OUTDOOR NATURAL SCENE IMAGE SEGMENTATION

KALAIVANI.K

10PCA05

A Project Report submitted to Avinashilingam Deemed University for Women, Coimbatore in partial fulfillment of the requirements for the Master of Computer Applications

MAY 2013

OUTDOOR NATURAL SCENE IMAGE SEGMENTATION

KALAIVANI.K

10PCA05

A Project Report submitted to Avinashilingam Deemed University for Women, Coimbatore in partial fulfillment of the requirements for the Master's Degree in Computer Applications

MAY 2013

SIGNATURE OF THE

HEAD OF THE DEPARTMENT

SIGNATURE OF THE

SUPERVISOR

SIGNATURE OF THE

EXTERNAL EXAMINER

ACKNOWLEDGEMENT

ACKNOWLEDGEMENT

I would like to express my sincere thanks to God Almighty, for His constant love and grace that He has showered upon me.

I am very grateful to **Dr.T.S.K.Meenakshi Sundaram, M.A., M.Phil., Ph.D., Chancellor,** Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for his support and encouragement during the course of my study.

I heartily thank **Dr. (Mrs).Sheela Ramachandran M.Sc., P.G. Dip., Ph.D., Vice Chancellor**, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore for extending all resources that facilitated the conduct of the presentstudy.

I express my humble gratitude to **Dr. (Mrs). Gowri Ramakrishnan M.Sc., M.Phil., Ph.D., Registrar**, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, for providing all facilities necessary for the study.

I am also thankful to **Dr. (Mrs). R. Parvatham M.Sc., Dip.Ed. M.Phil., Ph.D., Dean Faculty of Science**, for granting the facility required.

I wish to place on record my deep sense of gratitude to **Dr.(Mrs).G.Padmavathi M.Sc., M.Phil., Ph.D., Professor and Head, Department of Computer Science**, for providing all the facilities to complete the project.

I owe great deal of gratitude to my esteemed guide **(Dr).Mrs.Vasantha KalyaniDavid M.Sc.,M.Phil(Maths).,M.Phil(Comp.Sc).,Ph.d., Professor,Department of Computer Science**, for the constant encouragement and well timed support for the triumph of my project.

I take this unique opportunity to express my sincere thanks to my project Coordinator**Dr.(Mrs).V.Srividhya,M.Sc.,M.Phil.,Ph.D.,AssistantProfessor, Department of Computer Science**, for her kind advice and knowledgeable suggestion, which helped me to complete my project successfully.

I would extend my hearty thanks to my family members and all who helped me directly or indirectly for the successful completion of my project.

SYNOPSIS

SYNOPSIS

The aim of the project is image segmentation of outdoor scene based on Background Recognition and Perceptual Organization algorithm. Object boundaries in outdoor scene images are detected solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on a priori knowledge of the specific objects.

Based on background recognition and perceptual organization, background objects such as the sky, the ground, and vegetation based on the color and texture information are recognized. For the structurally challenging objects, which usually consist of multiple constituent parts, a perceptual organization model was developed that can capture the nonaccidental structural relationships among the constituent parts of the structured objects and, hence, group them together accordingly without depending on *a priori* knowledge of the specific objects. The experimental results show that the proposed method outperformed two state-of-the-art image segmentation approaches on challenging outdoor databases and achieved accurate segmentation quality on various twenty outdoor natural scene environments.

CONTENTS

CONTENTS

INTRODUCTION

1. INTRODUCTION

1.1 Overview of the project

Image segmentation is considered to be one of the fundamental problems for computer vision. A primary goal of image segmentation is to partition an image into regions of coherent properties so that each region corresponds to an object or area of interest. In general, objects in outdoor scenes can be divided into two categories, namely, unstructured objects (e.g., sky, roads, trees, grass, etc.) and structured objects (e.g., cars, buildings, people, etc.). Unstructured objects usually comprise the background of images. The background objects usually have nearly homogenous surfaces and are distinct from the structured objects in images. Many recent appearance-based methods have achieved without prior knowledge of its contents. The Gestalt psychologists summarized some underlying principles (e.g., proximity, similarity, continuity, symmetry, etc.) that lead to human perceptual grouping. They believed that these laws capture some basic abilities of the human mind to proceed from the part to the whole [8]. In addition to the classic Gestalt laws, recently, Jacobs [9] have pointed out that convexity also plays an important role on perceptual organization because many real-world objects such as buildings, vehicles, and furniture tend to have convex shapes. These Gestalt laws can be summarized by a single principle, i.e., the principle of non-accidentalness, which means that these structures are most likely produced by an object or process, and are unlikely to arise at random. In other words, the validation of Gestalt laws originates from the fact that these laws reflect the general properties of the man-made and biological objects in the world.

The medial axis transform decomposes a closed 2-D shape into a set of skeletal parts and their connections, providing a powerful parts-based decomposition of the shape that's suitable for shape matching [6]. While the medial axis-based research community is both active and diverse, it has not kept pace with the mainstream object recognition (categorization) community that seeks to recognize objects from cluttered scenes. The main reason for this disconnect is the restrictive assumption that the silhouette of an object is available – that the open problem of figure-ground segmentation has somehow been solved. Even if it were possible to segment the figure from the ground, a second source of concern arises around the instability of the resulting skeleton – the skeletal branches often don't map one-tone to the object's coarse symmetric parts.

A quantitative and objective measure of these grouping laws has to be found. The Gestalt laws are in descriptive forms. Therefore, one needs to quantify them for scientific use. Another challenge consists of finding a way to combine the various grouping factors since object parts can be attached in many different ways. Under different situations, different laws may be applied. Therefore, a perceptual organization system requires high accuracy in recognizing these background object classes.

The challenge for outdoor segmentation comes from the structured objects that are often composed of multiple parts, with each part having distinct surface characteristics (e.g., colors, textures, etc.). Without certain knowledge about an object, it is difficult to group these parts together. Some studies [2], [4] tackle this difficulty by using object-specific models. However, these methods do not perform well when the images contain objects that have not been seen before. Different from these studies, in this paper, our research objective is to explore detecting object boundaries in outdoor scene images solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on a priori knowledge of the specific objects.

It has been long known that perceptual organization plays a powerful role in human visual perception. Perceptual organization, in general, refers to a basic capability of the human visual system to derive relevant groupings and structures from an image combining as many Gestalt laws as possible. The greater the number of Gestalt laws incorporated, the better chance the perceptual organization systems may apply appropriate Gestalt laws in practices. Previous studies do not find elegant solutions for handling these two challenges.

1.2 Problem Description

The Bottom-up methods can be divided into two categories, namely, region-based and contour-based approaches. A group of approaches treats image segmentation as a graph cut problem. Finally the graph is bi-partitioned using the entries of the eigenvector. However the normalized cut criterion is an NP-hard computational problem.

Other problems are the high storage requirement and this approach has bias towards partitioning into equal segments. A state-of-the-art solution for the problems related to finding contours (segmentation curves), and finding junction (points joined by multiple contours). The contours are found by combining the local and global features.

The local cues are combined in a multi-scale oriented signal including brightness, color and texture gradients.

problem is formulated as minimizing a quadratic energy over binary variables. Let Xi Є {0, 1} be an indicator variable representing the presence of the i^{th} part in a cluster. We seek the subset of parts that minimizes the following energy,

$$E = \sum_{i} X_i \left(K - |Part_i|\right) + \sum_{i,j} X_i X_j O_{ij}$$

Where K controls the penalty of adding parts. In our experiments, it was found that K = 0.1. median {|$Part_i$|} is an effective setting for this parameter. The optimal X is found by solving a relaxed quadratic programming problem, in which real values are rounded to 0 or 1.

SYSTEM CONFIGURATION

2. SYSTEM CONFIGURATION

This section describes the hardware and software specification needed for both development and implementation phases of this project.

2.1 Hardware Specification

Processor	:	Intel® Pentium®
RAM	:	512 MB
Monitor	:	14 Inch HCL Color Monitor
Keyboard	:	HCL
Pointing device	:	Optical Mouse

2.2 Software Specification

Tool	:	MATLAB 7.10.0
Operating System	:	Microsoft Windows XP

2.3 About the software

Introduction About Matlab

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation.

Typical uses include Math and computation Algorithm development Data acquisition Modeling, simulation, and prototyping Data analysis, exploration, and visualization Scientific and engineering graphics Application development, including graphical user interface building MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This helps to solve many technical computing problems, especially those with matrix and vector formulations, in a fraction of the time it would take to write a program in a scalar non interactive language such as C or Fortran.

The name MATLAB stands for matrix laboratory. MATLAB was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects In university environments, it is the standard instructional tool for introductory and advanced courses in mathematics, engineering, and science.

Toolboxes are comprehensive collections of MATLAB functions that extend the MATLAB environment to solve particular classes of problems. Areas in which toolboxes are available include signal processing, control systems, neural networks, fuzzy logic, wavelets, simulation, and many others.

MATLAB has extensive facilities for displaying vectors and matrices as graphs, as well as annotating and printing these graphs. It includes high-level functions for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. It also includes low-level functions that allow you to fully customize the appearance of graphics as well as to build complete graphical user interfaces on your MATLAB applications.

The MATLAB API. This is a library that allows you to write C and Fortran programs that interact with MATLAB. It includes facilities for calling routines from MATLAB (dynamic linking), calling MATLAB as a computational engine, and for reading and writing MAT-files.

Key Features

- High-level language for technical computing
- Development environment for managing code, files, and data
- Interactive tools for iterative exploration, design, and problem solving
- Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
- 2-D and 3-D graphics functions for visualizing data
- Tools for building custom graphical user interfaces
- Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java™, COM, and Microsoft® Excel®

Syntax

- The MATLAB application is built around the MATLAB language. The simplest way to execute MATLAB code is to type it in the Command Window, which is one of the elements of the MATLAB Desktop. When code is entered in the Command Window, MATLAB can be used as an interactive mathematical shell. Sequences of commands can be saved in a text file, typically using the MATLAB Editor, as a script or encapsulated into a function, extending the commands available

Structures

- MATLAB supports structure data types. Since all variables in MATLAB are arrays, a more adequate name is "structure array", where each element of the array has the same field names. In addition, MATLAB supports dynamic field names (field look-ups by name, field manipulations etc). Unfortunately, MATLAB JIT does not support MATLAB structures, therefore just a simple bundling of various variables into a structure will come at a cost MATLAB can call functions and subroutines written in the C programming language or Fortran. A wrapper function is created allowing MATLAB data types to be passed and returned. The dynamically loadable object files created by compiling such functions are termed "MEX-files" (for MATLAB executable).

Interfacing with other languages

Libraries written in Java, ActiveX or .NET can be directly called from MATLAB and many MATLAB libraries (for example XML or SQL support) are implemented as wrappers around Java or ActiveX libraries. Calling MATLAB from Java is more complicated, but can be done with MATLAB extension, which is sold separately by MathWorks, or using an undocumented mechanism called JMI (Java-to-Matlab Interface), which should not be confused with the unrelated Java Metadata Interface that is also called JMI.

As alternatives to the MuPAD based Symbolic Math Toolbox available from Math Works, MATLAB can be connected to Maple or Mathematica.

MATLAB has a direct node with modeFRONTIER, a multidisciplinary and multi-objective optimization and design environment, written to allow coupling to almost any computer aided engineering (CAE) tool. Once obtained a certain result using Matlab, data can be transferred and stored in a modeFRONTIER.

Neural Network Toolbar

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. Neural network can train to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network.

Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings.

Throughout the toolbox emphasis is placed on neural network paradigms that build up to or are themselves used in engineering, financial, and other practical applications.

Key Features of Neural Network Toolbar

- Neural network design, training, and simulation
- Pattern recognition, clustering, and data-fitting tools
- Supervised networks including feedforward, radial basis, LVQ, time delay, nonlinear autoregressive (NARX), and layer-recurrent
- Unsupervised networks including self-organizing maps and competitive layers
- Preprocessing and postprocessing for improving the efficiency of network training and assessing network performance
- Modular network representation for managing and visualizing networks of arbitrary size
- Routines for improving generalization to prevent overfitting
- Simulink® blocks for building and evaluating neural networks, and advanced blocks for control systems applications

SYSTEM DESIGN

3. SYSTEM ANALYSIS

System analysis is the general term that refers to an orderly and structured procedure for identifying and solving problems. It involves the study of existing system to understand how they function. This knowledge will helps to identify what the new system should include.

3.1 Existing System:

- The outdoor segmentation comes from the structured objects that are often composed of multiple parts, with each part having distinct surface characteristics (e.g., colors, textures, etc.). Without certain knowledge about an object, it is difficult to group these parts together. Combining top-down and bottom-up segmentation, tackle this difficulty by using object-specific models. However, these methods do not perform well when the images contain objects that have not been seen before.
- Bottom-up image segmentation methods only utilize low-level features such as colors, textures, and edges to decompose an image into uniform regions. Bottom-up methods can be divided into two categories, namely, region-based and contour-based approaches.
- The normalized cut criterion that removes the trivial solutions of cutting small sets of isolated nodes in the graph.

- Contour closure is one of the important grouping factors identified by Gestalt psychologists. Early contour-based studies such as active contour methods only utilize boundary properties such as intensity gradients.
- The boundary detection as a supervised learning problem. They used a large data set of human-labeled boundaries in natural images to train a boundary model. Their model can then predict the possibility of a pixel being a boundary pixel based on a set of low-level cues such as brightness, color, and texture extracted from local image patches.

3.2 Proposed System

A new novel approach used to recovering and grouping the background objects such as the sky, the ground, and vegetation based on the color and texture information. A multi resolution super pixel segmentation to generate gestalt medial proximity point theory, and use a learned similarity function to perceptually group nearby medial points. A sparse set of multi scale medial hypotheses used to group those that are non-structure related parts. The learning of higher granularity similarity functions to group the resulting medial branches likely to belong to the same object.

SYSTEM DESIGN

4. SYSTEM DESIGN

System design is the process of planning a new system to complement or altogether replace the old system. The purpose of the design phase is the first step in moving from the problem domain to the solution domain. The design of the system is the critical aspect that affects the quality of the software. System design is also called top-level design. The design phase translates the logical aspects of the system into physical aspects of the system.

4.1 Input Design

As the project is concentrated fully on segmenting the image parts in outdoor scene which is considered for the process they convert image into small part of super pixel computation. Twenty images were taken for the study.

Outdoor image

A Natural image is simply one in which the 3 colors are shades of Red, Green and Blue. The reason for differentiating such images from any other sort of color image is that less information needs to be provided for each pixel. In fact a 'gray' color is one in which the red, green and blue components all have equal intensity in RGB space, and so it is only necessary to specify a single intensity value for each pixel, as opposed to the three intensities needed to specify each pixel in a full color image.

Often, the color image intensity is stored as a 16-bit integer giving 256 possible of 16*16*16 = 4096 bins. If the 3 levels are evenly spaced then the difference between successive levels are significantly better than the level resolving power of the human eye.

Figure 4.1: The Input image

4.2 Output design

Output design generally refers to the results and information that are generated by the system.

The first process is to load the image and calculate the dimensions. It has to be preprocessed for identifying the image values by calculating the mean and Co-variance. For the image color values are grouped into standard graph based algorithm. Then the image is tested for validation, removing the redundant parts in data and finding the error rate for the better performance on the basis of mean square error for the process.

SYSTEM DEVELOPMENT

5. SYSTEM DEVELOPMENT

5.1 Super Pixel computation

Most of the super pixels approximately correspond to object parts in that scene. A graph is built to represent these super pixels: Let G = {V, E} be an undirected graph. Each vertex corresponds to a super pixel, and each edge corresponds to a pair of neighboring vertices.

Super pixels are adequate for this task, balancing a data-driven component that's attracted to shape boundaries while maintaining a high degree of compactness. The super pixels at each scale are linked into a graph, with edges adjoining adjacent super pixels. Each edge is assigned an similarity that reflects the degree to which two adjacent super pixels represent medial points belonging to the same symmetric part.

In a region-based approach, super pixels effectively group together nearby contours that enclose a region of homogeneous appearance.

Each super pixel segmentation yields a super pixel graph, where nodes represent super pixels and edges represent super pixel adjacencies. If a super pixel represents a good medial point suggestion, it will extend to (and follow) the opposing boundaries of a symmetric part, effectively coupling boundaries through key form of perceptual grouping in continuity, where the intervening region must be locally homogeneous in appearance.

The original image Fig 4.1 will separated into four stage, that are 25, 50, 100, 200 and in each stage, super pixels check the similarity then group the pixels. The similarity is based on color and texture information

5.2 Background Identification in Outdoor Natural Scenes

The objects appearing in natural scenes can be roughly divided into two categories, namely, unstructured and structured objects. Unstructured objects typically have nearly homogenous surfaces, whereas structured objects typically consist of multiple constituent parts, with each part having distinct appearances (e.g., color, texture, etc.). The common backgrounds in outdoor natural scenes are those unstructured objects such as skies, roads, trees, and grasses.

5.3 Boundary Detection

Each boundary pixel in Fig 4.1 is mapped to a normalized coordinate system defined by the major and minor axes of the fitted circle, yielding a scale- and orientation-invariant representation of the region boundary. We compute a 2-D histogram on the normalized boundary coordinates weighted by the edge strength of each boundary pixel. This yields a shape context-like feature that reflects the distribution of edges along the presumed boundary of adjacent super pixels.

The symmetry law, in that the notion of maximal pixel translates to two opposing edges (soft (contour) and hard (image)) of a super pixel's boundary.

5.4 Clustering Affinity Points

If two adjacent super pixels represent two medial points belonging to the same symmetric section, they can be combined to extend the symmetry. This is the basis for defining the edge weights in the superpixel graph corresponding to each resolution. Specifically, the affinity between two adjacent superpixels represents the probability that their corresponding medial point hypotheses not only capture non-accidental relations between the two boundaries, but that they represent medial points that belong to the same skeletal branch. Given these affinities, a standard graph-based clustering algorithm applied independently to each scale yields clusters of medial points, each representing a medial branch at that scale.

Our Clustering affinity-based grouping yields a set of part clusters, each presumed to correspond to a set of attached parts belonging to a single object. However, any given cluster may contain one or more redundant parts. While such parts clearly belong to the same object, we prune redundancies to produce the final approximation to an object's skeletal part structure. The objective function selects a minimal number of parts from each cluster that cover the largest amount of image, while at the same time minimizing overlap between the parts.

5.5 Image Segmentation

A novel image segmentation algorithm for outdoor scenes is used. The research objective here is to explore detecting object boundaries solely based on some general properties of the real-world objects, such as perceptual organization laws, without depending on object-specific knowledge.

Given an outdoor scene image, the segment-merge technique is applied as described above to generate a set of improved superpixels. Most of the superpixels approximately correspond to object parts in that scene. A graph is built to represent these superpixels: Let G = (V, E) be an undirected graph. Each vertex $v_e \in E$ corresponds to a superpixel, and each edge $(v_e, v_f) \in E$ corresponds to a pair of neighboring vertices.

EXPERIMENTAL ANALYSIS

6. EXPERIMENTAL ANALYSIS

The images contain a wide variety of man-made and biological objects such as buildings, signs, cars, people, cows, and sheep. This data set provides ground truth object class segmentations that associate each region with one of eight semantic classes (sky, tree, road, grass, water, building, mountain, or foreground). In addition, the object class labels, the ground truth object segmentations that associate each segment with one physical object, are also provided.

Examining the results, the system has successfully extracted the major parts of the participant and correctly grouped them together. The parts were successfully recovered and clustered, but that the car was also recovered as a separate single-part cluster. The smaller trees, grass undetected in the background contains parts whose scale was smaller than our finest sampled scale.

A state-of-the-art class segmentation method Gould09 for reference on this data set. Like this method, Gould09 also used superpixels as a starting point. The normalized cut algorithm is used to generate 400 superpixels (per image) for use in the Gould09 method.

The small number of semantic classes does not affect this method. This method only requires identifying five background object classes (i.e., sky, trees, road, grass, and water). The remaining object classes are treated as structured objects. This method can handle many structured objects without recognizing them.

CONCLUSION

7. CONCLUSION

A novel image segmentation algorithm for outdoor natural scenes is used and this identifies some background objects as a starting point. Compared to the large number of structured object classes, there are only a few common background objects in outdoor scenes. These background objects have low visual variety and hence can be reliably recognized. After background objects are identified, the structured objects are known and then delimit perceptual organization in certain areas of an image. A constructive approach to detecting symmetric parts at different scales by grouping small compact regions that can be interpreted as deformable versions of maximal disks whose centers make up a skeletal branch. In this way, symmetry is integrated into the region segmentation process through a compactness constraint, while region merging is driven by a symmetry-based affinity learned from training data.

FUTURE ENHANCEMENT

8. SCOPE FOR FUTURE ENHANCEMENT

A number of limitations of the current framework will be addressed in future research. To improve the quality of medial point hypotheses, a more powerful superpixel extraction framework is explored that allows greater control over compactness, along with a multistage Pb detector. This linear axis model relaxed is to include curved shapes; for example, the ellipse model could easily be replaced by a deformable super ellipse. Finally, at the part grouping level, it is aimed to address the problem of object under segmentation (false positives) through the incorporation of closure constraints.

BIBLIOGRAPHY

BIBILIOGRAPHY

[1] T. Malisiewicz and A. A. Efros, “Improving spatial support for objects via multiple segmentations,” in Proc. BMVC, 2007.

[2] E. Borenstein and E. Sharon, “Combining top-down and bottom-up segmentation,” in Proc. IEEEWorkshop Perceptual Org. Comput. Vis., CVPR, 2004, pp. 46–53.

[3] X. Ren, “Learning a classification model for segmentation,” in Proc. IEEE ICCV, 2003, vol. 1, pp. 10–17.

[4] D. Hoiem, A. N. Stein, A. A. Efros, and M. Hebert, “Recovering occlusion boundaries from a single image,” in Proc. IEEE ICCV, 2007, pp. 1–8.

[5] D. Hoiem, A. A. Efros, and M. Hebert, “Recovering surface layout from an image,” Int. J. Comput. Vis., vol. 75, no. 1, pp. 151–172, Oct. 2007.

[6] D. D. Hoffman and M. Singh, “Salience of visual parts,” Cognition, vol. 63, no. 1, pp. 29–78, Apr. 1997.

[7] D. R. Martin, “An empirical approach to grouping and segmentation,” Ph.D. dissertation, U.C. Berkeley, Berkeley, CA, 2002.

[8] C. Pantofaru, C. Schmid, and M. Hebert, “Object recognition by integrating multiple image segmentations,” in Proc. ECCV, 2008, pp. 481–494.

[9] D. W. Jacobs, "What makes viewpoint-invariant properties perceptually salient?," J. Opt. Soc. Amer. A, Opt. Image Sci., vol. 20, no. 7, pp. 1304-1320, Jul 2003.

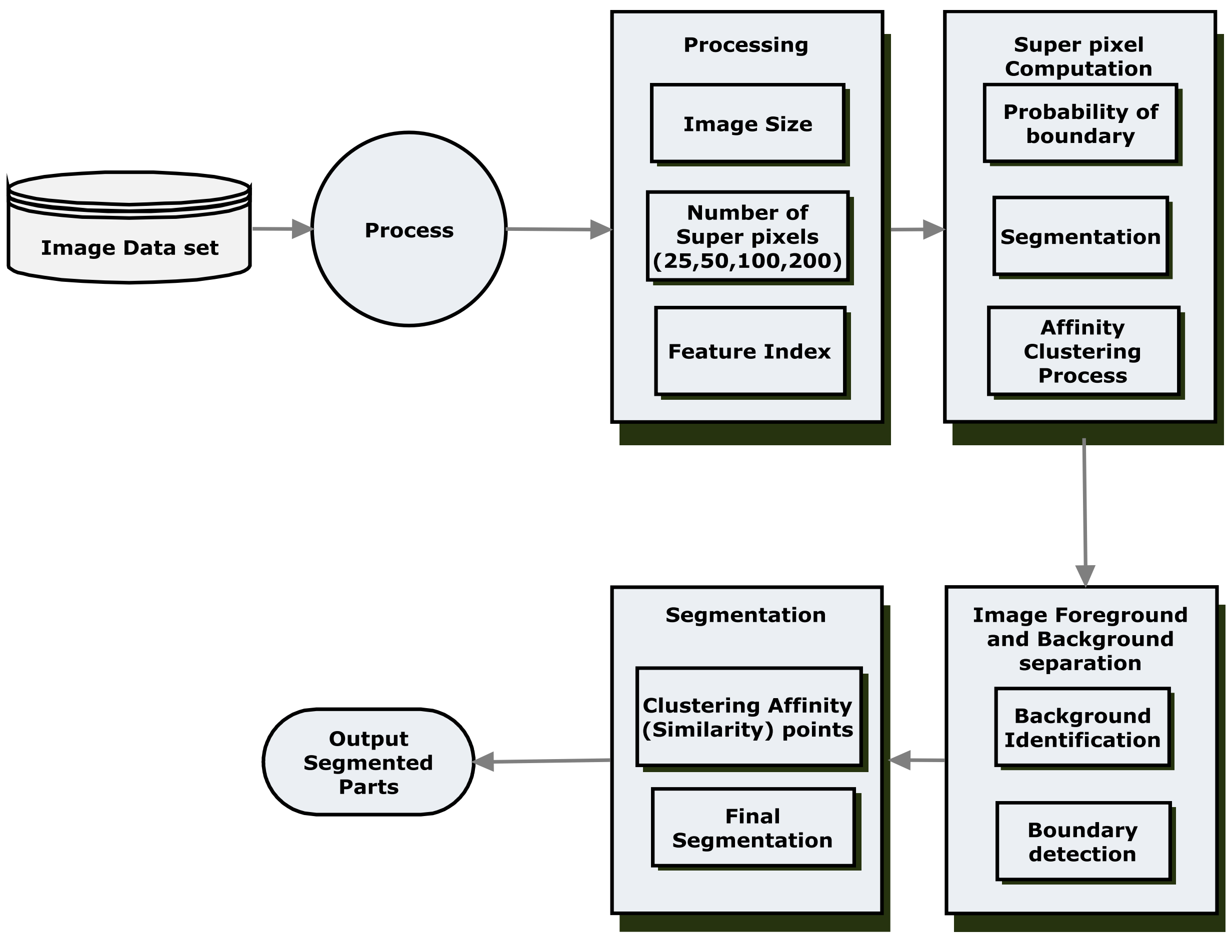
WEBSITE REFERENCES

1. www.cs.cmu.edu/~gunhee/publish/wacv08_gunhee.pdf
2. www.ijcsit.com/docs/.../vol3Issue6/ijcsit2012030627.pdf
3. www.cs.ru.nl/~marinav/Teaching/BDMinAI/kim95.pdf
4. www.comp.leeds.ac.uk/me/Publications/eccv02.pdf
5. www.computer.org/csdl/trans/tp/1996/01/i0069.pdf
6. www.bmva.org/bmvc/1995/bmvc-95-029.pdf
7. www.computer.org/csdl/trans/tp/2004/09/i1138.pdf

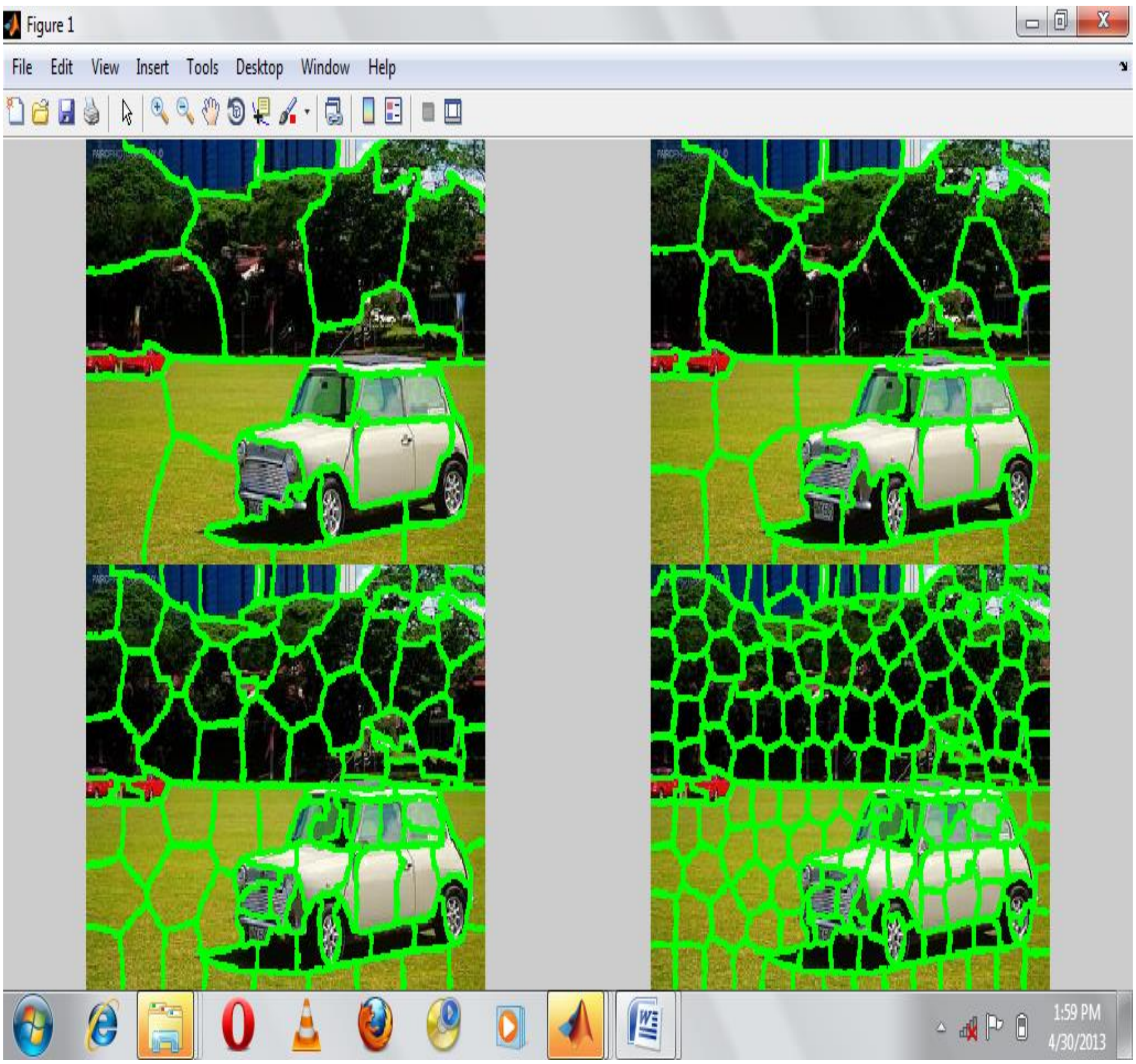
APPENDIX

APPENDIX

System Flow Diagram



Screen Shots



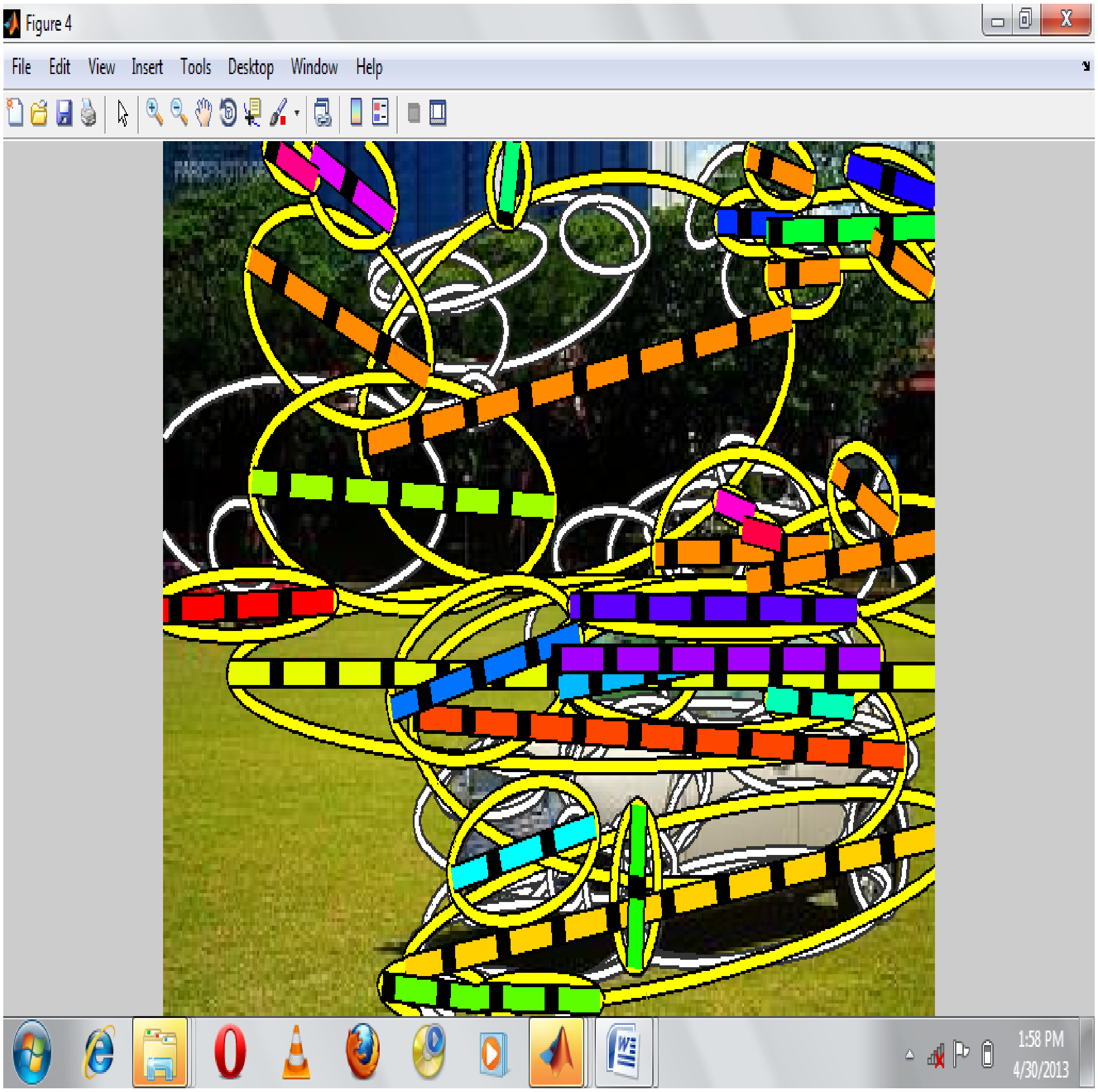


Figure 4
File Edit View Insert Tools Desktop Window Help
1:58 PM
4/30/2013

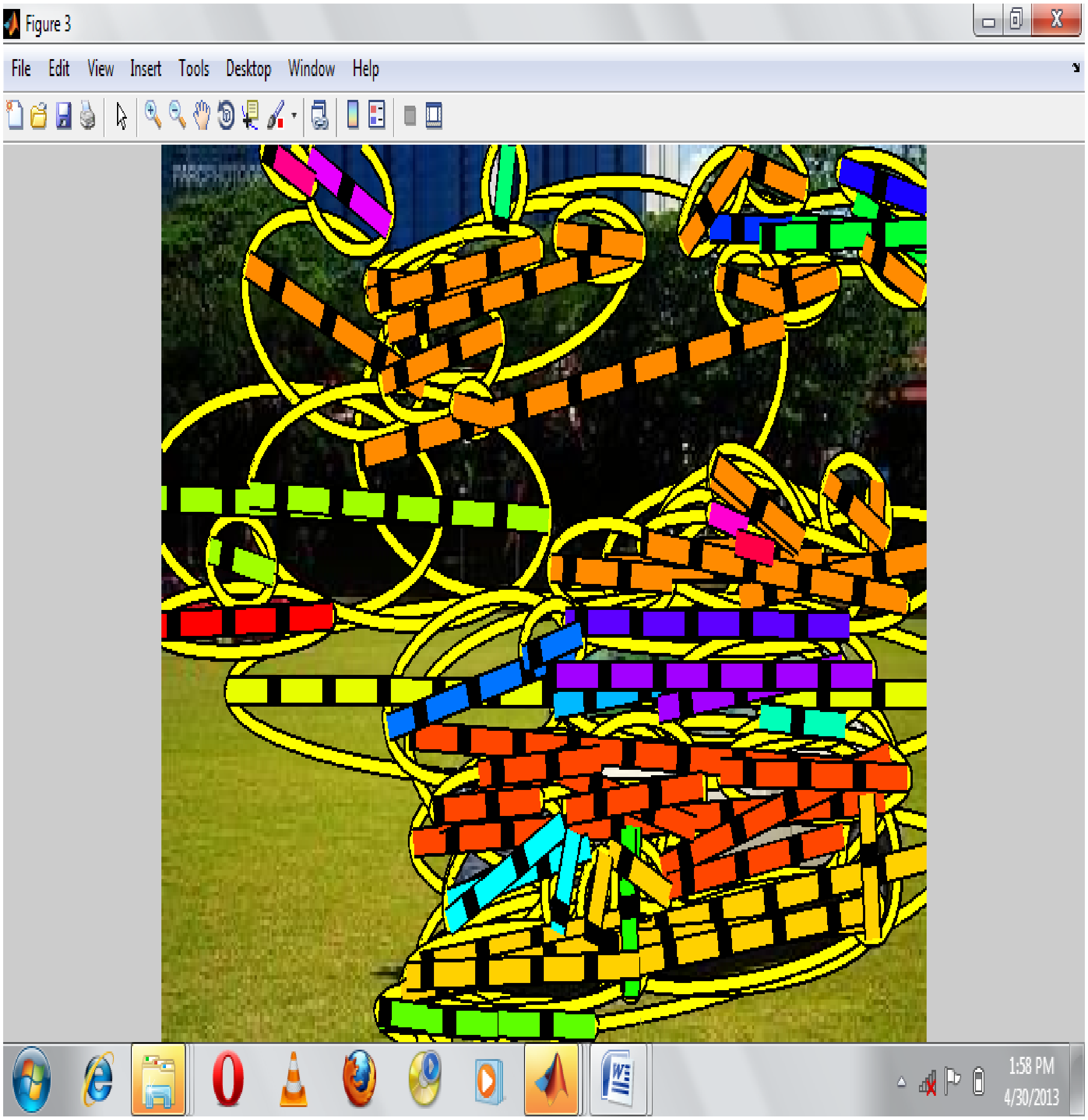


Figure 3
File Edit View Insert Tools Desktop Window Help
1:58 PM
4/30/2013

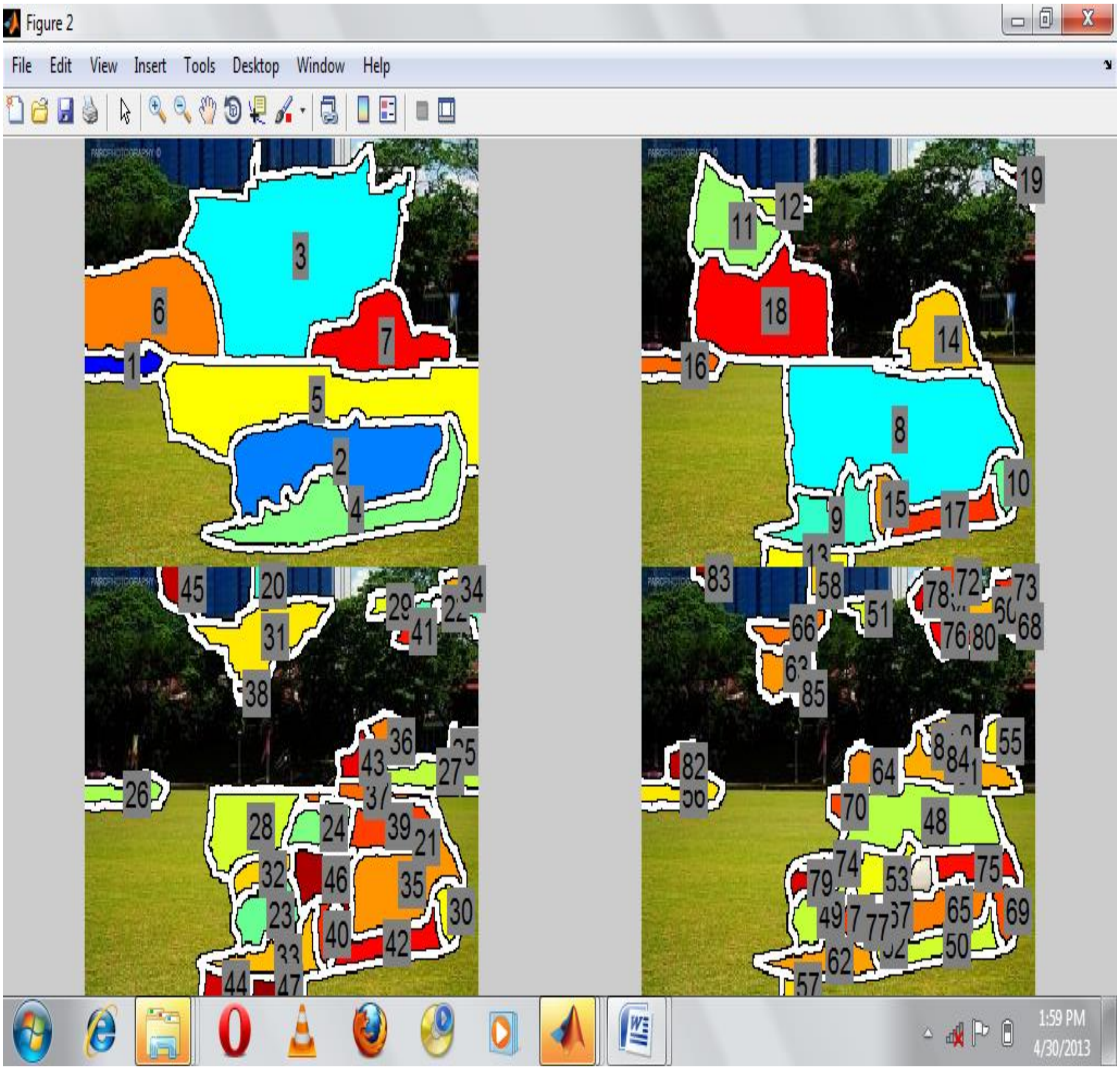


Figure 2
File Edit View Insert Tools Desktop Window Help
1:59 PM
4/30/2013