Simulink Component Recognition Using Image Processing

Ramya R, Anand Kumar S, Krinish N K, Suraj V

ABSTRACT: In early stages of engineering design, pen-and-paper sketches are often used to quickly convey concepts and ideas. Free-form drawing is often preferable to using computer interfaces due to its ease of use, fluidity and lack of constraints. The objective of this project is to create a trainable sketched Simulink component recognizer and classifying the individual Simulink components from the input block diagram. The recognized components will be placed on the new Simulink model window after which operations can be performed over them. Noise from the input image is removed by Median filter, the segmentation process is done by K-means clustering algorithm and recognition of individual Simulink components from the input block diagram is done by Euclidean distance. The project aims to devise an efficient way to segment a control system block diagram into individual components for recognition.

Keywords: MATLAB, Median filter, K-means clustering algorithm

INTRODUCTION

Thisprojectpresentsanewcomputational model for automatically interpreting hand-drawnsketches of schematicdiagrams. Ourmodelemploysamulti-levelparsingand recognition architecture. Ourapproach allows userstocontinuously sketch withouthavingtoindicatewhenonesymbolendsandanewonebegins. Additionally, itdoes notrestrict thenumberof strokesinasymbol,ortheorderinwhichtheyaredrawn. Hence,iteliminates many ofthe unnaturalconstraintsimposedbyexistingsketch understandingsystems, suchaslimitations tosingle-stroke objects, orthe needfor userinvolvementinseparating differentsymbols.

EXISTING METHOD:

Ourapproach differsfromearliertechniquesinthat itactsselectivelyintheearly stagestoidentifyasmallsetofeasilyrecognizable“markersymbols.” Thesemarkers anchoraspatialanalysiswhichparsestheuninterpreted strokesintodistinct clusters, eachrepresentingasinglesymbol. Finally,asymbolrecognizer,informedbyclustering anddomainspecificknowledge,isusedtofindthebestinterpretationsofthestrokes. Wehavearguedthat thisapproachhastheadvantageofquicklyguidingtherecognizer intherightdirectionwhilepreventing unfruitful explorations.

- *Ramya R, Anand Kumar S, Krinish N K, Suraj V*
- *Assistant Professor, Department of Electronics and Instrumentation Engineering, Sri Ramakrishna Engineering College, India*
- *Department of Electronics and Instrumentation Engineering, Sri Ramakrishna Engineering College, India*

Thisworkemphasizes that techniquesaimed at uncoveringtheunderlyingstructureofasketch, suchas preliminary recognitionandstrokeclustering,canhaveasignificantbeneficialimpact oncomputationalefficiencyandrecognitionaccuracy. Thecomputationalcostofthe resultingsystemislowenoughtobesuitable forinteractive sketchunderstanding.

PROPOSED METHOD:

Todemonstrateourtechniques, wehavebuilt SimuSketch, asketch-based interfaceforMatlab’s Simulink package, and VibroSketch, asketch-based interface for analysingvibratory mechanicalsystems. Inboth systems,userscanconstruct functionalengineeringmodelsbysimplysketching themonacomputer screen. Users cantheninteractively manipulatetheirsketchestochangemodelparameters andrun simulations.

PROJECT FLOW:

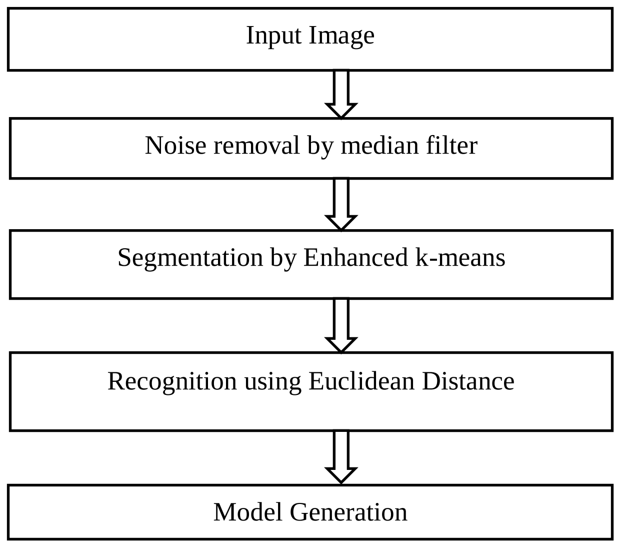
Input Image
Noise removal by median filter
Segmentation by Enhanced k-means
Recognition using Euclidean Distance
Model Generation

Fig 1.1 *Flow of Project*

The input image is scanned by the program. Noises are removed with the help of median filter. Objects on the image are segmented using K-means clustering algorithm.

The separate objects are recognised as theirrespective Simulink models. The new model is generated using the recognised components.

DIGITAL IMAGE PROCESSING

The Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modelled in the form of multidimensional systems.

GOALS OF DIGITAL IMAGE PROCESSING

The goal of digital processing is to improve the visualization of pathology by optimizing these physical parameters. Processing parameters need to be chosen correctly in order to overcome the inverse relationship between contrast and latitude while producing images that retain a conventional appearance. UMF is a simple technique for improving image quality. This technique, however, suffers from serious drawbacks, such as the suppression of pathologic lesions or artifacts that may simulate pathology. Manufacturers have developed different approaches in order to overcome problems and artifacts derived from this technique.

APPLICATIONS

Digital camera images

Digital cameras generally include dedicated digital image processing chips to convert the raw data from the image sensor into a colour-corrected image in a standard image file format. Images from digital cameras often receive further processing to improve their quality, a distinct advantage that digital cameras have over film cameras. The digital image processing typically is executed by special software programs that can manipulate the images in many ways. Many digital cameras also enable viewing of histograms of images, as an aid for the photographer to understand the rendered brightness range of each shot more readily.

Film

West world (1973) was the first feature film to use digital image processing to pixel late the android's point of view.

Intelligent transportation systems

Digital image processing has wide applications in intelligent transportation systems, such as automatic number plate recognition and traffic sign recognition.

COMPONENT RECOGNITION

There havebeennumerous effortstocreate experimental sketch understandingsystems. Thissectionbeginswithadiscussionofworkfocusedonsketch parsingandrecognition,andthensurveysexistingsketch based applications.

SYMBOL RECOGNITION

Graph basedmethods have beenoneofthe mostprominentapproaches to object representationandmatching, andhaverecentlybeenappliedtohand drawn patternrecognition problems. With thesemethods, sketched symbolsarefirstdecomposed intobasicgeometricprimitives,suchaslinesandarcs,whicharet henassembledinto agraph structurethat encodesboth the intrinsic attributesofthe primitives and the geometric relationships between them. Patterndetection isthen formulatedas agraph-sub graphisomorphismproblem,aproblemextensivelystudied bycomputer visionpractitioners. Thisapproach hasbeenusedtorecognize machine drawnsymbols, symbolsdrawn usingtemplates, and precisehand-drawn symbols. Thismethodprovidesautomatictraining, althoughthe drawingordermustbeconsistentacrossthetraining examples. Thesesortsofgraph- based approachesare sensitive tosegmentationerrors, andgraphmatchingcanbe expensive. Thismakesourapproachlesssensitivetosegmentationerrorsa nddrawing variations. Asan alternativeto graphicalmethods, therecognizeralsomakesuseofspecialgeometricpropertiesof particularshapes. Asitishard-coded, thisrecognizerisnoteasilyextended tonew symbols. Eachshapeisdescribedbyfour geometricfeaturescalculated fromthreespecialpolygonsdefinedbytheconvexhull oftheshape. Becausethisrecognizerworksfromtheconvexhullproperties, itcannot distinguish betweendifferentshapeswiththesameconvexhull.

SKETCH INTERPRETATION SYSTEM

Afewsketch-based interfaces havebeendevelopedforinterpretingelectricalcircuit sketches. Ituses hard-coded recognizersthat assume afixeddrawingorder. Also,the systemavoids issuesofparsing byrequiring theusertopause betweensymbols. Gatesmustbedrawnineitheroneortwostrokes. It describesatrainable recognizerforelectricalcircuitsymbols.Symbolsare classifiedbycomparing asymbol'sattributegraph tothat of aprobabilistic model of eachlearnedsymbol. Inaddition toelectriccircuits,recentyearshaveseenthedevelopmentof experimental sketch-based interfacesforavariety ofotherdisciplines. The program'staskisdetermine whatthegeometryof thesketchshouldhavebeentomakethesketcheddevicebehave asintended. Todo this, theprogram employsanovelbehavioural representation,calledqualitativecon- figuration space(qc-space), that captures the behaviour suggestedbyasketch while abstractingawaythe particulargeometry usedtosuggestthat behaviour. The programisconcernedonlywiththehigh-levelinterpretationof thesketch,anddoesnot considerthelow-levelissuesofparsingandsymbolrecognition.

PARSING AND RECOGNITION ARCHITECTURE

Thisapproach hasanumber ofdistinct advantages. First, byfocusingonmarker symbolsearlyon,itavoidsunfruitful explorationsandquicklydirectstheanalysis in therightdirection.Second,theapproachprovidesaplatformfor encodingcontextual knowledge. Forexample,attheconclusionoftheclustering step, thesystemcannarrow downthe set ofpossibleinterpretationsfor eachsymbol. Thisbothincreasesrecognitionaccuracyandreducesrecognitioncost. Finally, oncetheinitial analysisiscomplete,oursystemcanusedomainknowledge toidentifyandcorrecterrorsthat mayhaveoccurredduringparsingandrecognition.Whilethere aremany differentdomains thatcan makeuseofthe mark-group- recognizearchitectureoutlined above,thisthesisdemonstratesitsutility intwodo- mains. The firstinvolvesnetwork diagramsinwhichasetofsymbols(nodes) areconnected bya set ofarrows. The secondinvolvesvibratory mechanical systemswhichtypicallycontainobjectssuchasmasses,dampers,springs,external forcesand grounds.

FEATURE EXTRACTION

Afterresampling, afeature vectoriscomputed formingtheinput totheneuralnet- work. Unlikethe speedinformation usedinthepreviousrecognizer,thisrecognizer usesinformationrelatedtotheinverse-curvatureoftheresampledstroke. Theinverse-curvatureisrepresented asthecosineoftheanglesbetween linesegmentsconnectingconsecutivepoints. Althoughthecosineis notpreciselythe inverse-curvature,itiscloselyrelated toit,andisthussuitable forourpurposes. Hence,thesametechniquesusedfor identifyingthekey pointsinthespeed-basedrecognizercouldbeusedinthisrecognizer.Basedonthese keypoints, wecouldthen usethe samegeometric testsdescribed inSection4.2to decidewhether thestrokeisanarrow. Wehavetested thisidea,andfoundthat theperformanceofthehard-coded geometricteststobethesame,regardlessofwhether the keypoints aredetermined based onthe speedprofileorthe curvatureprofile.

Average

The average brightness of a region is defined as the sample mean of the pixel brightness within that region. The average, ma, of the brightness over the Λ pixels within a region (ℜ) is given by:

Avg=Σ a [m, n]

Alternatively, we can use a formulation based upon the (unnormalized) brightness Histogram, **h (a) = Λ•p (a)**, with discrete brightness values a. This gives:

m = Σ a•h[a]

The average brightness, ma, is an estimate of the mean brightness, µa, of the underlying brightness probability distribution.

Standard deviation and Variance

The unbiased estimateof the standard deviation of the brightness within a Region with Λ pixels is called the sample standard deviation and is given by: Often, we want some information about the precision of the mean we obtained. We can obtain this by determining the standard deviation of the sampled mean. The standard deviation of the mean is related to the standard deviation of the distribution by:

$$\sigma_{\mathrm{mean}} = \frac{1}{\sqrt{N}}\sigma$$

Where N is the number of observations in the sample used to estimate the mean. This can easily be proven with (see basic properties of the variance):

Covariance

For the covariance approximation we use the first-order Taylor expansion in matrix form

h(Y) M h(Y) + Vh(Y) (Y - Y)

Where,

V = [& . . . 21 denotes the (row) gradient operator.

Taking the covariance' of both sides yields the following

Well known approximation

Cov {B} = Cov {h(Y)} M Vh(Y) Cov{Y} Vh(Y)

STROKECLUSTERING

This sectiondescribesanalgorithm tolocate the distinctsymbolsinthe Simulinkdomain. Notethat thisstepisconcernedonlywithstrokeclusteringandnotrecognition. Recognitionisdeferreduntillater afteradditional sourcesofinformation, suchascontext, havebeenconsidered. The arrowanalysisidentifiesthe arrowsinthe sketchbutleavesthe restofthe strokesuninterpreted.Thegoalinthisstepistogrouptheuninterpreted strokesinto differentclusterssuchthat eachclusterformsadistinct Simulinkobjectthat canbe subsequently recognized. The keyideabehind strokeclusteringisthat strokes aredeemedtobelongtothesamesymbolonlywhentheyarespatially proximate. The challengeisreliably determiningwhentwopen strokes shouldbeconsidered close together. Here,werelyonthearrowstohelpmakethisdetermination. Innetwork diagrams,eacharrowtypically connectsasourceobjectatitstailtoatarget objectat itshead. Hence,differentclusterscanbe identifiedbygroupingtogetherall thestrokes that arenear theendof agivenarrow. Ineffect,twostrokesareconsideredspatially proximate ifthenearest arrowisthesameforeach.

SYMBOLRECOGNITION

Thischapter presentsanoverviewofthethreesymbolrecognizerswehavedeveloped, together withacomparative evaluationoftheadvantages anddisadvantagesofeach. Adetailed presentationofeachoftherecognizersiscontained inthefollowingchapters. Ashort descriptionofthe firsttworecognizerswerepresented previously.

Image-BasedRecognizer

Thedevelopmentofthefirstrecognizerwasinspired bytechniquesfrom imageprocessing.Symbolsareinternallyrepresented asquantized bitmap imageswecall"templates." Each symboliscantered within its template, and isuniformly scaledto fillit, thus making the approach insensitive to uniform scaling. Onedistinct advantageofthis recognizerovertraditionalonesisthat it canlearnnew definitionsfromsingle prototype examples. Anunknowntemplateis matched toadefinitiontemplate usinganensembleoffourdifferentclassifiers. These classifiersareextensionsofthe followingmethods:

1. Hausdorffdistance
2. ModifiedHausdorffdistance
3. Tanimoto coefficient
4. Yulecoefficient

Theseclassifierswereoriginallyintendedformatchingprecisebi tmaps. These rankings arecombined, and the definition with the best combined scoreisselected. Inpractice, thecombinedperformanceisbetter thanthatofanyof theindividual classifiers.Toachieverotation invariance, therecognizerusesanovel. Polar coordinate analysisthat avoidsexpensiverotations in thedrawingcoordinates. Therecognizerisversatileinthat weuseitbothforgraphicalsymbolrecognitionand digitrecognition.

K-means Clustering Algorithm of Segmentation

The K-means is another simple algorithm of segmenting or classifying images into k different clusters based on feature, attribute or intensity value. It is computationally efficient and does not require the specification of many parameters as compared to other method of segmentation. Unlike local thresholding, which can only group into two main classes while K-mean Algorithm can group into k different classes and that is part of the reason why we chosen as segmentation method for this work. The classification is done by minimizing the sum of the squares of distances between data and the corresponding clustering centroid. Type of distance calculation compatible with K-means Algorithm includes Manhalanobis and Euclidean distance etc.

LIMITATION AND FUTURE WORK

Obviously,thisworkisonlyasmallsteptowardachievingtrulynat ural andpractical pen-based computerinteraction and thereare many issuesthat remainunsolved. Someofthese issuesare notdirectlyaddressedby this study. For instance, ourtechniques aredevelopedprimarily for2Dsketches. Hence,itisnot clearwhether they canbeextended tosketches of3Dscenes. Likewise,ourtechniques aremost suitable forinterpreting"schematic" sketches, and are not particularlyusefulfor sketches that are "artistic"in nature. Also, although it would bean interesting study, this workdoesnot investigate howwellourtechniques canbeemployed in smallhand-held devices,suchaspersonaldigitalassistants. Insuchdevices,limited availability ofcomputationalresources,suchasprocessorspeedandRAM ,willplace additional constraintson thedesignofinteractiontechniques. Anotherareaofinterest maybetherecognitionof"static" inputsuchasscannedsketches. Insuchcases,the lackoftemporal dataleadingtothefinalsketchaddsanother levelofcomplexitynot addressedbythisstudy. Strokebeautification wouldnotonlycleanupunwarrantedartefacts inthesketcharisingfromtheimprecisionofthehumanhand,but couldalsoidentifyperceptually dominantattributesofthestrokes,suchasperpendicularity orenclosure. Wesuspectthat thiscouldsignificantlyaidsymbolrecognizers. Igarashi etal. presentasetoftechniques thatcan beusefulinthis endeavour. Similarly,morepsychologicallybasedapproaches, suchasGestalt principles,orthose presented bySaundmaybeconsidered.

CONCLUSION

Our userstudies haveindicated thateven noviceuserscaneffectively utilizethesesystemstosolverealengineeringproblems,without havingtoknowmuch about theunderlying recognitiontechniques. Toenhancetheuser's experiencewiththesesystems, however,itmaybenecessarytoadjustsomeofourassumptions aboutdrawingstyles, andimprovetherecognizersusedinthepreliminary recognitionstep. Althoughthetechniquespresentedinour projectaredemonstratedintwodomains, wespeculate that they are applicable to other domains aswell,such aselectrical circuitdiagrams, linkagedesigntools,userinterfacedesignsoftware,etc.Webelie veour symbolrecognizersformausefulandpractical suiteoftechniquesfortherecognition ofmultistroke symbols,andhencewehopeothersinthecommunity canmakeuseofthem.

REFERENCES

[1] Yuchi Liu and Yao Xiao, (2014) 'Circuit Sketch Recognition', Stanford University, Stanford, CA.

[2] Rajput G. G. and Mali S. M., (2010) 'Marathi Handwritten Numeral Recognition using Fourier Descriptors and Normalized Chain Code', IJCA, Special Issue on RTIPPR (3): 141–145.

[3] Scott D. Connell and Anil K. Jain, (1999) 'Template-based online character recognition'

[4] Levent Burak Kara and Thomas F. Stahovich, 'Hierarchical Parsing and Recognition of Hand-Sketched Diagrams', University of California.

[5] Joaquim A.Jorge and Manuel J.Fonseca, 'A Sample Approach to Recognise

Geometric Shapes Interactively', IST/UTL, Av.Rovisco Pais.

[6] Tracy Hammond and Randall Davis, 'Automatically Transforming Symbolic Shape Descriptions for Use in Sketch Recognition', MIT Computer Science and Artificial Intelligence Laboratory (CSAIL).

[7] Kevin Stolt, (2007) 'Sketch Recognition for Course of Action Diagrams', Massachusetts Institute of Technology.

[8] Gui-Huan Feng and Zheng-xing Sun, (2006) 'Sketch Understanding Using LR Modeling', Nanjing University.

[9] Howard Jay Siegel, Leah J. Siegel, Frederick C. Kemmerer, Philip T. Mueller, Jr., Harold E. Smalley, Jr. and S. Diane Smith, (1981) 'PASM: A Partitionable SIMD/MIMD System for Image Processing and Pattern Recognition', IEEE TRANSACTIONS ON COMPUTERS, VOL. c-30, NO. 12