoch: 3, training accuracy: 0.574999988079071, validation accuracy: 0.6499999761581421
epoch: 4, training accuracy: 0.4749999940395355, validation accuracy: 0.5249999761581421
epoch: 5, training accuracy: 0.5, validation accuracy: 0.4000000059604645
epoch: 6, training accuracy: 0.574999988079071, validation accuracy: 0.5
epoch: 7, training accuracy: 0.5, validation accuracy: 0.6000000238418579
epoch: 8, training accuracy: 0.675000011920929, validation accuracy: 0.574999988079071
epoch: 9, training accuracy: 0.6000000238418579, validation accuracy: 0.675000011920929
epoch: 10, training accuracy: 0.6000000238418579, validation accuracy: 0.574999988079071
epoch: 11, training accuracy: 0.675000011920929, validation accuracy: 0.550000011920929
epoch: 12, training accuracy: 0.699999988079071, validation accuracy: 0.824999988079071
epoch: 13, training accuracy: 0.699999988079071, validation accuracy: 0.699999988079071
epoch: 10, training accuracy: 0.574999988079071, validation accuracy: 0.5
epoch: 11, training accuracy: 0.625, validation accuracy: 0.550000011920929
epoch: 12, training accuracy: 0.75, validation accuracy: 0.625
epoch: 13, training accuracy: 0.625, validation accuracy: 0.6000000238418579
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Fig.10.PartialResultsofNeuralNetworkTraining

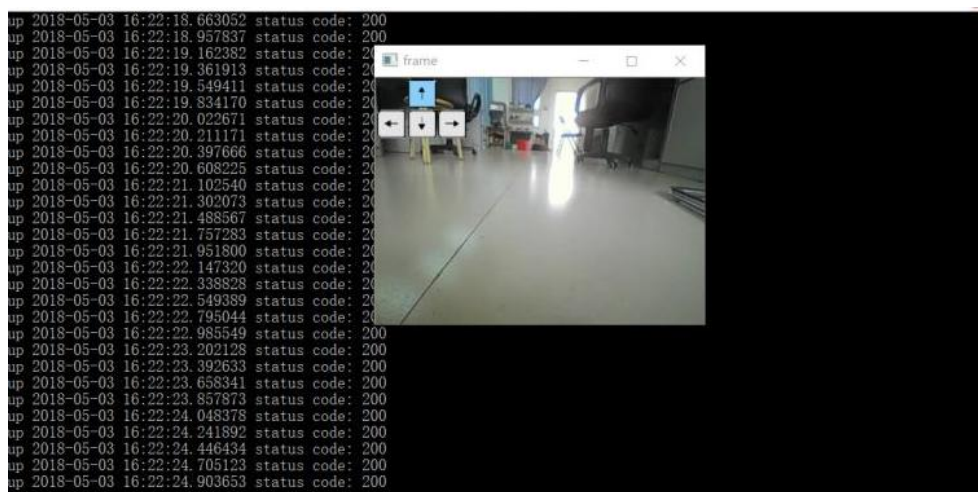Fig.11.TestResultUsingNeuralNetwork

5.Conclusions

Inthisresearch,anend-to-enddrivingschememodelbas edondeeplearningwasdesignedandimplemented.Ther eal-timetrafficimageswerelearnedthroughtheconvolut ionalneuralnetworktomapoutthecardrivingactions.Th isresearchfirstlyintroducedthedeeplearningalgorithm, namelythedeepconvolutionalneuralnetworkalgorithm ,anddescribedthestructuremodel,principleandmethod oftheconvolutionalneuralnetwork.Secondly,thestruct ureoftheconvolutionalnetworkmodelwaspresentedin detail.Thirdly,theGoogleTensorFlowdeeplearningope nsourceframeworkwasusedtotrainalgorithm.Experim entalresultsverifiedthefeasibilityofend-to-endautono mousdrivingtechnology.Thedefectofthissystemisthatt hesensorisnotperfectandthesystemislimitedbytheunc omplicatedfield.Theoveralldesignofthesystemneedst obefurtherimprovedwithcorrecttheoreticalsupport,wh iletheeeplearningalgorithmtheoryneedstobedevelop edoveralongerperiodoftime.

Acknowledgement

References

1. X. Chen. The Study on the Challenge and Development Prospect of Automated Vehicles. CHINA TRANSPORTATION REVIEW, 2016, (38): 9-13.

2. J. Long, E. Shelhamer, T. Darrell. Fully Convolutional Networks for Semantic Segmentation, Proc of IEEE Conference on Computer Vision and Pattern Recognition, 2015: 3431-3440.

3. K. Simonyan, A. Zisserman. Very Deep Convolutional Networks for Large-scale Image Recognition. Computer Science, 2014:1409+1556.

4. V. Badrinarayanan, A. Kendall, R. Cipolla. Segnet: a Deep Convolutional Encoder-decoder Architecture for Image Segmentation. IEEE Trans on Pattern Analysis and Machine Intelligence, 2017, (39); 2481-2495.

5. S. Ren , K. He, R. Girshick, et al. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2015, 39(6): 1137-1149.

6. Krizhevsky, I. Sutskever, G. E. Hinton. ImageNet Classification with Deep Convolutional Neural Networks, Proc of International Conference on Neural Information Processing Systems, 2012: 1097-1105.

7. H.C. Shin, H.R. Roth, M. Gao, et al. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Transactions on Medical Imaging, 2016: 1-1.

8. Szegedy, W. Liu, Y. Jia, et al. Going Deeper with Convolutions, Proc of IEEE Conference on Computer Vision and Pattern Recognition, 2015: 1-9.

9. S. Ullman. Against Direct Perception, Behavioral & Brain Sciences, 1980,3(3):373-381.

10. Chen, A. Seff, A. Kornhauser, et al. Deep Driving: Learning Affordance for Direct Perception in Autonomous Driving, 2015 IEEE International Conference on Computer Vision(ICCV), 2015: 2722-2730.

11. Y. Lecun, U. Muller, J. Ben, et al. Off-road Obstacle Avoidance through End-to-end Learning, International Conference on Neural Information Processing Systems, 2005: 739-746.

12. A. POMERLEAU. ALVINN: an Autonomous Land Vehicle in a Neural Network, Advances in neural information processing systems 1. Morgan Kaufmann Publishers Inc. 1989.

13. X. Han. Deep Learning Based Scene Recognition for Autonomous Driving, Sun Yat-Sen University, 2017.

14. Z. Yang. Research on Computer Vision Feature Representation and Learning for Image Classification and Recognition, South China University of Technology, 2014.

15. Y. Li , Z. Hao , H. Lei. Survey of Convolutional Neural Network, Journal of Computer Applications, 2016, (36): 2508-2515+2565.

16. Z. Sun, Chengxing Lu, Zhongzhi Shi, Gang Ma. Research and advances on Deep Learning, Computer Science, 2016, (43): 1-8.