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Image retrieval by shape and texture

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Abstract

Effective image retrieval by content from database requires that visual image properties are used instead of textual labels to recover pictorial data. Retrieval by image similarity given a template image is particularly challenging. The difficulty is to derive a similarity measure that combines shape, grey level patterns and texture in a way that closely conforms to human perception. In this paper a system is presented which supports retrieval by image similarity based on elastic template matching. The template can be both a 1D template modeling the contour of an object, and a 2D template modeling a part of an image with a significant grey level pattern. The retrieval process is obtained as a continuous interaction by which the original query of the user can be refined or changed on the basis of the results provided by the system.

Keywords: Image databases; Texture analysis; Elastic models

1. Introduction

The recent emergence of multimedia digital libraries makes image retrieval an interesting and challenging problem. Image databases are now currently employed in an eclectic range of different areas such as entertainment, art history, advertising, medicine and industry among others. In all these contexts, the key problem to be solved is the development of algorithms and techniques which are able to efficiently describe image content.

The effectiveness of textual description to represent visual data is limited to very narrow contexts, and in general, items retrieved through a textual query could not be relevant at all for user's expectation. Iconic indexes have been proposed in Ref. [1] to effectively support image retrieval by content. Iconic indexes are in the form of symbolic descriptions of pictorial data or pictorial data relationships but may also include the actual values of object features, or be in the form of abstract images taking the salient features of the original image. The use of iconic indexes naturally fits with the accomplishment of image retrieval according to visual querying by-example. Visual queries by-example for pictorial data exploit human natural capabilities in picture analysis and interpretation and largely reduce the cognitive effort of the user in accessing the database. A number of techniques have appeared in the literature which deal with iconic indexing and visual querying by example of single images; different approaches depend on what facets of pictorial data are taken into account. Indexing and querying based on spatial relationships have been proposed in Ref. [2–4].

Indexing and querying based on shape similarity have also been proposed. The traditional approach to shape description is to extract a suitable number of features

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from the shape, and represent it as a point in a multi-dimensional feature space. Moment invariants have been used as a set of features representing shape attributes which are invariant under translation, rotation, and scale [5–7]. Boundary features such as chain codes of contour segments or high–curvature points, whose saliency is demonstrated in Refs. [8] and [9], have been used as well [10–13]. In recent works [14,15], elastic approaches have been used to provide an effective measure of perceptual similarity between shapes, avoiding the need to evaluate shape features.

Indexing and querying based on picture color distribution have also been proposed. In Ref. [16], image content is described through a global color histogram and queries are expressed by means of example images. Retrieval is performed by evaluating the similarity between the global color histograms of user provided examples and stored images. The QBIC database system [7] allows user composed queries, but still evaluates similarity in terms of global properties of color histograms. The *distance measure* considers a weighted cross correlation between histogram bins. In Ref. [17], both color and shape features are used for retrieval. In this system the query is formulated through an example image and retrieval is accomplished by a similarity measure computed on the basis of global color histogram and image edges.

It is almost impossible to express textures in words, and it is also difficult to sketch it. Therefore, the only way to specify a texture in a query by content is to use sample texture models. These can either be extracted from images that have been answered in a previous query, or selected from a set of predefined texture samples.

The Candid system [20], developed by P.M. Kelly and M.T. Cannon supports image retrieval through global signatures of textures about the entire image. Texture features are first computed at every pixel in the image, and then a probability density function is derived that describes the distribution of these features.

The QBIC system [7] supports texture based retrieval using the Tamura, Mori, and Yamawaki's decomposition [18]. Features of *coarseness*, *contrast* and *directionality* are computed on gray scale images after conversion from original color images. Queries are expressed visually, by taking a model from a texture picker. Image comparison is carried out by evaluating the weighted Euclidean distance in the three-dimensional space of texture features.

In the Photobook system [21], texture description is carried out according to the Wold texture model, which describes textures in terms of periodic, oriented, and random components [19]. Features are compared using one out of a library of matching algorithms. These include Euclidean, Mahalanobis, divergence, vector space, histogram, Fourier peak, and wavelet tree distances, as well as any linear combination of these.

Search by matching portions of images is a very natural way to pose a query in interactive image databases. Consider the following scenario: you have just entered a query using some method, and the answer just popped out on your screen. Some of these images will be considered "good" answers, while others will be probably completely off the point. You might want to refine the query that is, you might try to get more "meaningful" images and less "meaningless" one. Instead of drawing another contour, or making another kind of query, a natural way to do it is to pick the image you like the best, and use it as the new query, effectively saying something like "Here: get me some more of these."

This type of query-by-example requires a good and robust way to determine the similarity between images. Image similarity in presence of textures is commonly measured using either feature-based or statistical methods:

- *Feature-based* methods extract a limited number of features from the two images to be compared, and then use some suitable metric in the feature space $\mathscr{F}$ as a measure of similarity.
- *Statistical* methods consider the pixels as a realization of a particular multivariate stochastic process, usually described by a Gibbs distribution of the form $P(I) = \exp(-E(I))$, and try to determine the probability that the same parameters of the energy function E gave rise to the two images [22].

Both these methods suffers from serious drawbacks when applied to image databases:

- Feature-based methods can compare images only as long as the comparison criterion is captured by the features. For instance, similarity or dissimilarity in color cannot be captured is there are no color features. Given the generality of possible queries, this is a major problem, although can be solved by concepts like the adaptive "society of models" [23].
- Statistical methods are tractable only if certain locality assumptions are made on the random process that generates the images. Because of this, it is impossible to model accurately long-range effects like geometric distortions. Statistical methods are good at recovering from pointwise noise, for which the information contained in the local structure is sufficient. When images are actually different, and not different noisy versions of the same image, long-range effects come into the picture, and Statistical methods are no longer so useful.

In this paper, we present an elastic based approach to measure image similarity. Given two images (namely a *template* and a *target* image) that we want to compare, one of the two (e.g. the template) is considered as an elastic body. The template is stretched in order to achieve the best match with the target in terms of difference in grey level of corresponding pixels. The measure of match and the amount of *energy* used to warp the template are used to derive a similarity measure between the two images.

The paper is organized as follows: in Section 2 the elastic approach to image matching is introduced and expounded. In Section 3 retrieval examples for a prototype system are presented and discussed.

2. Image matching: 2D elastic models

Consider the case in which you are asked to match two images as well as possible, with one of the two images being painted on a transparent rubber foil. You can superimpose the rubber foil to the other image, and start deforming the foil, pulling it here and there, trying to match the two images as well as possible. During this process, you are not allowed to rip the rubber, or to compress it so much that a region of finite area disappears. If you obtain a good match without deforming too much—i.e. keeping the elastic deformation energy low—you can say that the two images were pretty similar to begin with, while if you have to spend a lot of energy in the deformation, or you just cannot get a good match, then you can say that the two images were not similar.

Mathematically, this is equivalent to the solution of an elastic deformation problem in which one of the two images—which is considered as an elastic body—is deformed under the action of a force field generated by the difference between the two images, and its own elastic reaction to deformation. When equilibrium is reached between the two forces, we have the optimal deformation.

The theory behind the approach has been worked out in several places, under different assumptions [24]. Call *template* (T) the image we use to make the query, and *target image* (I) the image we want to compare the template against. Suppose the comparison is done by deforming the template and that the deformation in the point x_1, x_2 of the template is $u(x_1, x_2) = (u_1(x_1, x_2), u_2(x_1, x_2))$. The function $u = (u_1, u_2)$ models the deformation of the template as shown in Fig. 1: $u_1(x_1, x_2)$ and $u_2(x_1, x_2)$ provide the new coordinates of the point (x_1, x_2) according to the deformation u. To discover similarity between the template and the target image, we must set some constraint on deformation. In our approach the optimal deformation is obtained as a compromise between two opposite requirements. As first, we want to maximize the match between the deformed template and the target image. That is we want to minimize the distance between the two images:

$$\mathscr{D}(T, I, u) = \iint_S (T(u_1(x_1, x_2), u_2(x_1, x_2)) - I(x_1, x_2))^2 \, \mathrm{d}(x_1, x_2).$$

As second, we want to minimize the deformation energy of the template image. For a function $f: \mathbb{R}^2 \to \mathbb{R}$ the total amount of bending of the surface $(x_1, x_2, f(x_1, x_2))$ can be measured as:

$$\mathscr{J}(f) = \iint_S ((f_{x_1x_1})^2 + 2(f_{x_1x_2})^2 + (f_{x_2x_2})^2) \, \mathrm{d}(x_1, x_2). \quad (1)$$

The deformation energy of the template image is therefore measured as

$$\mathscr{J}(u_1) + \mathscr{J}(u_2).$$

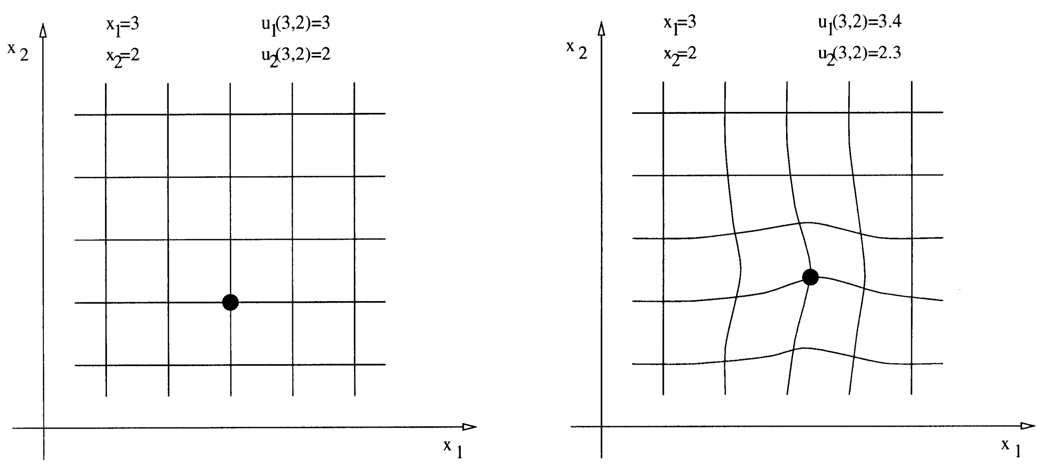


Fig. 1. The function $u = (u_1(x_1, x_2), u_1(x_1, x_2))$ provides the new coordinates of the point (x_1, x_2) after the deformation.

A compromise between these two opposite requirements is thus achieved by minimizing the compound functional:

$$\mathscr{F} = \mu(\mathscr{J}(u_1) + \mathscr{J}(u_2)) + \mathscr{D}(T, I, u), \quad (2)$$

where μ is a parameter that determines the "stiffness" of the template. The higher μ the less the template will warp.

2.1. Numerical solution

We approximate the deformation u through a linear combination of radial functions defined on a regular rectangular grid of N points $\bar{p}_1, \ldots, \bar{p}_N$:

$$u(\bar{x}, \mathbf{C}) = \sum_{i=1}^{N} \bar{c}^i g(\|\bar{x} - \bar{p}_i\|) \quad \text{with } \bar{x} = (x_1, x_2) \quad (3)$$

being $g: \mathbb{R}^+ \to \mathbb{R}$ the radial basis function, $\|\cdot\|$ the usual Euclidean norm on $\mathbb{R}^2$, and $\mathbf{C} = \{\bar{c}^1, \ldots, \bar{c}^N\}$ with $\bar{c}_i = (c_1^i, c_2^i)$ the array of 2D coefficients.

The minimization of the functional $\mathscr{F}(\mathbf{C})$, obtained substituting Eq. (3) in Eq. (2), with respect to the variables $(c_1^1, \ldots, c_1^N, c_2^1, \ldots, c_2^N)$ is achieved through a gradient descent technique. Variables are determined iteratively

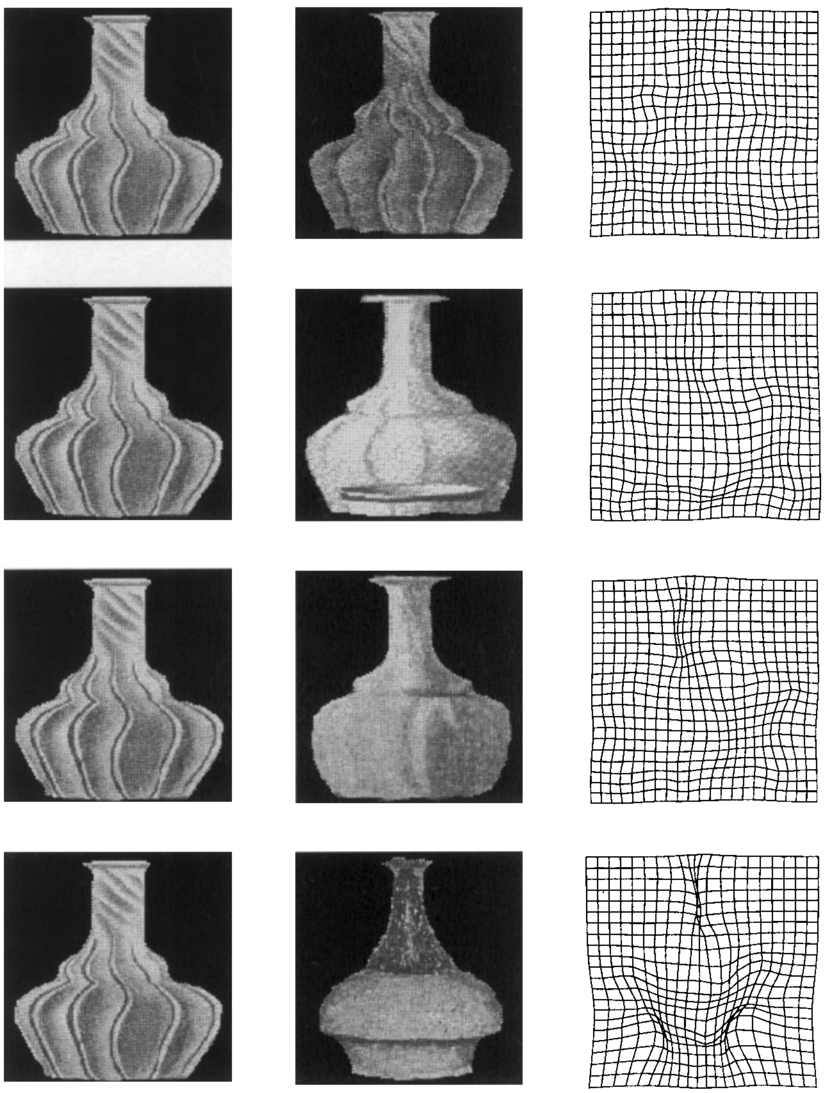


Fig. 2. Elastic deformation of a bottle image over different bottles. In the first three cases, the bottle grey level pattern is similar to that exhibited by the template bottle. In the last case the two grey level patterns are different. The deformation of a regular grid is show on the right part of the figure. In the first three cases the deformation of the grid keeps smooth whereas in the last case it is subjected to a considerable change.

according to

$$\mathbf{C}(k+1) = \mathbf{C}(k) - \varepsilon\nabla\mathscr{F}(\mathbf{C}),$$

where

$$\nabla\mathscr{F}(\mathbf{C}) = \left(\frac{\partial\mathscr{F}}{\partial c_1^1}, \ldots, \frac{\partial\mathscr{F}}{\partial c_1^N}, \frac{\partial\mathscr{F}}{\partial c_2^1}, \ldots, \frac{\partial\mathscr{F}}{\partial c_2^N}\right),$$

$$\frac{\partial\mathscr{F}}{\partial c_1^k} = \frac{\partial\mathscr{J}(u_1)}{\partial c_1^k} + \frac{\partial\mathscr{D}(T,I,u)}{\partial c_1^k}, \quad (4)$$

$$\frac{\partial\mathscr{F}}{\partial c_2^k} = \frac{\partial\mathscr{J}(u_2)}{\partial c_2^k} + \frac{\partial\mathscr{D}(T,I,u)}{\partial c_2^k}. \quad (5)$$

From Equation (3) it follows that

$$\mathscr{J}(u_1) = \iint_S \left[\left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_1^2}\right)^2 + 2\left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_1 \partial x_2}\right)^2 + \left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_2^2}\right)^2\right] \mathrm{d}(x_1, x_2)$$

and similarly for $\mathscr{J}(u_2)$.

According to this, it can be derived that:

$$\frac{\partial\mathscr{J}(u_1)}{\partial c_1^k} = \iint_S \left[2\left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_1^2}\right)\frac{\partial^2 g(\|\bar{x}-\bar{p}_k\|)}{\partial x_1^2} + 4\left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_1\partial x_2}\right)\frac{\partial^2 g(\|\bar{x}-\bar{p}_k\|)}{\partial x_1\partial x_2} + 2\left(\sum_i c_1^i \frac{\partial^2 g(\|\bar{x}-\bar{p}_i\|)}{\partial x_2^2}\right)\frac{\partial^2 g(\|\bar{x}-\bar{p}_k\|)}{\partial x_2^2}\right] \times \mathrm{d}(x_1, x_2).$$

That is, by taking the summations out of the integrals:

$$\frac{\partial\mathscr{J}(u_1)}{\partial c_1^k} = \sum_i c_1^i \gamma_{i,k}, \qquad \frac{\partial\mathscr{J}(u_2)}{\partial c_2^k} = \sum_i c_2^i \gamma_{i,k}$$

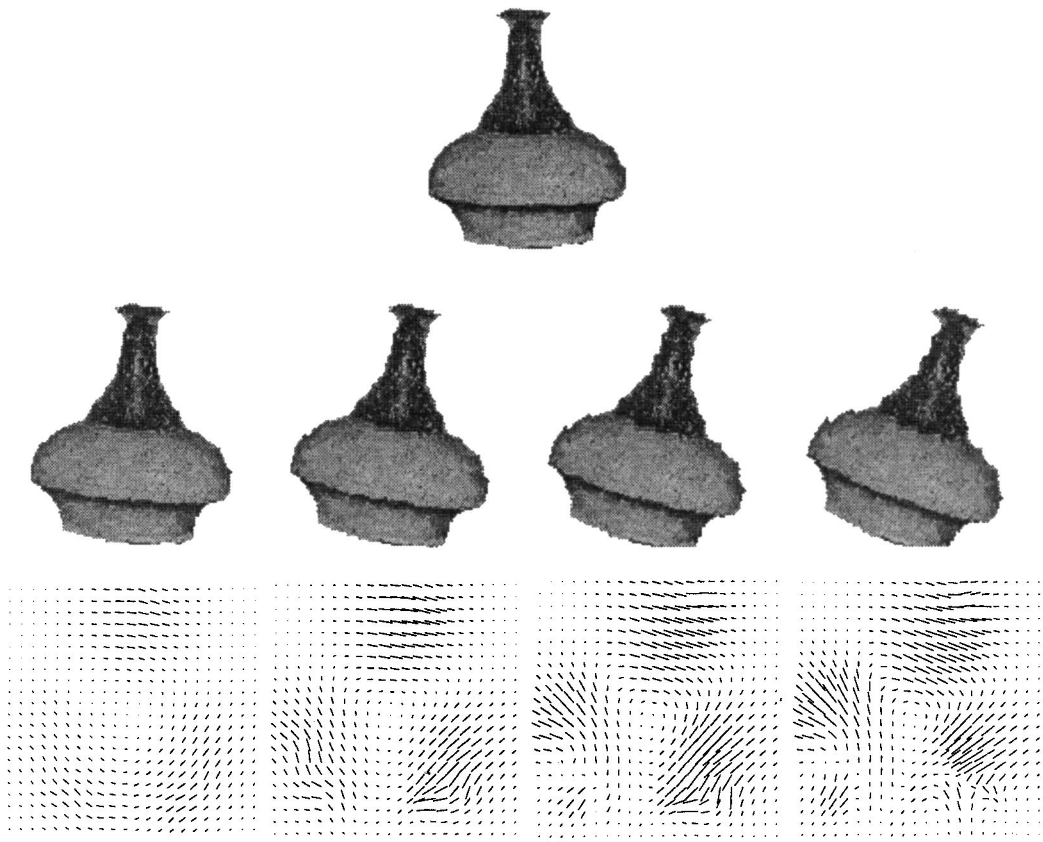


Fig. 3. Elastic deformation of a bottle image over images representing the same bottle rotated by 5, 10, 15, 20°, respectively. For each deformation the displacement filed induced by the elastic deformation is also shown.

with

$$\gamma_{i,k} = \iint_S \left[2\frac{\partial^2 g(\|\bar{x} - \bar{p}_i\|)}{\partial x_1^2} \frac{\partial^2 g(\|\bar{x} - \bar{p}_k\|)}{\partial x_1^2} + 4\left(\frac{\partial^2 g(\|\bar{x} - \bar{p}_i\|)}{\partial x_1 \partial x_2} \; \frac{\partial^2 g(\|\bar{x} - \bar{p}_k\|)}{\partial x_1 \partial x_2} \right. + 2\,\frac{\partial^2 g(\|\bar{x} - \bar{p}_i\|)}{\partial x_2^2} \frac{\partial^2 g(\|\bar{x} - \bar{p}_k\|)}{\partial x_2^2} \right] \mathrm{d}(x_1, x_2).$$

According to this, Eqs. (4) and (5) can be written as

$$\frac{\partial \mathscr{F}}{\partial c_1^k} = \mu \sum_i c_1^i \gamma_{i,k} + \frac{\partial \mathscr{D}(T, I, u)}{\partial c_1^k}, \tag{6}$$

$$\frac{\partial \mathscr{F}}{\partial c_2^k} = \mu \sum_i c_2^i \gamma_{i,k} + \frac{\partial \mathscr{D}(T, I, u)}{\partial c_2^k}. \tag{7}$$

The first term of Eqs. (6) and (7) depends on μ and models the elasticity of the template, that is the behavior of every point of the template to move in the same direction as its neighbors. The higher μ, the less the template can warp. The value of μ is initially low and is increased during the deformation process. In this way at the beginning of the deformation process a precise adaptation is achieved essentially for those parts which are similar in both the template and the image, while approximate adaptation is determined for those which are not equally represented in the two. In the second stage, the increased value of μ compels the template to regularize its deformation without loss of match.

At the end of the deformation process, the value of $\mathscr{F}$ provides a measure of the similarity between the template and the target image.

As an example in Fig. 2 they are shown the deformations of a template image representing a bottle with a particular grey level pattern, over images of bottles. The grey level pattern of the template image exhibit a remarkable vertical striature which is present, even if with different significance, in some other bottles. For each deformation the template and the target images as shown, with the deformation subjected by a regular grid of points (on the right). It can be noticed that the

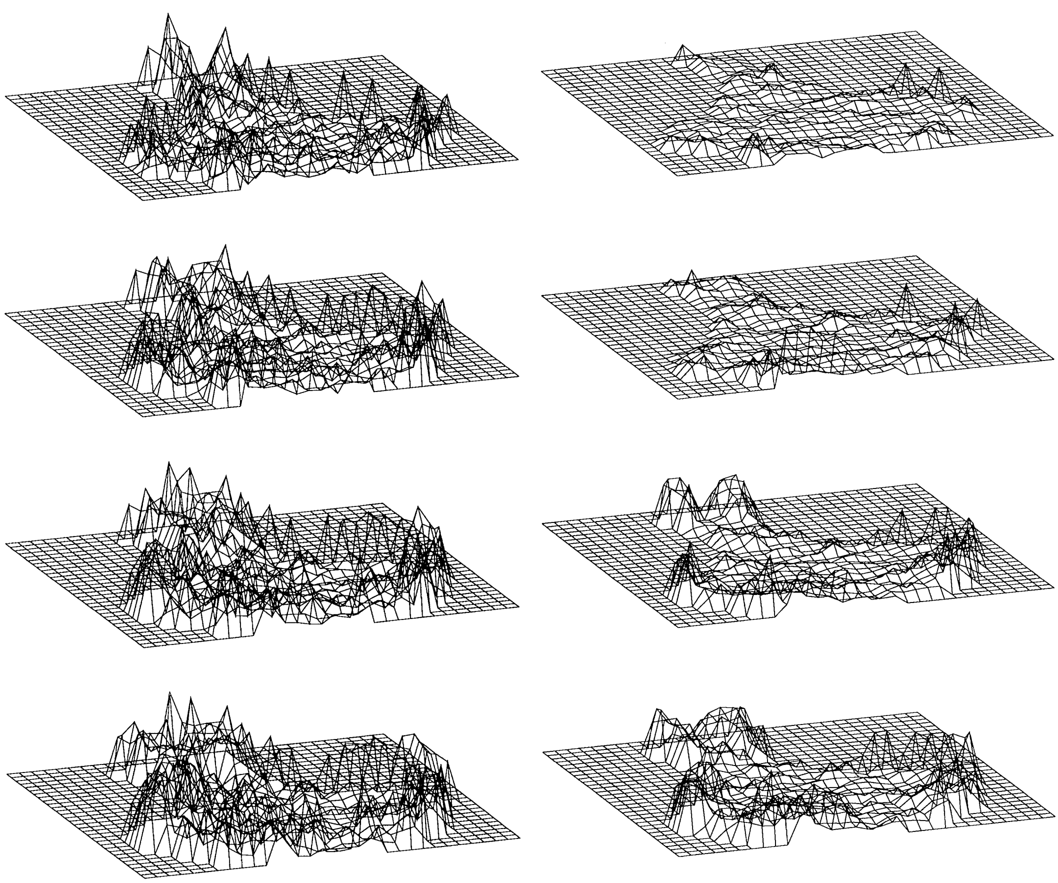


Fig. 4. Differences in term of grey level distance are shown between the template image (not rotated) and the target images (rotated by 5, 10, 15, 20°, respectively). For each rotation angle, values of grey level differences are shown before (on the left) and after (on the right) the deformation process.

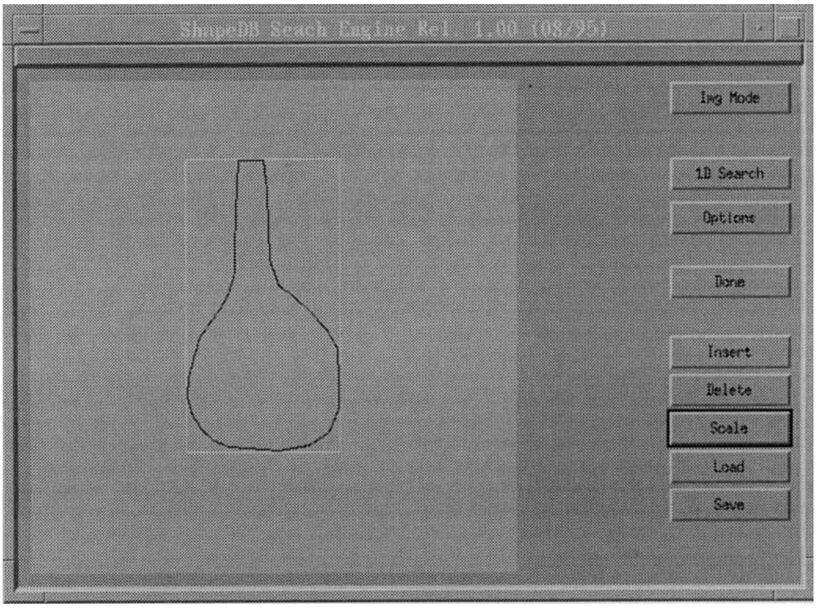


Fig. 5. User-drawn sketch representing the shape of a rounded-body bottle.

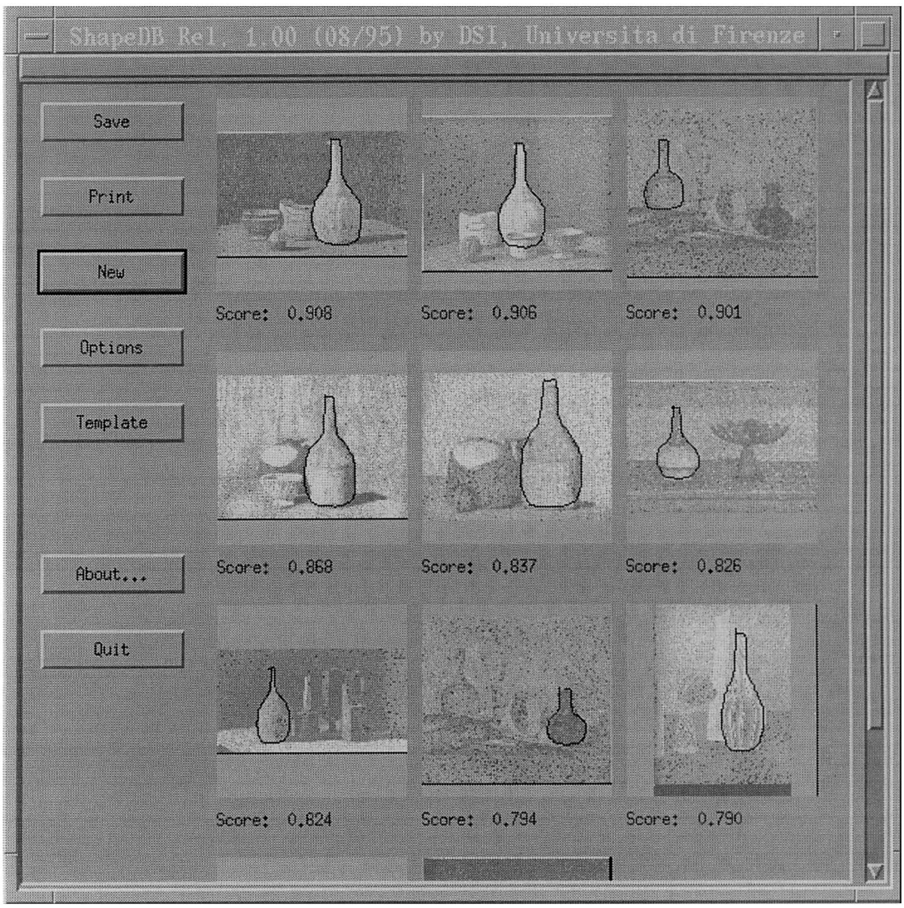
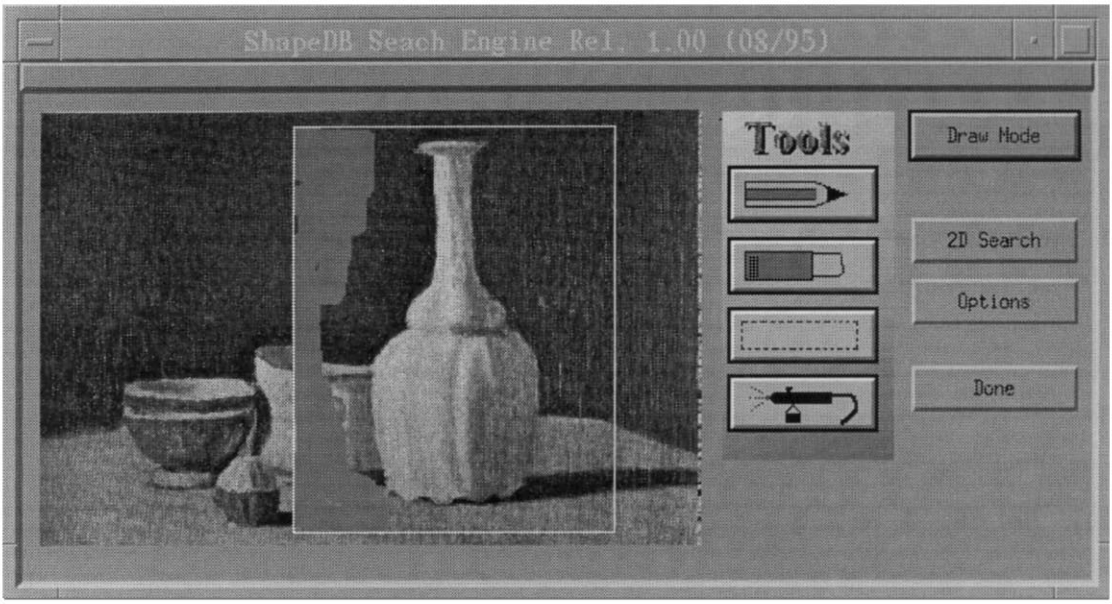
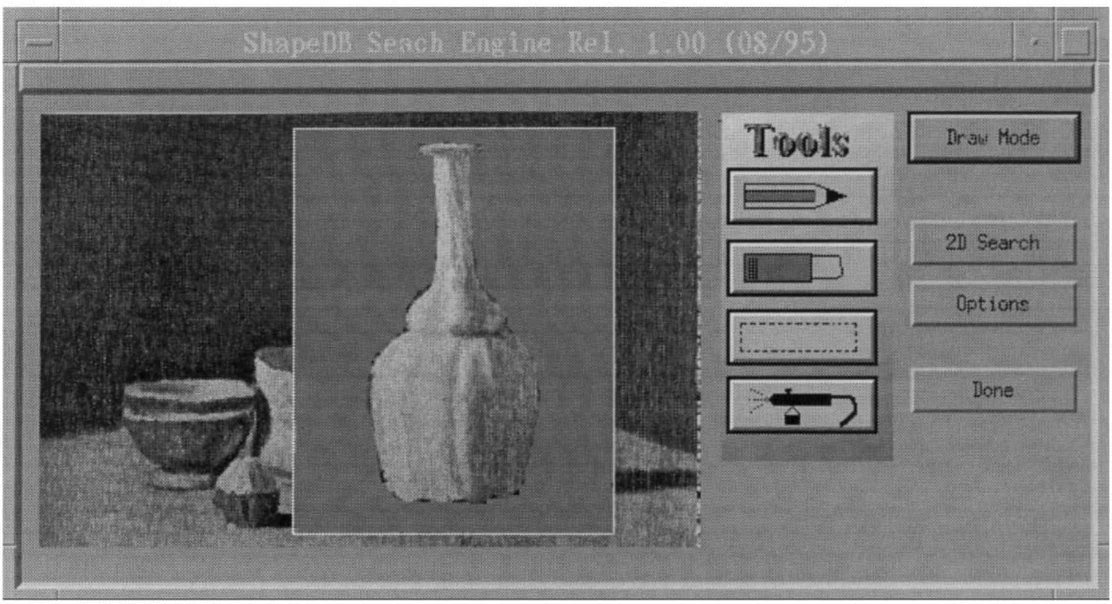


Fig. 6. Retrieved images with highest similarity ranks with respect to the sketch of Fig. 5.

deformation keeps low values in the first three cases, showing the fact that even if the grey levels of the target and the template image are different, nevertheless the elastic approach permits to capture the similar grey level pattern of the two images. Differently, in the fourth case, the template is subjected to a considerable deformation, highlighting a structural difference between the grey level pattern of the template and target images.



(a)



(b)

Fig. 7. (a) Image with similarity score 0.908 output by the system is used as a new query by image. Editing allows to eliminate details in the image that are not significant for elastic matching. (b) Edited image used for the query by image. Images are searched with similar image patterns in the same relative positions.

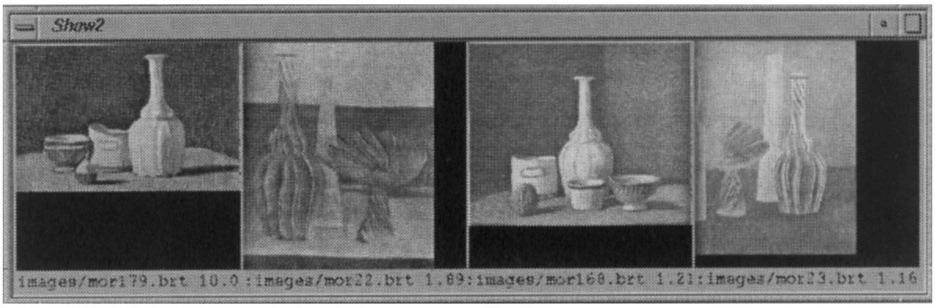


Fig. 8. Result of the query by image. Retrieved images are ranked according to pattern similarity.

2.2. Rotation invariance

From a theoretical point of view, rotation invariance is a direct consequence of the definition of the functional (1). If this functional is rotation invariant, then a rotation of the template image will not contribute to the deformation energy and therefore will not be penalized. Of course, this is true only if the method used to minimize Eq. (2) succeeds to find the global minimum. Since the gradient descent technique does not guarantee such condition, our approach is not rotation invariant, and minimization of Eq. (2) is expected to stop in local minima.

However, the presence of local minima is reduced in the case of small rotations, and in these cases the proposed approach is able to manage the deformation. As an example, in Fig. 3 a template image representing a bottle is warped over a set of images representing the same bottle rotated by an angle of 5, 10, 15, 20°, respectively. Also shown are plots of the displacement fields induced by the deformation process. Plots highlight the rotation of the template image during the deformation. In Fig. 4 they are shown the plots of the grey level distance between the template and the target images before (on the left) and after (on the right) the deformation process. It can be noticed how these values keep low in the case of small rotations and increase with increasing values of the rotation angle.

3. Image retrieval system

The elastic based approach to image similarity has been coupled with a system which supports content-based image retrieval by shape and spatial relationships [14] into a unified framework, to provide retrieval modalities based both on shapes, spatial relationships, and image patterns. At database population time, in the images of the database, rectangular areas corresponding to interesting regions of the image are selected. A region can be interesting both for the presence of a particular image pattern or for the presence of an interesting object. For each rectangular area, the raw image is processed to extract the contours of the object eventually included: in the present implementation, it is passed through a Canny edge extraction processing. A symbolic description of spatial relationships among rectangular areas is also computed and stored in an image signature file. Queries by sketch and image patterns are matched with edge images and raw images respectively. Signature files are used as an index to prune out uninteresting images according to spatial relationships and positions.

The system interface allows the user to select the preferred type of search. To draw a contour the user has simply to enter a curve. In the case of 2D search the user picks an image from the database eventually selecting it from a set of images which were retrieved by the system in a preceding search. The user can select just a portion of an image, bounding with a rectangle the area of interest. He can interactively clean the selected region from those details which he is not interested in. In this way, the search process takes into account only those parts of the region which the user feels as the most interesting. In Fig. 7 it is shown an example of the interactive editing of a selected image.

An example of shape based retrieval of pictures with query refinement by image pattern is shown in Figs. 5–8. The database includes images from a Morandi's catalogue representing bottles with other still life objects of different aspect and in different combinations. Fig. 5 shows the sketch drawn by the user, roughly representing the contour of a rounded body bottle. Results of the similarity retrieval through 1D elastic matching are shown in Fig. 6. Rounded bottles are ranked in the first places; also different sized and shaped bottles but with a certain roundness in their shape are extracted from the database.

Query refinement is shown in Figs. 6–8. Among the retrieved images the user is now interested in selecting those images which include a rounded bottle, like that depicted in the first ranked image (top left image), in the same position in the picture, and with a similar grey level pattern. Interactive editing of this image is shown in Fig. 7a and b. The rubber tool is used to wipe out uninteresting grey level patterns and details. Results of querying by image patterns through 2D elastic matching are shown in Fig. 8.

The prototype system is presently engineered to be included and used for the electronic cataloging of paintings and sculptures of museums and galleries in the area of central Italy, and for the development of multimedia systems to access these databases. The elastic-based retrieval by-content system is intended as a special part of a multimedia system, especially oriented to support specialists and researchers to discover similarities among pictures or, more generally, relationships between different paintings which are not explicitly expressed or known. Retrieval by similarity and relative positions supports the critic in the analysis of the artists' periods, as well as of the influences and commonalities between different paintings.

4. Conclusions

Effective image retrieval by content from database requires that visual image properties are used instead of textual labels to recover pictorial data. Shape has proven to be a significant clue to represent image contents, however, there are cases in which there is no natural specification of a portion of an image in terms of contours. In this paper, 2D elastic models have been used to provide an effective measure of similarity between two grey level patterns. According to this approach, in order to compare two images, one is considered as an elastic body, and is warped to adapt as much as possible to the target image. The amount of deformation and the match achieved are used to compute the similarity between the two images. Based on this approach, a prototype system has been developed which provides access by content to a database of images based both on shapes and grey-level patterns of objects represented in the images.

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