CONTENT BASED MEDICAL IMAGE RETRIEVAL USING SHAPE DESCRIPTORS

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Abstract - Content-Based Image Retrieval (CBIR) refers to image retrieval system that is based on visual properties of image objects rather than textual annotation. Contents of an image can be of various forms like, texture, color, and shape etc. In this work, shape is selected as a primary feature in indexing the image database. CBIR for medical images has become a major necessity with the growing technological advancements. This paper presents the basics of image retrieval process that includes the two techniques for image retrieval and about the Fourier descriptor to extract the features of image which is one of the important research contents in content based image retrieval process. Different shape signatures have been exploited to derive Fourier descriptors, however Fourier descriptors derived from different signatures can have significant different effect on the retrieval process.

Keywords - CBIR, Shape Signatures, Medical Image Database, Fourier Descriptors.

I. INTRODUCTION

Image retrieval is the task of retrieving digital images from a database. An image retrieval system in medical applications is often part of or has to interact with a PACS-System. Image retrieval systems are used in the way in which querying and retrieval is done. The possible kinds of queries were already introduced in the introduction:

- Meta information, like the patient’s name
- A textual description, like “An X-ray image showing a fracture in the lower left arm”.
- Visual information.

Computer technologies progress makes yesterday’s imagination today’s reality. The evolvement of the Internet is the main stream of this wave. Internet is the reinvention of Gutenberg printing. With the same goal – information distribution and sharing, the Internet does it much better.

On internet one of the most engaging projects happening is the digital library, which is, in the simplest term, the digitalization of library. Although modern technology provides enough storage capacity and computing power to manipulate the digital information, the biggest problem is left unsolved – the integration of human's knowledge and perception for automation. The digitalization of information surely increases the amount of available information for anyone, but the usability does not increase with the amount. Usually, most people will be scared by the huge information monster.

A digital image is a numeric representation (normally binary) of a two-dimensional image. Images are of two types:

- Raster Images
- Vector Images

Raster images have a finite set of digital values, called picture elements or pixels. The digital image contains a fixed number of rows and columns of pixels. Raster images can be created by a variety of input devices and techniques, such as digital cameras, scanners, coordinate-measuring machines, seismographic profiling, airborne radar, and more.
A. Applications of Image Retrieval

- Crime prevention.
- Medicine.
- Fashion and graphic design.
- Publishing and advertising.
- Architectural and engineering design.

B. Types of Image Retrieval

There are two major approaches of image retrieval

- Text-based (description based) image retrieval (TBIR)
- Content based image retrieval (CBIR)

Text-based image retrieval (TBIR) makes use of the text descriptors to retrieve relevant images. Some recent studies found that text descriptors such as time, location, events, objects, formats, absolutionness of image content, and topical terms are most helpful to users. The advantage of this approach was that it enabled widely approved text information retrieval systems to be used for visual retrieval systems.

Content-based means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself.

C. Image Features

Various types of image features are:

- Color (histograms, gridded layout, wavelets)
- Texture (Laws, Gabor filters, local binary partition)
- Shape (first segment the image, then use statistical or structural shape similarity measures) [2]
- Objects and their Relationships

D. Applications of CBIR

Examples of CBIR applications are:

- Crime prevention: Automatic face recognition systems, used by police forces.
- Security Check: Finger print or retina scanning for access privileges.
- Medical Diagnosis: Using CBIR in a medical database of medical images to aid diagnosis by identifying similar past cases.
- Intellectual Property: Trademark image registration, where a new candidate mark is compared with existing marks to ensure no risk of confusing property ownership.

E. Medical CBIR Systems [4]

Medical images play a pivotal role in surgical planning, medical training, and patient diagnoses. In large hospitals thousands of images to be managed every year. These images need to be indexed, classified, and searched for easy retrieval.

II. PROBLEM FORMULATION

A. Problem Motivation

Image databases and collections can be enormous in size, containing hundreds, thousands or even millions of images. The conventional method of image retrieval is searching for a keyword that would match the descriptive keyword assigned to the image by a human categorizer. Currently under development, even though several systems exist, is the retrieval of medical images based on their content, called Content Based Medical Image Retrieval, CBMIR.

B. Problem Statement

The problem involves entering a medical image as a query into a software application that is designed to employ CBMIR techniques for medical images in extracting visual properties, and matching them. This is done to retrieve images in the database that are visually similar to the query image.

C. Implemented Solution

The solution initially proposed was to extract the primitive features of a query image and compare them to those of database images. The image features under consideration were shape. Thus, using matching and comparison algorithms shape features of one image are compared and matched to the corresponding features of another image. This comparison is performed using shape distance metrics. In the end, these
metrics are performed one after another, so as to retrieve database images that are similar to the query.

**CBMIR Framework**

![CBMIR Framework Diagram](image)

**III. IMPLEMENTED ALGORITHM**

**A. Pre-processing**

To extract the coordinates of the boundary from the object shape a pre-processing step is performed, which consists of the following stages.

- Initially binarise the shape image.
- A denoising step is performed to eliminate isolated pixels and small isolated segments.
- Shape is then traced using the 8-connectivity contour tracing technique. Let \( z(t) = (x(t), y(t)) \), \( t = 0, 1, \ldots, L-1 \) be the obtained coordinates.

By using equal arc length sampling method the above obtained coordinates is sampled to fixed number of points, which is termed as shape signature, \( s(t), t = 0, 1, \ldots, L-1 \).

**B. Shape signatures**

In general, a shape signature is any 1-D function representing 2-D areas or boundaries. Three shape signatures are considered in this paper, these are complex coordinates (position function), curvature and cumulative angular function. The reason for choosing these three shape signatures for test and comparison is because they are mostly used in recent FD implementations and have been shown practical for general shape representation. In the following, we assume the shape boundary coordinates \( (x(t), y(t)), t = 0, 1, \ldots, L-1 \) have been extracted in the preprocessing stage.

1) **Complex coordinates**: A complex coordinate’s function is simply the complex number generated from the boundary coordinates:

\[
z(t) = x(t) + iy(t) \quad (2.1)
\]

In order to eliminate the effect of bias, we use the shifted coordinates function

\[
z'(t) = [x(t) - x_c] + i[y(t) - y_c] \quad (2.2)
\]

where \( (x_c, y_c) \) is the centroid of the shape, which is the average of the boundary coordinates

\[
x_c = \frac{1}{L} \sum_{t=0}^{L-1} x(t), \quad y_c = \frac{1}{L} \sum_{t=0}^{L-1} y(t) \quad (2.3)
\]

2) **Centroid distance**: The centroid distance function is expressed by the distance of the boundary points from the centroid \( (x_c, y_c) \) (2.3) of the shape

\[
r(t) = [(x(t) - x_c)^2 + (y(t) - y_c)^2]^{1/2} \quad (2.4)
\]

Due to the subtraction of centroid, which represents the position of the shape, from boundary coordinates, the centroid distance representation is also invariant to translation.

3) **Curvature signature**: Curvature represents the second derivative of the boundary and the first derivative of the boundary tangent. The curvature function used is defined as the differentiation of successive boundary angles calculated in window \( w \):

\[
k(t) = \theta(t) - \theta(t - 1) \quad (2.5)
\]

however, this curvature function defined in this way has discontinuities at size of \( 2\pi \) in the boundary, therefore, in this paper we use:

\[
\theta'(t) = \arctan \frac{y(t) - y_c}{x(t) - x_c} \quad (2.6)
\]

where \( (t) \) is defined in (2.8).

\[
k'(t) = \theta'(t) - \theta'(t - 1) \quad (2.7)
\]

Curvature is invariant under translation and rotation.

4) **Cumulative angular function**: Shape can also be represented by boundary angles, but due to that the tangent angle function \( \theta(t) \) (3.6) can only assume values in a range of length \( 2\pi \), usually in the interval of \( [-\pi, \pi] \) or \([0, 2\pi]\). Therefore \( \theta(t) \) in general contains discontinuities of size \( 2\pi \). Because of this, a cumulative angular function is introduced to overcome the discontinuity problem. The cumulative angular function \( (t) \), is the net amount of angular bend between the starting position \( z(0) \) and position \( z(t) \) on the shape boundary

\[
\varphi(t) = [\theta(t) - \theta(0)] \mod(2\pi) \quad (2.8)
\]

In order to make it accord with human intuition that a circle is “shapeless”, a normalized cumulative angular function \( \psi(t) \) is used as the shape signature (assuming shape is traced in anti-clockwise direction)

\[
\psi(t) = \varphi(L/2\pi) - t \quad (2.9)
\]

Three of the smoothed shape signatures:
All the four shape signatures described in this section are derived from shape boundary coordinates and are information preserving, i.e. they allow full reconstruction of the shape of the contour. This is an important property for shape representation.

IV. SHAPE INDEXING USING FOURIER DESCRIPTOR

Fourier transformation on shape signatures is widely used for shape analysis; there are also some recent attempts to exploit it for shape retrieval.

Shape size normalization

Before applying Fourier transform on the shape signature, shape is first sampled to fixed number of points.

For a given shape signature described in Section 3, s(t), t = 0, 1, ..., L, assuming it is normalized to N points in the sampling stage, the discrete Fourier transform of s(t) is given by

\[ u_n = \frac{1}{N} \sum_{i=0}^{N-1} s(i) \exp \left( -\frac{2\pi in}{N} \right), \quad n = 0, 1, ..., N - 1 \]

The coefficients \( u_n \), n = 0, 1, ..., N-1, are usually called Fourier descriptors (FD) of the shape, denoted as FD, n = 0, 1, ..., N-1.

V. INDEXING SHAPE USING FOURIER DESCRIPTORS

In shape retrieval, user is only interested in the outline features of similar shapes, the position, size and rotation of the shapes is not important. In order to make model shape and data shapes comparable, the shape representations must be invariant to translation, rotation and scale. Shape invariance is difficult to achieve under spatial domain, most invariance techniques in spatial domain, especially rotation invariance techniques, involve large amount of computation. However, shape invariance is easy to achieve for the FDs. For complex coordinates signature, all the N descriptors except the first one (DC component) are needed to index the shape. The DC component depends only on the position of the shape, it is not useful in describing shape thus is discarded. Scale normalization is achieved by dividing the magnitude values of all the other descriptors by the magnitude value of the second descriptor. The invariant feature vector used to index the shape is then given by

\[ f = \left[ |FD_1| / |FD_1|, |FD_2| / |FD_1|, ..., |FD_{N-1}| / |FD_1| \right] \]

For centroid distance signature and curvature signature, because the functions are real valued, there are only N/2 different frequencies in the Fourier transform, therefore, only half of the FDs is needed to index the shape. Scale invariance is then obtained by dividing the magnitude values of the first half of FDs by the DC component

\[ f = \left[ |FD_1| / |FD_0|, |FD_2| / |FD_0|, ..., |FD_{N/2}| / |FD_0| \right] \]

The periodic cumulative angular function of is itself invariant under translations, rotations and scales, therefore, the FDs derived form this signature can be directly used to index the shape. The feature vector to index the shape is then

\[ f = \left[ FD_1, FD_2, ..., FD_{N/2} \right] \]

Now for a model shape indexed by FD feature \( f_m = [f_m^1, f_m^2, ..., f_m^{N_c}] \) and a data shape indexed by FD feature \( f_d = [f_d^1, f_d^2, ..., f_d^{N_c}] \), since both features are normalized as to translation, rotation and scale, the Euclidean distance between the two feature vectors can be used as the similarity measurement

\[ d = \left( \sum_{i=0}^{N_c} \left( f_m^i - f_d^i \right)^2 \right)^{1/2} \]

Where \( N_c \) is truncated number of harmonics needed to index the shape.

VI. EVALUATION OF THE RETRIEVAL SYSTEM

Performance measures are based on precision and recall\(^6\). They are defined as follows:

\[ \text{Precision} = \frac{\text{No. of relevant items retrieved}}{\text{No. of all items retrieved}} \]
\[ \text{Recall} = \frac{\text{No. of relevant items retrieved}}{\text{No. of all relevant retrieved}} \]

Performance measures in form of Precision and recall are computed to compare all shape signatures.
VII. CONCLUSION

Medical Images have been matched with good precision and recall values. As per our implementation we have applied on the 95 medical images in our medical image database the algorithm. As shown in the results we took the cardiac image for retrieval and got the result with 6 similar images of cardiac. Also we have drawn with the graph between Precision and Recall.

The goal of medical imaging databases is to provide a means for organizing large collections of heterogeneous, changing, pictorial, and symbolic data. This must reside in a structured environment that can be synthesized, classified, and presented in an organized and efficient manner to facilitate optimal decision making in a health care environment.

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