

**The ALISA Shape Module: Adaptive Shape Recognition  
using a Radial Feature Token**

by  
**Glenn C. Becker**

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**The ALISA Shape Module:  
Adaptive Shape Classification  
using a  
Radial Feature Token**

**By**

**Glenn Charles Becker**

**M.S. (CS), 1988 The George Washington University  
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**Dissertation directed by:**

**Peter Bock  
Professor of Machine Intelligence and Cognition**

## **Abstract**

The ALISA Shape Module: Adaptive Shape Classification

using a Radial Feature Token

By Glenn Charles Becker

Directed by Professor Peter Bock

Shape classification is a challenging image processing problem because shapes can occur in any position, at any orientation, and at any scale in an image. Shapes can also be obscured by gaps in their boundaries, occlusions, and noise. General shape classifiers often suffer from low precision, and specialized shape classifiers rely on specific features, like vertices or connected boundaries, making them difficult to generalize. The objective of this research is to design, implement, and test a general, high-precision two-dimensional shape classifier that is invariant to translation, scale, and rotation, as well as robust to gaps in the shape boundary, occlusions, and noise. To achieve this objective, the radial feature token (RFT) is implemented as the ALISA Shape Module, which learns to classify shapes in ALISA geometry maps derived from a supervised set of training images. These learned shapes are stored as a set of vectors that are then used to classify shapes in test images. Experiments have demonstrated that this method can learn to classify general shapes from small training sets, as well as effectively classify similar shapes independent of their position, scale, and orientation. The Shape Module is also robust to gaps in shape boundaries, occlusions, and noise. The Shape Module is also shown to outperform some established shape recognition techniques, such as the Generalized Hough Transform.

## **Dedication**

This dissertation is dedicated to my loving and patient family

Linda, Adam, & Melissa

## **Acknowledgements**

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## Acronyms and Abbreviations

### A

ALISA Adaptive Learning Image and Signal Analysis system  
ART Adaptive Resonance Theory

### B

B/W Black and white

### C

CVL Class vector list

### G

GHT Genralized Hough Transform

### L

LGN Lateral Geniculate Nucleus

### M

MAT Medial Axis Transformation

### N

NLP Natural Language Processing

### O

OCR Optical Character Recognition

### R

RFT Radial Feature Token  
RM Reconstructive Matching

### S

STM Symbolic Translation Matrix

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## List of Symbols

$\mu$	arithmetic mean
$\sigma$	standard deviation
$\theta_R$	radii angle in Radial Feature Token
$C()$	confidence
$\mathcal{D}$	distance metric
$\mathcal{V}$	coefficient of variation

# 1. Introduction

## 1.1 Summary

This dissertation presents a process for classifying shapes in digital images using a radial feature token (RFT) and classical statistical methods to learn shapes from training examples and then classify similar shapes in test images. Shape classification is a very important part of image analysis because it identifies the objects of interest in an image. Finding and classifying general shapes in images is a difficult process that is exacerbated by variations in translation, rotation, and scale, as well as gaps, occlusions, and noise. For purposes of this research, all shape classes are assumed to be translation, rotation, and scale invariant.

Assumption 1: All shape classes are translation, rotation, and scale invariant.

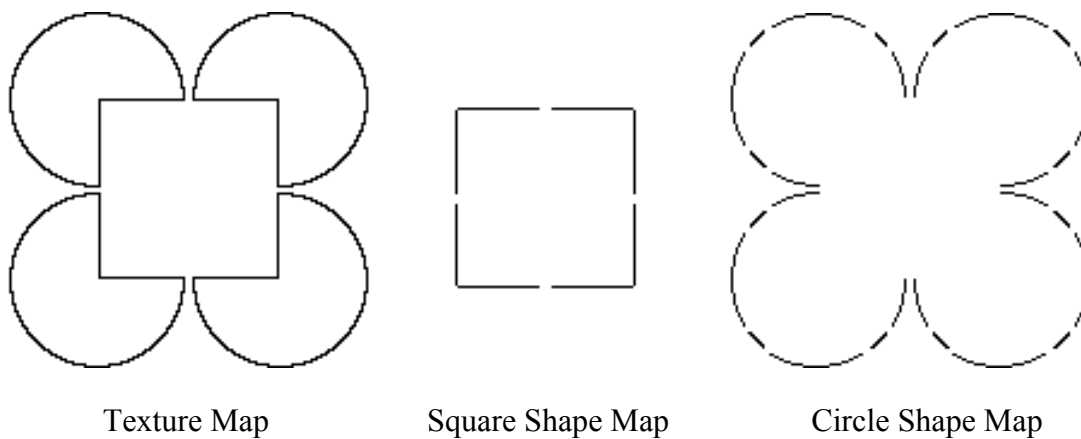
### 1.1.1 Problem Description

This research addresses shape classification in digital images, a common problem in the field of image analysis. Image analysis is the process of transforming image data to enhance or isolate particular information in an image. Image enhancement techniques improve the aesthetic appearance of an image or enhance a particular characteristic of an image making it easier to analyze. Examples of image enhancement transforms include algorithms that sharpen edges, blur edges, increase contrast, or increase color saturation. Isolating particular information in an image is a critical step in many forms of image analysis. Examples of these transformations include the Fourier transform and the

discrete cosine transform used to isolate frequency information, the Hough transform used to isolate simple shape information, and Sobel operators used to find intensity gradients or edges.

Image characteristics must be isolated and quantized so that a classification process can assign these characteristics to a particular class. Suitable characteristics used to classify images or image regions must be carefully selected for each application. Selected characteristics must consistently represent the information needed to discriminate among potential classes.

The radial feature token (RFT), introduced in this work, has proven to be a very effective way to represent the characteristic spatial relationship among edges that make up a shape. One goal of this research is to show that the RFT's ability to classify shapes is robust to gaps in shape boundaries. One example of this is the Kanizsa Square (Figure 1-1), which is easy for humans to see but has proven to be difficult for machine vision algorithms. [GROS88]



**Figure 1-1 Kanizsa Square**

### **1.1.2 Performance Criteria**

The quantitative performance metrics recall, precision, and F1 (widely used in information retrieval) are used to objectively evaluate the performance of the ALISA Shape Module. These metrics are used to measure the **correctness** of the Shape Module's classifications. Where "correctness" means the correspondence between the hypothesis output by the system and the expected class defined by the experimenter.

### **1.1.3 Related Work**

The review of related work looks at typical features used in image analysis and classification, the biological precedents and motivations behind the RFT design, and existing shape classification methods.

Selecting well-suited features for a particular application is critical for achieving good results from a classifier. Features must preserve and isolate the discriminating image characteristics needed for a particular application. Feature extraction transforms the data represented in an image region into a single value. The feature value must preserve that part of the information used by the classifier to discriminate among the available classes. The feature value must also isolate the discriminating information, to the greatest extent possible, from extraneous information that does not participate in class discrimination.

The design of the RFT has been motivated by recent studies into the operation of the retina and visual cortex of mammals. Although the RFT does not model the operation of

these cortical structures, its radial configuration and focus within an image are motivated by these biological systems.

The shape class representation must store the data extracted as representative shape features and allow for the manipulation of that data by the classifier. The two main class representation paradigms discussed are constraint satisfaction methods, which represent shapes as basic constituent parts, and adaptive classification methods, which learn from examples how best to characterize a shape. Both of these broad categories of shape recognition algorithms are currently in use. Constraint satisfaction algorithms take information about edges and vertices in images and try to match it with its own internal model of shapes. Adaptive classification systems extract features from images and match them with class clusters in feature vector space. Several examples of each of these methods are discussed along with their advantages and disadvantages.

#### ***1.1.4 Research Objective***

**To design, implement, and test a general high-precision two-dimensional shape classifier that is invariant to translation, scale, and rotation, as well as robust to gaps in the shape boundary, occlusions, and noise.**

#### ***1.1.5 Solution***

The Radial Feature Token (RFT) is introduced and used to build feature vectors that are used to classify shapes. The RFT classifies shapes based on their edges, which will be described as segments. The RFT is centered on individual segments to make all feature calculations relative to the segment position and thus independent of translation. The

radial nature of the RFT makes it insensitive to rotation. The distance measures accumulated by the RFT are normalized to make the resulting vector scale independent as well. The experiments detailed in this research show the effectiveness of the RFT to learn and classify shapes independent of their position, scale, or orientation in an image.

The RFT and its supporting processes are implemented as the ALISA Shape Module which is an integrated module of the ALISA system. Appendix A contains a detailed discussion of the other modules in the ALISA system.

### **1.1.6 Research Goals**

The Research Objective is restated as a set of formal Research Goals. The main goal and its tree of supporting goals are shown. Formal experiments are then designed and conducted to determine whether or not the Shape Module can satisfy the goals at the leaf nodes of the goal tree.

***Primary Research Goal: To measure the performance of the ALISA Shape Module using the radial feature token (RFT) for classifying general two-dimensional shapes independent of translation, scale, rotation, presence of gaps, occlusions, and noise.***

### **1.1.7 Formal Experiments**

The performance of the ALISA Shape Module was measured using formal performance metrics. Validating the Primary Research Goal required testing each possible combination of experiment factors

### **1.1.8 Conclusions**

Conclusions include a summarization of experimental results and the conclusions that can be drawn from them. The conclusions also include recommendations for future research in this area.



## 1.2 Original and Significant Contributions

The following ideas and techniques are believed to be the major original and significant contributions presented in this research:

1. Shape classification in a hierarchical system, based first on texture and geometry classifications.
2. The radial feature token used to characterize the spatial relationships among edges.
3. Generalized shape classification that is high precision, rotation invariant, and has continuous scale invariance.

## 1.3 Document Organization

**Chapter 2** reviews the related work, terminology, and precedents that form a context for understanding the Shape Module. The basics of feature extraction and quantization are discussed, as well as, several paradigms already in use for storing this feature information and using it to classify image contents. Chapter 2 also contains a discussion of the biological motivations that led to the design of the RFT.

**Chapter 3** discusses the operation of the ALISA Shape Module in the context established in Chapter 2. Chapter 3 presents the processes of segmentation, training, and classification that are performed within the Shape Module.

**Chapter 4** presents the formal research goals that are tested by the experiments described in Chapter 5.