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# Advanced Techniques for Image Segmentation

Image Processing

 **LAMBERT**  
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Sultan H. Aljahdali  
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**Advanced Techniques for Image Segmentation**

# **Advanced Techniques for Image Segmentation**

**Dr. Sultan H Aljahdali & Mohd. Junedul Haque**

## **PREFACE**

This field of image and video segmentation is very hot topic, with much advancement in recent years. As a consequence, there is considerable need for books like this one, which attempts to bring the selection of latest results from the researchers involved in the area of image segmentation.

The purpose of this book is to assemble under one cover a brief knowledge about image segmentation techniques. This book provides an in-depth knowledge of the most important aspects of image processing, especially the image segmentation. The content of the book is designed to suit the requirements of computer science students at the undergraduate and postgraduate levels as well as for the advanced learners.

Image segmentation is one of the most critical task which has the objective of extracting information from an image or a sequence of images.

### **KEY FEATURES**

- Book is written in a clear, concise, and lucid manner, which makes it student-friendly.
- Text is well-structured and illustrated with solved examples and block diagrams.
- Inter-chapter dependencies are kept to a minimum.
- Chapter objectives at the beginning of each chapter describe what lies ahead in the chapter for the reader.
- Features like Notes, Key Points, Learn More, and Things to Remember appear throughout the book which enhances the reader's learning.
- Detailed coverage of the topics makes the book useful to both undergraduate and postgraduate students.

### **TARGET AUDIENCE**

- Primary usage of the book for the students of the courses offered by computer science, computer engineering, and information technology departments of various colleges and universities and research scholars.
- Professionals working in the areas of image processing.

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# **CHAPTER 1**

## **IMPROVED FUZZY ALGORITHMS FOR AUTOMATIC IMAGE SEGMENTATION**

In this chapter seeks an answer to the question: Can the fuzzy k-means (FKM), c-means (FCM), kernelized FCM (KFCM), and spatial constrained (SKFCM) work automatically without pre-define number of clusters. We present automatic fuzzy algorithms with considering some spatial constraints on the objective function. The algorithms incorporate spatial information into the membership function and the validity procedure for clustering. We use the intra-cluster distance measure, which is simply the median distance between a point and its cluster centre. The number of the cluster increases automatically according the value of intra-cluster, for example when a cluster is obtained; it uses this cluster to evaluate intracluster of the next cluster as input to the fuzzy method and so on, stop only when intra-cluster is smaller than a prescribe value. The most important aspect of the proposed algorithms is actually to work automatically. Alternative is to improve automatic image segmentation The proposed methods are evaluated and compared with the established methods by applying them on various test images, including synthetic images corrupted with noise of varying levels and simulated volumetric Magnetic Resonance Image (MRI) datasets.