Analysis of similarity measurements in CBIR using clustered Tamura features for biomedical images

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Abstract. Content based image retrieval (CBIR) is an important research topic in many applications, in particular in the biomedical field. In this domain, the CBIR has the aim of helping to improve the diagnosis, retrieving images of patients for which a diagnosis has already been made, similar to the current image. The main issue of CBIR is the selection of the visual contents (feature descriptors) of the images to be extracted for a correct image retrieval. The second issue is the choice of the similarity measurement to use to compare the feature descriptors of the query image to ones of the other images of the database. This paper focuses on a comparison among different similarity measurements in CBIR, with particular interest to a biomedical images database. The adopted technique for CBIR is based on clustered Tamura features. The selected similarity measurements are used both to evaluate the adopted technique for CBIR and to estimate the stability of the results. A comparison with some methods in literature has been carried out, showing the best results for the proposed technique.

Keywords: content based image retrieval, tamura features, similarity measurement, CBIR by clustering

1 Introduction and background

In the biomedical field, information systems help to improve the efficiency and the quality of a diagnosis. In particular, for the clinical decision-making process it can be very useful to find images with characteristics similar (same anatomic region, same disease, ...) to a given image. For this purpose a content based image retrieval (CBIR) system could be used [11, 14, 19], both to benefit the management of increasingly large image collections, and to support clinical care, biomedical research, and education. However, although the number of experimental algorithms comprehending specific problems and databases is growing, few systems exist with relative success [3, 7, 29]. So, biomedical applications are one of the priority areas where CBIR can meet more success outside the experimental sphere, due to population aging in developed countries.

The CBIR is the technique that allows retrieving images similar to a query image, in a large unannotated database. The retrieval of the similar images is based on the extraction of some visual contents of the images, called feature descriptors.

Many different feature descriptors have been proposed and used in the past years [19, 25, 26]. These feature descriptors are usually low level features, easy to extract and they are mainly of two types: *global* as shape, color or texture [1, 5, 6, 12, 24] and *local*, that focus mainly on key points or salient patches [10, 15, 21, 22, 28].

After the choice of the most appropriate feature descriptors, these are extracted both from all the images in the database and from the query image. At this point, a similarity measurement should be chosen to compute the distance between the feature descriptors of the query image and the feature descriptors of all the images in the database. The choice of the appropriate similarity measurement could be another crucial element for the correct design of a CBIR system [16].

In some cases, it results necessary to make CBIR techniques more efficient and accurate, above all when the databases are very large. In this case, the aim is to decrease the number of the images for which to compute the distance from the query image. Many clustering techniques with some feature descriptors of the images can be used [2, 8, 9, 18].

In this paper, the retrieval of images more similar to a query image is performed using textural features, in particular Tamura features, that correspond to human visual perception [27]. Then, a clustering using K-Means Algorithm [13] is carried out to obtain homogeneous groups, based on Tamura features [23].

The main contribution of the paper is the validation of the use of Tamura features, for content based image retrieval, in particular for biomedical databases, compared with the use of local descriptors. Moreover, a comparison among different similarity measurements is performed both to evaluate the adopted technique for CBIR and to estimate the stability of the results.

2 CBIR steps

CBIR technique proposed in this paper is composed by the following steps:

- the extraction of Tamura features from all the images in the database and from the query image;
- the clustering of the Tamura features, extracted from all the images in the database, using K-Means algorithm;
- the computation of five distance metrics both to evaluate the adopted technique for CBIR and to estimate the stability of the results.

2.1 Tamura features

Tamura features correspond to human visual perception. They were designed in accord to psychological studies on the human perception and they capture the high-level perceptual attributes of a texture. They define six textural features: coarseness, directionality, contrast, roughness, line-likeness and regularity. The first three features are the most similar to human visual perception, and they are considered in the present work; they are extracted both from all images in the database and from the query image. More details of these features can be found in [27].

Coarseness The aim of this feature is to find a repetitive pattern in the texture, which can have several orders of magnitude, depending on whether you are in front of a coarse or fine texture. So, operators to several orders of magnitude are computed. If the texture is fine, the highest response will be given by the operator of magnitude lower, vice versa, if the texture is coarse, the highest response will be given by the operator of magnitude greater.

The computation of the coarseness is given from:

$$F_{crs} = \frac{1}{m \times n} \sum_{i=0}^{m} \sum_{j=0}^{n} S_{best}(i,j)$$

where $m \times n$ is the resolution of the image and $S_{best}(i,j)$ is computed for each pixel and it provides the information about the magnitude of the pattern. It is important to underline that the coarseness feature is influenced both by the size of the pattern to find and by its repetitiveness.

Contrast The contrast of Tamura features takes into account both the variation range of the gray levels and the polarization of white and black pixels. A measurement for the variation range is the variance σ^2 of the pixels of the image. In fact, they measure the dispersion present in the distribution of the gray levels. However this single measurement does not appear to be very significant when the image histogram shows a prominent peak towards white or towards black. A measurement for the polarization of white and black pixels is given by the *kurtosis*, defined as $\alpha_4 = \mu_4/\sigma_4$, where μ_4 is the moment of fourth order. At this point, the two measurements are combined, obtaining the feature of the contrast:

$$F_{con} = \frac{\sigma}{(\alpha_4)^n}$$

where n can be equal to $8, 4, 2, 1, 1/2, 1/4, 1/8$. In this paper, for the experiments, n is set to 1.

Directionality The directionality is a feature that can be calculated from the analysis of the Fourier spectrum. However, the features obtained by the Fourier spectrum do not behave in the same way as those calculable in the spatial domain. Tamura preferred to get a global feature of the image, analysing the histogram of the directions of the edges, the form of the gradient image and the peaks of the histogram. In particular, the sum of the moments of second order around each peak, from to a valley to another valley is computed, and this measurement is defined in the following way:

$$F_{dir} = 1 - rn_p \sum_{p}^{n_p} \sum_{\phi \in w_p} (\phi - \phi_p)^2 H_D(\phi)$$

where n_p is the number of the peaks, ϕ_p is the p-th peak of H_D, w_p is the range of the p-th peak between two valleys, ϕ is the quantized directionality, r is a normalization factor, related to the quantized levels of ϕ.

2.2 Clustering

After the extraction of the Tamura features from all images in the database, these features are clustered, using K-Means algorithm. For the experiments in this paper, the number of clusters is set to 2. These information are saved in a data structure in order to use them for the following experiments.

2.3 Distance metrics

The choice of the similarity measurement is the second issue in CBIR. For the proposed technique, first the distances between the feature descriptors of the query image and the centroids of the clusters are computed. The cluster at minimum distance is selected. Then, the distances between the feature descriptors of the query image and the feature descriptors of all the images of the selected cluster are computed. The images with feature descriptors with small distance from the feature descriptors of the query image are considered as the images more similar to the query image. In this work, some distance metrics are used as similarity measurements. In particular, well-known distance metrics are used [4]:

- **Euclidean distance**;
- **City block distance**;
- **Minkowski distance**, with order $p = 3$.

Moreover, let the vector of the feature descriptors of the query image be represented by Q, and the vector of the feature descriptors of an image of the database be represented by I, two additional distance metrics are calculated:

Canberra distance, that normalizes each feature pair difference by dividing it by the sum of a pair of feature descriptors:

$$D = \sum_{i=1}^{n} \frac{(|Q_i - I_i|)}{|Q_i| + |I_i|}$$

d1 distance, where the distance between two vectors of feature descriptors is calculated based on the formula described in [21]:

$$D = \sum_{i=1}^{n} \frac{|Q_i - I_i|}{|1 + Q_i + I_i|}$$

3 Experimental Results and Discussion

In order to analyse the performance of the proposed technique, some experiments have been performed. The experiments have been conducted on the Open Access Series of Imaging Studies (OASIS) [17]. It is a series of magnetic resonance imaging (MRI) database that is publicly available for study and analysis. This dataset consists of a cross-sectional collection of 421 subjects aged between 18 to 96 years, including individuals with early-stage Alzheimer's Disease (AD). For image retrieval purpose, these 421 images are grouped into four categories (124, 102, 89, and 106 images) based on the ventricular shape in the images. Sample images for each category are displayed in the figure 1.

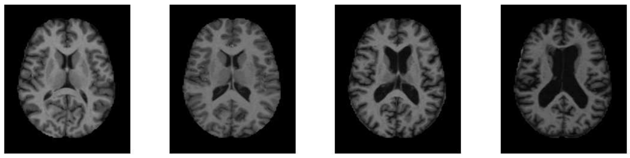

Fig. 1: Sample images from OASIS database (one image per category).

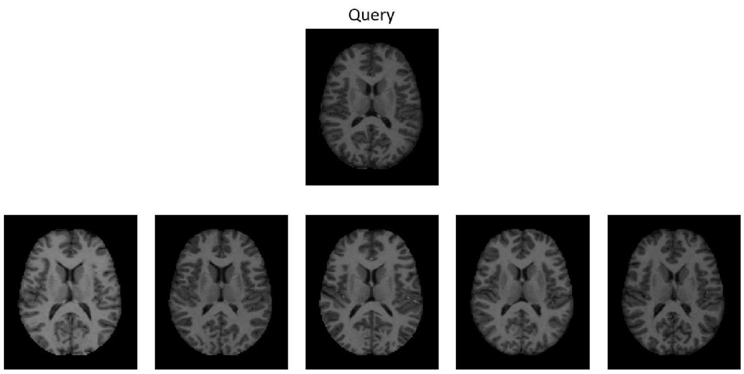

Fig. 2: The results for a query image of the group 1.

For the proposed CBIR technique, each image of the database is used as a query image and the distances from the clusters are calculated, based on the distance metrics of the section 2.3. When the cluster containing images more similar to the query image is found, the distances between the query image and each image of the cluster are computed, and the images more similar to the query are displayed.

Some results for two query image examples, for groups 1 and 4, are shown in the figures 2 and 3.

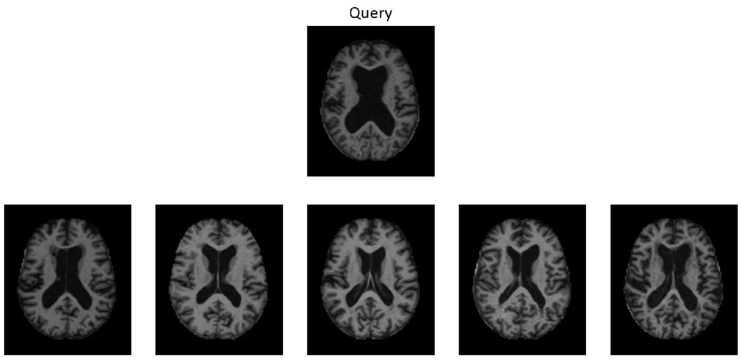

Fig. 3: The results for a query image of the group 4.

The *average retrieval precision* (ARP) and the *average retrieval rate* (ARR) are calculated, to evaluate the performance:

$$ARP = \frac{1}{N}\sum_{i=1}^{N} PR(Q_i)\Bigg|_m$$

$$ARR = \frac{1}{N}\sum_{i=1}^{N} RE(Q_i)\Bigg|_p$$

where Q is the query image and N is the total number of images in the database and where *precision* (PR) and *recall* (RE) are:

$$PR(Q) = \frac{Number\ of\ Relevant\ Images\ Retrieved}{Total\ Number\ of\ Images\ Retrieved}$$

$$RE(Q) = \frac{Number\ of\ Relevant\ Images\ Retrieved}{Total\ Number\ of\ Relevant\ Images\ in\ the\ Database}$$

As specified in [20], to calculate *precision* and *recall* the number of images retrieved should be specified, (e.g. *precision* with $m = 20$ images and *recall* with $p = 100$ images are retrieved). So, for the current experiment, the number m of images retrieved for *precision* is 100 and for *recall* is specific for each group, i.e. $p = 124$ for the group 1, $p = 102$ for the group 2, $p = 89$ for the group 3, $p = 106$ for the group 4.

In tables 1 and 2 the results of ARP and ARR for all similarity measurements and for all groups are reported. The performance of the proposed technique is better for group 1 and 4, independently from the chosen similarity measurement. Moreover, all similarity measurements for each group, provide values very similar among them, showing a stability and a robustness of the technique. However, ARP and ARR show a consistent behaviour for all groups: for the groups 1 and 2, they show the best values for the City Block distance, for the group 3 the best values are given by the Minkowski distance, for the group 4 are given by the d1 distance and for all groups the best values of ARP are given by the City Block and Minkowski distance and the best values of ARR are given by the City Block, Minkowski and Euclidean distance.

ARP (%)					
	Group 1	**Group 2**	**Group 3**	**Group 4**	**Total**
Euclidean	0.500	0.378	0.334	0.710	0.480
City Block	**0.505**	**0.381**	0.329	0.711	**0.482**
Canberra	0.461	0.375	0.276	0.735	0.462
Minkowski	0.497	0.379	**0.338**	0.713	**0.482**
d1	0.465	0.377	0.279	**0.736**	0.465

Table 1: Average retrieval precision (ARP) of all similarity measurements for each category

ARR (%)					
	Group 1	**Group 2**	**Group 3**	**Group 4**	**Total**
Euclidean	0.464	0.392	0.357	0.817	**0.507**
City Block	**0.465**	**0.394**	0.351	0.817	**0.507**
Canberra	0.425	0.388	0.297	0.843	0.488
Minkowski	0.463	0.388	**0.358**	0.819	**0.507**
d1	0.428	0.391	0.301	**0.844**	0.491

Table 2: Average retrieval rate (ARR) of all similarity measurements for each category

Finally, a comparison with some methods in literature are reported in table 3 [28]. In order to compare with these methods, the number of retrieved images is 10 ($m = 10$), as in [28]. As similarity measurement the Euclidean distance has been chosen.

These methods are all based on local information of the pixels [28]:

- **CSLBP**: center simmetric local binary pattern;
- **LEPINV**: local edge pattern for image retrieval;
- **LEPSEG**: local edge pattern for segmentation;
- **LBP**: local binary pattern;
- **LMEBP**: local maximum edge binary pattern;
- **DLEP**: directional local extrema pattern;
- **CSLBcoP**: CSLBP + gray level co-occurrence matrix (GCLM).

The results show that the proposed CBIR technique outperforms the other methods for groups 1 and 4 and in terms of total ARP.

The promising results prove that the Tamura features represent good global visual descriptors and that the local visual descriptors are less representative for the kind of examined images. In particular, the difference between ventricular shape of healthy subjects and subjects with early-stage Alzheimer's Disease is well highlighted by Tamura features, above all for the groups 1 and 4, for which the best results are obtained.

ARP ($m = 10$) (%)					
	Group 1	**Group 2**	**Group 3**	**Group 4**	**Total**
CSLBP	0.46	0.36	0.29	0.4	0.38
LEPINV	0.48	0.34	0.29	0.41	0.38
LEPSEG	0.51	0.34	0.29	0.43	0.39
LBP	0.56	0.34	0.34	0.45	0.42
LMEBP	0.55	0.35	**0.39**	0.54	0.46
DLEP	0.51	0.37	0.38	0.53	0.45
CSLBCoP	0.55	**0.39**	0.38	0.64	0.49
CBIR proposed	**0.58**	0.34	0.37	**0.78**	**0.52**

Table 3: Comparison of the CBIR proposed technique with other methods in literature.

4 Conclusion

In this paper a CBIR technique based on the clustering of the Tamura features has been proposed. A biomedical database, containing MRI images (OASIS) has been used for the experiments and different similarity measurements have been used both to evaluate the proposed technique and to verify the stability of the technique. The results show that the proposed technique is stable and robust, independently from the selected distance metric; in fact both the Average Retrieval Precision (ARP) and the Average Retrieval Rate (ARR) show similar results for all distance metrics. Moreover, the comparison with other methods in literature, that use local information of the pixels, show that the proposed technique, based on global information, outperforms these methods in terms of ARP, with a number of retrieved images equal to 10.

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