# Similarity Shape Retrieval from Image Database 

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#### Abstract

In this paper we present a new technique for retrieval of images from image database that are similar by shape to the objects they contain. Our shape similarity retrieval model is based on histogram description of object shape that is independent on translation, scale and rotation transformations.


Key words - image database, query processing, content based image retrieval, shape description.

## I. Introduction

The content based image information systems require a new visual approach for query specification, new indices for data assignation and new methods for similarity retrieval between the query and the target. These are more and more challenging tasks due to the extreme increase of the number and sizes of image archives.

In this paper we present a new technique for image retrieval from image database that are similar by shape to the objects they contain. Our shape similarity retrieval model is based on histogram description of object shape that is independent on the translation and rotation transformations. This description forms a multi-dimensional index for the object shape with a relatively low dimension. The defined similarity distance reflects the understanding for shape similarity in the medical applications. We illustrate a similarity query processing architecture consistent with our model. The carried out experiments demonstrate the applicability and the efficiency degree of the proposed technique.

## II. Object Shape Description

The following methods are used in the existing visual systems for shape description: boundary based geometrical methods; geometrical region based methods and region based transform methods, described in [1]. Most of the methods derive object shape description with no dependence on translation. Just a few of the shape descriptions are invariant in case of rotation and scaling.

The method, proposed in this paper describes object shape but this description does not depend on possible translation, scale and rotation of the object and has relatively low dimension.

[^0]The object of application interest is derived through segmentation by one of the existing methods from the assigned on pixel level image. We assume that a gray scale image of dimension $\mathrm{m} \times \mathrm{m}$ contains only one object $\mathrm{F}: \mathfrak{I} \mathrm{m} \times \mathfrak{I} m \rightarrow \mathfrak{R}$. The pixel based description of F is geometrically described by $n$ contours of the object $\mathrm{F}=(\mathrm{Cj}, 0 \leq$ $\mathrm{j} \leq \mathrm{n}-1$ ). The object contours $\mathrm{C}_{0}, \mathrm{C}_{1}, \ldots, \mathrm{C}_{\mathrm{n}}$ are obtained by a common algorithm. The contours $\mathrm{C}_{\mathrm{j}}$ are joint multitudes of pixels assigned by their k-number of coordinates $\mathrm{C}_{\mathrm{j}}=((\mathrm{xji}$, $\mathrm{yji}), 1 \leq \mathrm{i} \leq \mathrm{k}$ ), where $\mathrm{C}_{0}$ is the external k -dimension contour of the object and $\mathrm{C}_{1}, \mathrm{C}_{2} \ldots, \mathrm{C}_{\mathrm{n}-1}$ are possible internal contours.

Fig. 1 illustrates the obtainment of histogram object shape description.


Fig.1: (a) segmented object; (b) object contours, p.Acontour sequent point, p.B-contour guiding point, p.O"reper" point; (c) pre-oriented object, sequent axis i and cross-points $\mathrm{A}_{1}, \ldots, \mathrm{~A}_{2}$, ; (d) histogram form description.

As "repere" point for the outer contour is assigned its centroid obtained by averaging the outer contour coordinates $\left(\mathrm{X}_{0}, \mathrm{Y}_{0}\right)$, Eq. (1). This "reper" point accounts translation, translation from rotation and translation provoked by scaling when using different points the contour is scaled towards. The point $\left(\mathrm{X}_{0}, \mathrm{Y}_{0}\right)$ keeps its relational spatial location with respect to the contour points regardless of translation, rotation and scaling transformation.

$$
\begin{equation*}
\mathrm{X}_{0}=\frac{1}{\mathrm{k}} \sum_{i=1}^{k} \mathrm{x}_{0 i} \quad \mathrm{Y}_{0}=\frac{1}{\mathrm{k}} \sum_{i=1}^{k} \mathrm{y}_{0 i} \tag{1}
\end{equation*}
$$

The coordinate system center is conventionally displaced to the point $\left(\mathrm{X}_{0}, \mathrm{Y}_{0}\right)$. The external and the internal contours Decart coordinates are transformed into polar coordinates $\mathrm{C}_{\mathrm{j}}=\left((\mathrm{rji}, \alpha \mathrm{ji}), 1 \leq \mathrm{i} \leq \mathrm{k}, 0 \leq \alpha_{\mathrm{ji}}<\pi\right)$. The transformation is presented by Eqs. (2) and (3).

$$
\alpha_{\mathrm{ji}}=\left\{\begin{array}{cc}
\operatorname{arctg} \frac{\mathrm{y}_{\mathrm{ji}}-\mathrm{Y}_{0}}{\mathrm{x}_{\mathrm{ji}}-\mathrm{X}_{0}}, & \mathrm{x} \neq \mathrm{X}_{0} \quad 0 \leq \alpha<\pi  \tag{2}\\
\pi / 2, & \mathrm{x}=\mathrm{X}_{0}
\end{array}\right.
$$

$$
\mathrm{r}_{\mathrm{ji}}=\left\{\begin{array}{c}
+\sqrt{\left(\mathrm{x}_{\mathrm{ji}}-\mathrm{X}_{0}\right)^{2}+\left(\mathrm{y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)^{2}},  \tag{3}\\
\text { for }\left(\left(\mathrm{y}_{\mathrm{ji}}>\mathrm{Y}_{0}\right) \cup\right. \\
\left.\left(\left(\mathrm{y}_{\mathrm{ji}}=\mathrm{Y}_{0}\right) \cap\left(\mathrm{x}_{\mathrm{ji}}>\mathrm{X}_{0}\right)\right)\right) \\
-\sqrt{\left(\mathrm{x}_{\mathrm{ji}}-\mathrm{X}_{0}\right)^{2}+\left(\mathrm{y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)^{2}}, \\
\text { for }\left(\left(\mathrm{y}_{\mathrm{ji}}<\mathrm{Y}_{0}\right) \cup\right. \\
\left.\left(\left(y_{j i}=\mathrm{Y}_{0}\right) \cap\left(\mathrm{x}_{\mathrm{ji}}<\mathrm{X}_{0}\right)\right)\right)
\end{array}\right.
$$

The maximal Euclidian distance from the centroid to the external contour points is determined $r_{0 \max }=\max \left|r_{0 i}\right|$. Then $a$ guiding for the outer contour pixel is determined. A first- rate criterion for guiding pixel assignation is its coordinate to satisfy the requirement $\left|r_{0 i}\right|=r_{0 \max }$. In case of more than one pixel available, for which $\left|\mathrm{r}_{0 \mathrm{i}}\right|=\mathrm{r}_{0 \max }$, a more complicated criterion is utilized, accounting the number and coordinates of the points of the contour between the maximums. The guiding pixel with polar coordinates ( $\mathrm{r}_{0 \mathrm{M}}, \alpha_{0 \mathrm{M}}$ ) determine angle $\beta\left(\mathrm{r}_{0 \mathrm{M}}, \alpha_{0 \mathrm{M}}\right)$, presented by Eq. (4).

$$
\beta\left(\mathrm{r}_{\mathrm{oM}}, \theta_{\mathrm{M}}\right)= \begin{cases}-\alpha_{0 \mathrm{M}} & \mathrm{r}_{\mathrm{oM}} \geq 0  \tag{4}\\ -\alpha_{0 \mathrm{M}}-\pi & \mathrm{r}_{0 \mathrm{M}}<0\end{cases}
$$

A rotation of the contour $\mathrm{C}_{\mathrm{j}}$ around point $\left(\mathrm{X}_{0}, \mathrm{Y}_{0}\right)$ with angle $\beta$ comes after so that the specified as guiding pixel lies on the positive direction of the 0 X axis after the rotation. This rotation aims the orientation of every one contour in one and the same way $\mathrm{C}_{\mathrm{j}}=\left((\mathrm{rji}, \theta \mathrm{ji}), 1 \leq \mathrm{i} \leq \mathrm{k}, 0 \leq \theta_{\mathrm{ji}}<\pi\right), 0 \leq \mathrm{j} \leq \mathrm{n}-1$. The
described 2 Dimensional transformation for point $\left(\mathrm{x}_{\mathrm{j} i}, \mathrm{yji}\right)$ are determined by the Eqs. (5), (6) and (7):

$$
\begin{gather*}
\mathrm{X}_{\mathrm{ji}}=\left(\mathrm{x}_{\mathrm{ji}}-\mathrm{X}_{0}\right) \cos \beta-\left(\mathrm{y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right) \sin \beta \\
\mathrm{Y}_{\mathrm{ji}}=\left(\mathrm{x}_{\mathrm{ji}}-\mathrm{X}_{0}\right) \sin \beta-\left(\mathrm{yji}-\mathrm{Y}_{0}\right) \cos \beta \tag{5}
\end{gather*}
$$

$$
\mathrm{r}_{\mathrm{ji}}=\left\{\begin{array}{c}
+\sqrt{\left(\mathrm{X}_{\mathrm{ji}}-\mathrm{X}_{0}\right)^{2}+\left(\mathrm{Y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)^{2}}  \tag{6}\\
\quad\left(\left(\mathrm{Y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)>0\right) \cup \\
\left(\left(\mathrm{Y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)=0,\left(\mathrm{X}_{\mathrm{ji}}-\mathrm{X}_{0}\right)>0\right) \\
-\sqrt{\left(\mathrm{X}_{\mathrm{ji}}-\mathrm{X}_{0}\right)^{2}+\left(\mathrm{Y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)^{2}} \\
\left(\left(\mathrm{Y}_{\mathrm{ji}}-\mathrm{Y}_{0}\right)<0\right) \cup \\
\left(\left(Y_{j i}-\mathrm{Y}_{0}\right)=0,\left(\mathrm{X}_{\mathrm{ji}}-\mathrm{X}_{0}\right)<0\right)
\end{array}\right.
$$

$$
\begin{align*}
& \theta_{\mathrm{ji}}=\left\{\begin{array}{l}
\operatorname{arctg} \frac{\mathrm{Y}_{\mathrm{ji}}}{\mathrm{Xji}}, \\
\text { for } \mathrm{X}_{\mathrm{ji}} \neq 0\left\{\begin{array}{l}
0 \leq \theta_{j i}<\pi / 2, \mathrm{XY} \geq 0 \\
\pi / 2<\theta_{j i}<\pi, \mathrm{XY}<0
\end{array}\right. \\
\begin{array}{l}
\pi / 2, \\
\text { for } \quad \mathrm{X}_{\mathrm{ji}}=0
\end{array} \\
\end{array} \begin{array}{l}
0 \leq \theta_{j i}<\pi
\end{array}\right.
\end{align*}
$$

From this way transformed contour coordinates the multidimensional index $\mathrm{F}=\left(\left(\mathrm{F}_{\mathrm{Pi}_{\mathrm{i}}}\right), 1 \leq \mathrm{i} \leq .1\right)$, describing the object shape in type of histograms is obtained. The value of the histogram is formed by the intersection points of the contours with axes, passing through the coordinate system beginning and subtending an angle $\theta_{i}$ with the positive direction of the X axis. The angle $\theta\left(0 \leq \theta_{i}<\pi\right)$ varies from 0 up to $\pi$ by uniform step $\Delta \theta=\pi / 1$, where the overall number 1 of the axes may have a value $2^{1}, 2^{2}, 2^{3}, \ldots, \mathrm{~m}$. In order to describe all pixels $\Delta \theta$ $\approx \pi / \mathrm{m}$, for images with dimension $\mathrm{m} \times \mathrm{m}$, the number 1 of the axes intersecting the contours is $1 \approx \mathrm{~m}$.

The fact, that an arbitrary line intersects any contour $\mathrm{C}_{\mathrm{j}}$ even number of times is used. Let the line passing through the beginning of the coordinate system and subtending with the X axis angle $\theta_{i}=$ const intersects the contour $C_{j}$ in $P_{j}$ points were $P_{j}$ is an even number: $F \cap \theta_{i}=\left(\left(r_{j i s}\right), 1 \leq s \leq P_{j}, P_{j} \geq 2\right)$. Eq. (8) presents three histograms obtained for one axis of intersection, where i is the consecutive number the axis $\theta_{\mathrm{i}}=$ const $\left(\theta_{\mathrm{i}}=\Delta \theta(\mathrm{i}-1) 0 \leq \theta_{\mathrm{i}}<\pi\right) \quad(1 \leq \mathrm{i} \leq 1)$ and 1 is the number of axes.

$$
\mathrm{F}_{\theta}\left(\mathrm{f}_{\mathrm{i}}, \mathrm{f}_{\mathrm{i}+1}, \mathrm{f}_{\mathrm{i}+21}\right)=\left\{\begin{array}{c}
\mathrm{f}_{\mathrm{i}}=\frac{1}{\mathrm{r}_{0 \max }} \mathrm{r}_{0 \mathrm{il}}  \tag{8}\\
\mathrm{f}_{\mathrm{i}+1}=\frac{1}{\mathrm{r}_{0 \max }} \mathrm{r}_{0 \mathrm{ip}} \\
\mathrm{f}_{\mathrm{i}+21}=\frac{1}{\mathrm{r}_{0 \max }} \sum_{\mathrm{j}=0}^{\mathrm{n}-1}(-1)^{j} \sum_{s=1}^{\mathrm{Pj}}(-1)^{+1} \mathrm{r}_{\mathrm{jis}}
\end{array}\right.
$$

Object shape description gets the mode $F\left(f_{1}, f_{2}, \ldots, f_{n}\right)$. It forms the multidimensional index for shape, stored in the databases. The multidimensional index for shape have dimension 31. The maximal index dimension for image with dimension $\mathrm{m} \times \mathrm{m}$ is 3 m , or, for image $512 \times 512$ the maximal dimension is 1536 D , that is a relatively low dimension for such an image.

## III. Shape Query Processing

Shape queries are content based .The processing of this type of queries must efficiently find and derive those images that look maximally similar to the assigned by the user sample image. A similarity search is realized instead of exact concurrence search. Both basic variants of this query type are processed in this research.

## A. Similarity Retrieval

Content based query processing imposes the definition of a similarity evaluation criterion, named retrieval value or similarity distance. Let the shape query is transformed into an image histogram description $\mathrm{Q}\left(\mathrm{q}_{1}, \mathrm{q}_{2}, \ldots, \mathrm{q}_{\mathrm{n}}\right)$, and the image in the database has histogram description $F\left(f_{1}, f_{2}, \ldots, f_{n}\right)$, where $q_{i}$, $f_{i}$ are histograms. The retrieval value between $Q$ and $F$ for the examined retrieval model is determined by Eqs. (9) and (10), where $-\operatorname{sim}\left(q_{i}, f_{i}\right)$ is the similarity function between the histograms $q_{i}$ and $f_{i}$.

$$
\begin{gather*}
\mathrm{d}(\mathrm{~F}, \mathrm{Q})=\frac{1}{l} \sum_{i=1}^{l} \operatorname{sim}\left(\mathrm{q}_{i}, \mathrm{f}_{i}\right)  \tag{9}\\
\mathrm{d}(\mathrm{~F}, \mathrm{Q})=\frac{1}{l} \sum_{i=1}^{l}\left[\left(\mathrm{f}_{\mathrm{i}}-\mathrm{q}_{\mathrm{i}}\right)^{2}+\left(\mathrm{f}_{\mathrm{i}+1}-\mathrm{q}_{\mathrm{i}}\right)^{2}+\frac{1}{4}\left(\mathrm{f}_{\mathrm{i}+21}-\mathrm{q}_{\mathrm{i}}\right)^{2}\right] \tag{10}
\end{gather*}
$$

The used quadratic functions are already approved as appropriate distance functions for similarity search. In the chosen by us similarity distance the first two components account the external contours similarity and the third component accounts the similarity of all the internal contours. In our understanding for similarity, consistent with the medical appliance, the similarity weight of the external contour is much higher than that of the internal contours similarity.

## B. Query Processing Architecture

For the overall architecture we use the paradigm of multistep query processing where an index-based filter step produces a set of candidates and the subsequent refinement step performs an exact evaluation of the candidates. Whereas the filter step has to guarantee completeness, i. e., no actual result is missing from the set of candidates, the refinement step ensures the correctness, i. e., no falls hit belongs to the answer. For similarity range query ("retrieve all images with a similarity distance of at most $\varepsilon$ to the query image"), we use the algorithm of [2]. For K-nearest neighbor queries we use the algorithm of [3], that employs rectilinearly organized multidimensional index structures. We may use also any one of the existing frames for similarity query processing on multidimensional index structures. Fig. 2 illustrates the architecture of the processing.


Fig. 2 Similarity query processing

## IV. Experimental Results

Our algorithms are implemented in MatlabR12 and C+ + and are evaluated on test database of 2000 images from a medical image collection of hystologic investigations for the needs of morphological diagnostics. The images are transformed in order to get dimensions $256 \times 256$, and their index with dimension $31=384$ for $1=128$. The presented results illustrate the desired behavior of our similarity model with respect to the returned answers. The results demonstrate good filter selectivity and performance in the highdimensional image space.

## A. Similarity ranking

As a sample query we chose the image of object - human arteriosclerosis coronary artery existing in DB. The collection includes also some modified by us images of the same object, transformed by translation or rotation and also images of the same transformed object but with different number of internal contours addedThe expectations for the values of the similarity distances were confirmed. Fig. 3 depicts k most similar images from the database.


Fig.3. K-nearest neighbors among 2000 images


Fig.4: (a) Performance depending on the index dimension; (b)The average overall runtime is composed from the runtimes of the filter step and of the refinement step.

## B. Performance evaluation

We performed the experiments on HP 9000/780 H machines. In the first experiment for $\mathrm{K}=10$ we retrieved $0.5 \%$ of the objects from the database. Fig. 4 shows the number of candidates that correspond to the filter selectivity and also the overall average time of query processing for various dimensions of the index. The results show that the
number of candidates and the accessed index pages are the main cost factors in query processing. We observe from the diagrams that with increasing the index, the number of candidates significantly decreases since the index provides an increasing amount of information to the index step. On the other hand the increase of dimension imposes decrease of quickness. The filter selectivity and the overall query processing time greatly depend also on the query parameter K .

## V. Conclusions

In this paper we presented a histogram based shape similarity model. This model is independent with respect of the transformations translation, scaling and rotation and possesses invariability and stability. We illustrated a similarity query processing architecture consistent with our model. . The carried out experiments demonstrate the applicability and the efficiency degree of the proposed technique. In our future work we are planning to make our model capable of catching mirror-similar shapes.

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