Textural Features and Relevance Feedback for Image Retrieval

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Abstract

This paper focuses on the retrieval of complex images based on their textural content. We use GMRF for texture discrimination and a region-growing algorithm for texture segmentation. Relevance feedback is introduced to improve retrieval accuracy.

Keywords

Textures, relevance feedback, image features, Gaussian Markovian Random Fields.

1 INTRODUCTION

Content-based image classification, indexing and retrieval requires semantic interpretation and cannot be afforded with current technology. A surrogate of semantic interpretation is the computation of visual features that can be used as quantitative parameters for the identification of similar images. Thus, the problem of retrieving images with some content is substituted with the problem of retrieving images visually close to a target one. Image features like colors, contours, textures, have been used in various systems. Related work includes, but it is not limited to Flickner (1995), Bach (1996), Ma (1997), Popat (1997), Rui (1997), Celentano (1998). Texture is one of the characteristics the human beings normally use to perceive the content of an image. In this paper we focus on the retrieval of complex images based on their textural content.

We evaluated various texture analysis algorithms, i.e. Spatial Gray-level Co-occurrence Matrices (SGCLM) (Raalick 1973, Davis, 1989), Power Spectral Density (PSD) (Dyer, 1990), and Gaussian Markovian Random Fields (GMRF) (Khotanzad, 1987). We selected GMRF for texture discrimination; further we designed a simple region growing textures segmentation algorithm. Relevance feedback, a technique widely used in conventional textual retrieval, was introduced to improve retrieval accuracy.

2 TEXTURE ANALYSIS

Image retrieval based on texture analysis requires image segmentation during the database population in order to identify areas having homogeneous texture content. Following the method proposed by Reed (1990) we subdivide the image in measurement windows. A sub-sampling is performed on each image, associating a measurement window to each n pixels (in our implementation a 32×32 pixels window for each 16 pixels). The image is hence associated to a sub-sampled "textural" image where each texture element (texel) is associated with a vector of coefficients **f**, relative to the corresponding measurement window, that characterises it. If an image has dimensions N × M its corresponding textured image will have dimensions:

$$K \times L = \left[2 \cdot floor\left(\frac{N}{32}\right) - 1\right] \times \left[2 \cdot floor\left(\frac{M}{32}\right) - 1\right]. \quad (1)$$

Similarity measurement between texels requires the evaluation of the distance between their corresponding vector coefficients. We used a simple metric that consists of the sum of corresponding coefficients differences, normalised with their arithmetical mean; i.e. given two texels Ti and Tj and the corresponding vectors **f**i and **f**j the distance is measured as:

$$d(T_i, T_j) = \sum_{r=1}^{R} 2 \times \left| \frac{f_i(r) - f_j(r)}{f_i(r) + f_j(r)} \right| \quad (2)$$

where R is the number of coefficients in the vector (R=7 for GMRF). This metric allows to measure differences between coefficients regardless of their absolute values, and the distance between two texels does not depend on the starting one. The determination of starting seeds is crucial; for each texel T_i the texel having the smaller distance in a NN=3×3 is computed:

$$T_{\min} \ni' d(T_{\min}, T_i) = \min_{T_j \in NN} \{d(T_i, T_j)\} \quad (3)$$

The texel Ti can be assumed as starting seed if all other texels within the neighborhood have a distance which is less than a given threshold t:

$$Ti\text{=seed} \Leftrightarrow \forall T_j \in NN : d(T_i, T_j) \le d(T_i, T_{\min}) \cdot (1 + t) \quad (4)$$

The segmentation process, starting from identified seed texels is performed in a way that can be assimilated to the diffusion of a particle towards texels having a minimum distance from the starting seed. The diffusion is forbidden if the distance is higher than the threshold or if all texels in the neighbourhood of the seed have already been included. Detected texture areas are characterised by two vectors, one storing mean values and the other storing variance values for each of the rectangular windows the area is subdivided into.

3 QUERY PROCESSING

Queries by example can be submitted either as a sample texture image or selecting a rectangular area within a submitted image; the selected area is subdivided into windows according to the previously described segmentation stage; for each window coefficients are extracted applying the GMRF model and creating the correspondent vectors. The similarity measure between the selected query area, represented by its feature vector **Q**, and textured areas of images in the database, represented by their feature vectors **T***i* is performed computing the Euclidean distance between vectors storing associated mean values. Such distance is normalised with associated variance values providing the following expression:

$$d(\boldsymbol{Q},\boldsymbol{T}i)=\sqrt{\sum_{j=1}^{4}\frac{\left(\bar{f}_j(Q)-\bar{f}_j(Ti)\right)^2}{\sigma_j^2(Ti)}} \tag{5}$$

Resulting retrieved image are indexed according to a growing distance score.
Relevance feedback is a query refinement technique widely used in text retrieval system (Salton, 1989). Due to uncertainty in the interpretation of word meaning, some of the retrieved documents can be not relevant to the user, while other low-ranked documents can be more meaningful. By submitting a modified query that increases the contribution of the terms of meaningful documents, and lowers the contribution of terms of less relevant documents, a better retrieval performance can be achieved. Uncertainty is even more critical in image retrieval, due to the weaker correspondence between the features and the image as perceived by the user, i.e., the system may not match the user perception of similarity. Relevance feedback, consisting in marking some of the retrieved images as good or bad, can improve the computation of similarity by giving different weights to the compared features (Celentano, 1998, Rui, 1997).
In conventional document retrieval systems, the retrieved items normally do not match exactly the user expectations. Uncertainty is even more present in image retrieval, due to the weaker correspondence between the computed features and the image content perceived by the user. In other words, the system may not match the user perception of similarity. In Salton (1989), it was proposed to obtain the modified query **Q'** by adding to the original query vector **Q** the vectors of relevant documents **X**i and subtracting the irrelevant ones **Yi**, both weighted with proper coefficients:

$$\boldsymbol{Q'}=\boldsymbol{Q}+\chi\sum_{i=1}^{N_{rel}}\boldsymbol{X}_i-\delta\sum_{i=1}^{M_{irrel}}\boldsymbol{Y}_i \tag{6}$$

This basic expression has been modified here in order to adapt it to our particular domain of operation. We compute the nearing operation of the new query to the relevant texture set, while preserving the different validity domain of the features in the query vector, by adopting a simple arithmetical mean between the central vector of the relevant queries N_{rel} and the original query $\boldsymbol{Q}$:

$$Q' = \frac{Q + \frac{1}{N_{rel}} \sum_{i=1}^{N_{rel}} X_i}{2} \tag{7}$$

that corresponds to expression (6) with $\chi = \frac{1}{2 \cdot N_{rel}}$, $\delta = 0$.

Figure 1 Test textures

It is worth noting that, though the application of relevance feedback in our framework has proved to be effective, a conceptual difference exists with respect to the same approach applied on textual documents. In that case, an index term either appears in a document, with some weight, or it does not appear. In image retrieval, basically all index terms are present in the whole collection, though with different contributions. The relevance feedback operates by changing the amount of contribution of the feature components.

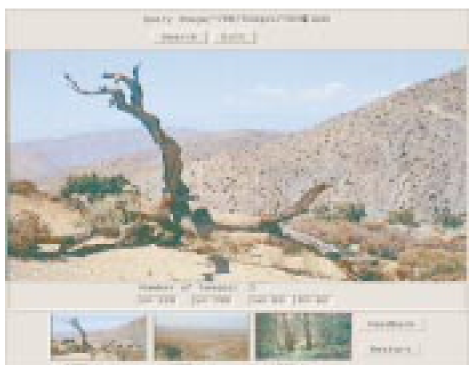

Figure 2 An example retrieval: query and the three highest ranking retrieved images.

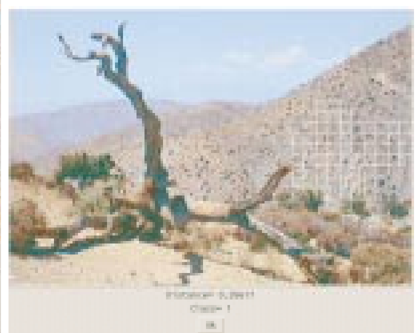

Figure 3 Relevant texture area for the retrieved image in figure 2.

4 EXPERIMENTAL RESULTS AND CONCLUSIONS

The system has been implemented in Java and Tcl-Tk. Comparative retrieval times refer to the system on a PC endowed of a Pentium 100 and 16 MB RAM under LINUX operating system. The evaluation of the texture discrimination capabilities has been carried out for three algorithms, namely GLCM, PSD and GMRF. A classification process has been implemented starting from 22 texture images, 512*512 pixels, shown in figure 1. From each image a sub-image 256*256 (parent texture) has been extracted to serve as reference and six others 128*128 (son

textures) have been extracted to serve as queries. The classification process has been considered positive if the son textures were correctly associated to the parent one. Obtained results, in terms of hit-rate and retrieval time were: 88.64%-17.24 s for GLCM, 93.94%-14.78 s for GMRF and 87.12%-58.95 for PSD. We experimented the segmentation algorithm starting from measures obtained applying SAR and CSAR models, which came out as the most effective in our test database characterisation. We assumed a measure window having 32 x 32 pixels size moving along the image with a 16 pixels step. We set the threshold to 0.2, in order to obtain a high selectivity in the texture discrimination process. The experiments proved that the segmentation algorithm performed well enough, identifying homogeneous texture areas. It must also be admitted that the conservative threshold and the lack of a merge of similar textured areas may produce not completely satisfactory results.
The system has a low level of human interaction: the whole analysis stage, i.e. texture feature extraction and segmentation, is automatic; user intervention is only requested in the relevance feedback stage. To perform a query, the user can either submit a sample texture image or select a rectangular area the user is interested to, within a picture selected from the database. Retrieved images are ranked in decreasing order of similarity. The number of retrieved images, displayed according to the highest ranking is user selectable.

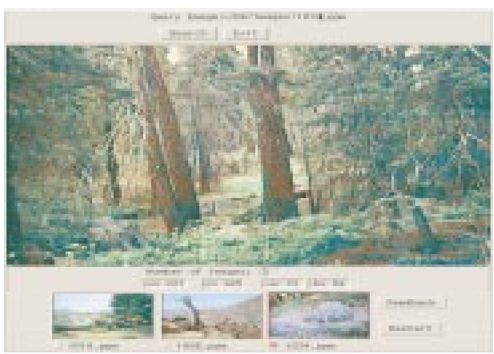

Figure 4 The image with check-button pushed was identified as relevant by the user.

Figure 5 Relevant texture area for the retrieved image in figure 4.

Figure 2 shows an example retrieval by pictorial example on the image collection: the query image is shown on the top left and the queried area is in the white bordered rectangle; retrieved images are displayed in the lower part, ranked in decreasing order of similarity. Figure 3 shows, for the highest ranking retrieved image, the area found as most similar to the query. Figure 4 shows another example of query and retrieval. Figure 5 shows the area found as most similar in image 24, i.e. the highest ranking one in the retrieved set. As it can be noticed, retrieval results may not appear satisfactory: the second higher ranking image does not appear to have the same textural content of the query and the original image was not retrieved, though the other two images that are present in the retrieved set are visually similar to the query. Relevance feedback is introduced to improve

retrieval accuracy. If the results of the query are not satisfying, the user can select, within the retrieved subset, the images he/she considers relevant. The system modifies the query by increasing the query feature vector with the contribution of the selected images. By selecting as relevant the image that appeared more similar to the query (the one with check buttons marked in figure 4), relevance feedback was applied, stressing distinguished feature in the "relevant" image and obtaining the results displayed in figure 6. It can be noticed how the selected image now ranks highest, the one less similar has been withdrawn and the image the query area was selected from now appears in the retrieved set. A classification experiment was undertaken considering a small repository of 40 images picturing natural scenes. Despite the toy size of the collection we believe the test allows to sufficiently evaluate the proposed approach. Each image was used as query, selecting a texture area, against the whole database; retrieval results were considered correct if the original image was retrieved in the first three higher ranking pictures. Results proved a good performance of the system: original images were correctly retrieved with a percentage of 77.5 %. This percentage raised to 100 % after relevance feedback.
Further work is in progress in two main directions: improvement of the segmentation algorithm to allow an automatic merging of similar texture areas and integration of the system with other feature extraction approaches we already developed, including extension to coloured textures.

Figure 6 Query and retrieval results after application of relevance feedback.

5 ACKNOWLEDGEMENTS

This work was carried out in the framework of the projects: CNR “Image Coding in Mobile Communication” and MURST “Basi di dati evolute: modelli, metodi e strumenti”.

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