

# Fuzzy Clustering Paradigm and the Shape-Based Image Retrieval

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## Abstract

This paper presents a strategy for shape-based image retrieval in which moment invariants form a feature vector to describe the shape of an object. Fuzzy  $k$ -means clustering is used to group similar images in an image collection into  $k$ -clusters whereas neural network is used to facilitate efficient retrieval of similar images against a given user-provided query image. Retrieval results and performance of the proposed scheme are compared with a setup involving  $k$ -means clustering.

## Introduction

Shape is one of the most important image features for use in Content-Based Image Retrieval. Though difficult, this feature alone has the ability to provide image recognition and similarity based image retrieval. An effective use of this feature requires a meaningful description of salient shape features. A review of shape representation and description techniques and a set of criteria for evaluation of a shape can be found in (Zhang & Lu 2004). The most popular and widely used among such schemes is the one proposed by Pavlidis (Pavlidis 1978). It is based on the use of shape boundary points and does not use any other features of a shape.

## Proposed Scheme

In this paper, we propose an efficient indexing and shape-based retrieval scheme. In this scheme, moment invariants (MI) are used for shape representation using boundary points while neural network (NN) is used as an intelligent search engine. Fuzzy  $k$ -means (FKM) clustering is used to manage extracted image features and to provide learning samples for the NN. The moments of a given query image are computed on-the-fly and the established index consisting of moments of stored images is utilized to retrieve similar shape images. Figure 1 shows the overall architecture of the proposed system.

Moments (Hu 1962) are widely used in a number of visual information processing applications. MI are derived from shape moments and are not changed during two-dimensional geometric transformations. They are compact and provide low calculation overhead. Details of moments and MI can be

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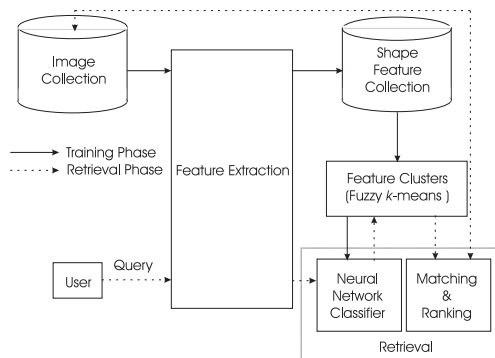


Figure 1: System Architecture

found in (Chen & Ahmad 2007). The boundary information of a shape is used to compute its MI. Therefore, the feature vector in our case consists of the seven computed moments and is used to index shapes in the image database. All of the computed moments are normalized into [0,1] by the limit values of each dimension.

Simply speaking, clustering is the grouping of *similar* data. Fuzzy  $k$ -means and fuzzy  $k$ -means are two different types of clustering schemes. In  $k$ -means clustering, a data item can belong to one and only one of the  $k$  clusters whereas the FKM clustering (deGrujter & McBratney 1988) facilitates identification of overlapping clusters of objects by allowing an object to belong to one or more clusters.

Let  $N$  is the number of data items,  $K$  is the number of clusters and  $u_{ij}$  represents the membership values of data among given clusters such that  $1 \leq i \leq N$  and  $1 \leq j \leq K$ . If  $D_{ij}$  is the measure of distance from sample  $x_i$  to the center of a cluster  $c_j$  then the objective of FKM clustering is to minimize the objective function:

$$J = \sum_{j=1}^K \sum_{i=1}^N u_{ij}^m D_{ij}^2$$

Larger membership values indicate higher confidence in assignment of a pattern to a given cluster. The *fuzziness* of clustering is controlled by the parameter  $m$ ,  $m \geq 1$ . As  $m$  approaches 1, the partition of data is based on binary decision. However, as  $m$  is increased, membership degrades towards a fuzzy state that may also be more robust to outliers

(Bezdek 1981). Initial values of  $u$  are either selected at random or determined according to prior information about the group structure. In our experiments, we randomly selected initial values of  $u$  and selected  $m = 3$ . This value provides us a reasonable overlap of clusters while still allowing to maintain their individualistic characteristics.

Performance of a classification system like this one is highly dependent on the clustering technique. If the underlying clustering scheme involves hard decisions, an image can be part of only one cluster. In these situations, if the query image is determined to belong to a specific cluster that does not happen to contain this image, one may never be able to find it even though it does exist in the database. However, if fuzzy clustering is used, the query image may point to one or more clusters. This may increase the possibility of finding relevant images even though the system may retrieve some additional non-relevant images.

Our choice of NN design is a 3-layer architecture since it can form arbitrarily complex decision regions and is based on the study presented in (Lippmann 1988). As mentioned earlier, MI are used as a training sample for our NN, feeding the input layer. Therefore, the input layer consists of 7-nodes while the number of nodes in the output layer are same as the number of clusters  $k$ . The NN has two hidden layers. In our scheme, NN training is a two step process: (i) feed-forward and (ii) back-propagation. During the back-propagation, the associated error of each layer is fed to its previous layer and weights connecting the two layers are adjusted accordingly. The extent of similarity between the query image and the database images is determined using correlation distance function.

## Experimental Results and Discussions

For performance evaluation, our image database consists of 10,000 images from a number of different domains, obtained from the Amsterdam Library of Object Images (ALOI) (URL 2008). Selected image set contains 200 different groups of images such that each group has 50 images which are identified as relevant whereas images from different groups are all considered to be irrelevant images.

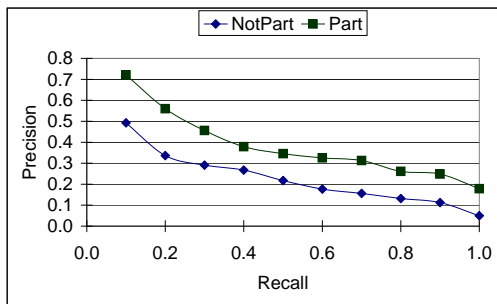


Figure 2: Evaluation of system performance

We have evaluated the performance of our system for a number of different parameters using various different distance functions. Due to space limitations, results presented here are based only on the correlation distance function since it focuses on similar variations of the feature vector.

Average results of one such set of experiments are presented in Figure 2. In these experiments, one of the database images is selected as the query image to imply that the system has encountered similar images during its training phase. In another set of experiments, images used as query images are not part of the training samples, implying that the system has not encountered similar shapes before. In both of these cases, we are able to retrieve nearly all of the relevant images (i.e., 100% recall) but at the expense of reduced precision, i.e., some non-relevant images are also retrieved. In practice, it is always better to find all of the relevant images even at the expense of reduced precision rather than not being able to find some of the potentially relevant images.

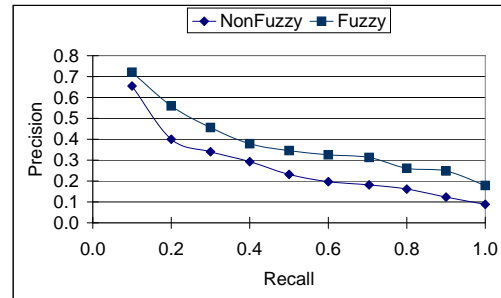


Figure 3: Fuzzy  $k$ -means clustering Vs  $k$ -means clustering

We have compared the performance of our proposed system with the one given in (Chen & Ahmad 2007) employing simple  $k$ -means clustering. Results of these comparisons for  $k = 5$  and thresholds  $\gamma = 0.4$  are given in Figure 3. It is obvious that the FKM clustering always performs better than the  $k$ -means clustering since the selection of appropriate cluster(s) is not based on hard decisions but on the degree of membership as mentioned earlier.

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