

Wavelet Based Image Texture Segmentation using a Modified *K*-means Algorithm

by

Brian W. Ng

B.E. (FIRST CLASS HONOURS), B.Sc. (MA. & COMP. SC.)

Thesis submitted for the degree of

Doctor of Philosophy

in

Department of Electrical and Electronic Engineering,

Faculty of Engineering,

Computer and Mathematical Sciences

University of Adelaide, Australia

August, 2003

Contents

Contents	iii
Abstract	ix
Statement of Originality	xi
Acknowledgements	xiii
List of Figures	xv
List of Tables	xxv
Chapter 1. Introduction	1
1.1 Texture Analysis and Computer Vision	1
1.1.1 Texture Analysis	1
1.1.2 Texture Segmentation	2
1.2 Historical Perspective of Wavelets: Fourier Analysis	4
1.3 Time-frequency Representations	5
1.4 Wavelet Theory	7
1.5 Aims of this Thesis	8
1.6 Contributions of Thesis	9

Contents

1.7 Thesis Overview 10

Chapter 2. Wavelet Transforms 13

2.1 Multiresolution Analysis and Wavelet Transforms 13

2.1.1 Continuous Wavelet Transforms 13

2.1.2 Discrete Wavelet Transforms 15

2.1.3 Multiresolution Analysis and Orthonormal Wavelets 16

2.2 Fast Wavelet Transform and Perfect Reconstruction 21

2.2.1 The Fast Wavelet Transform algorithm 22

2.2.2 Perfect Reconstruction Filters 24

2.2.3 Implementation Issues 26

2.2.4 Symmetric Extended FWT 29

2.3 Wavelet Transforms by Lifting 32

2.3.1 The Lifting Theorem 32

2.3.2 Computational Advantages 35

2.4 Wavelet Packets and Best Basis 36

2.5 Multidimensional Wavelets 37

2.6 Dual-Tree Complex Wavelet Transform 40

2.7 Summary 48

Chapter 3. Texture Features 49

3.1 Historical Texture Features 50

3.1.1 Statistical Texture Analysis 51

3.1.2 Structural Texture Analysis 57

3.2 Filter-based Texture Features 59

3.2.1 Paradigm of Filter-based Approaches 60

3.2.2	Survey of Existing Filter-based Approaches	61
3.3	A Novel Feature Extraction Method	68
3.3.1	Features From Discrete Wavelet Transforms	69
3.3.2	Features From Complex Wavelet Transforms	72
3.4	Feature Conditioning	73
3.4.1	Feature Reduction	74
3.4.2	Normalisation	79
3.4.3	Windowing	80
3.4.4	Non-linear Transformation	83
3.5	Summary	85
 Chapter 4. Texture Feature Clustering		 87
4.1	<i>K</i> -means Clustering	87
4.1.1	Initialising <i>K</i> -means Clustering	90
4.1.2	Distance Measures in <i>K</i> -means	91
4.1.3	Estimating <i>K</i>	93
4.1.4	Algorithmic Variations of <i>K</i> -means Clustering	94
4.2	Fuzzy <i>K</i> -means Clustering	97
4.3	KLM Algorithm	100
4.4	Neural Networks	105
4.5	Support Vector Machines	107
4.5.1	Learning Machines	108
4.5.2	Capacity: the VC Dimension	109
4.5.3	Linear SVM	110
4.5.4	Non-Linear SVM	113

4.5.5 Multi-class Problems 114

4.5.6 Concluding Remarks 116

4.6 Summary 116

Chapter 5. Texture Segmentation Experiments **119**

5.1 Data and Experimental Setup 119

5.1.1 Input Images and Methodology 119

5.1.2 Feature Parameters 120

5.1.3 Clustering Parameters 122

5.2 Feature Properties 126

5.2.1 Spatial Separation Criterion 127

5.2.2 Feature Contrast 128

5.2.3 Distance Histogram 129

5.2.4 Summary of Feature Separability 135

5.3 Experiments with K -means 138

5.4 Experiments with Fuzzy K -means 145

5.5 A Modified K -means Clustering 150

5.5.1 Modification to Existing K -means 150

5.5.2 Expected Behaviour of Modified K -means 152

5.5.3 Distance Histograms for Modified K -means 153

5.5.4 The Distortion Measure 156

5.5.5 Results from Experiments 160

5.5.6 Segmented Images 171

5.5.7 A Potential Indicator 176

5.6 Experiments with Modified Fuzzy K -means 179

5.7 Experiment Summary	182
Chapter 6. Application Examples	185
6.1 Surveillance	185
6.2 Object Segmentation	189
6.3 Document Processing	195
6.4 Applications Summary	197
Chapter 7. Conclusions and Future Work	199
7.1 Summary	199
7.2 Future Directions	202
7.2.1 Smart Feature Selection	202
7.2.2 Classifier Improvements	203
7.2.3 Integration with Other Vision Systems	204
7.3 Closing Remarks	204
Appendix A. Texture Segmentation Data	207
A.1 Ground Truth Images	207
A.2 Two-texture mosaics	210
A.3 Five-texture mosaics	211
A.3.1 Original mosaics	211
A.3.2 Randen mosaics	212
A.3.3 University of Bonn database	214
A.4 Ten-texture mosaics	231
A.5 Sixteen-texture mosaics	231
Appendix B. Detailed Texture Segmentation Results	233

Contents

B.1 Conventional <i>K</i> -Means	234
B.2 Fuzzy <i>K</i> -Means	240
B.3 Modified <i>K</i> -Means	246
B.4 Modified Fuzzy <i>K</i> -Means	252
Appendix C. List of Publications	259
Bibliography	261

Abstract

In the field of computer vision, texture analysis has historically been an important topic of study. Texture is one of the major primary visual cues to image understanding. The human visual system relies on texture, among other types of cues, to effectively interpret the information contained in an image. Therefore, it is imperative that a fully functional artificial vision system must perform texture analysis. However, effective texture analysis has proved to be a difficult problem. This is mainly due to fundamental difficulties with texture - it is more of a concept than a well-defined object or property. Without an unambiguous definition of texture, researchers have to resort to various models and techniques, all of which have their own advantages and disadvantages. Traditionally, there have been three main approaches to texture analysis: statistical, structural and filter-based. While statistical and structural approaches have been favoured by early researchers, more modern techniques are typically filter-based. This thesis presents a type of filter-based technique. There are two main areas within texture analysis: classification and segmentation, but this thesis only covers the segmentation problem.

Wavelet transforms are a relatively new analytical tool in the scientific community. It is commonly accepted that wavelet theory grew out of classic Fourier analysis. Despite its widespread usefulness, Fourier analysis has several deficiencies; wavelet theory is among many others that attempt to address such problems. Primarily, wavelet transforms decompose signals into joint time-frequency bases, instead of harmonic ones. The inherent multiresolution property associated with joint time-frequency representations makes wavelet transforms far more suitable for analysing non-stationary signals. As a result,

wavelets have been used in many different applications in the relatively short period of time since its introduction.

In this thesis, wavelet transforms are chosen as the primary analytical tool for texture analysis. In particular, a recent advancement in wavelet transforms, called the Dual-Tree Complex Wavelet Transform, is applied to the texture segmentation problem. While the wavelet transform is believed to be a suitable analytical tool, there are other problems to be overcome before a texture segmentation system can be built. Specifically, the feature extraction and feature clustering methods need to be investigated. This thesis examines several possibilities for feature extraction and clustering steps. In particular, novel feature extraction and clustering schemes are introduced and compared to other known techniques. An extensive range of experiments are performed on the texture mosaics, to verify the effectiveness of the proposed feature extraction and clustering methods. The set of inputs to the experiments are carefully chosen as to allow direct comparison with existing methods, so a meaningful indication of the quality of the proposed segmentation system can be obtained. It has been found that the proposed system is capable of producing accurate, highly consistent segmentations on the test mosaics. With the success on the test mosaics, the segmentation system is then applied to several real-world applications. In the real examples, it is found that the system produces more erratic results, often as a consequence of the lack of any problem-specific input to assist the segmentation process. Overall, the proposed system, using wavelet based features, compares well with existing schemes for basic texture segmentation tasks.