Statistical Features for Image Retrieval
A Quantitative Comparison

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Abstract: In this paper we present a comparison between various statistical descriptors and analyze their goodness in classifying textural images. The chosen statistical descriptors have been proposed by Tamura, Battiato and Haralick. In this work we also test a combination of the three descriptors for texture analysis. The databases used in our study are the well-known Brodatz's album and DDSM (Heath et al., 1998). The computed features are classified using the Naive Bayes, the RBF, the KNN, the Random Forest and Random Tree models. The results obtained from this study show that we can achieve a high classification accuracy if the descriptors are used all together.

1 INTRODUCTION

Texture analysis is a process that allows the characterization of different surfaces and objects by identifying their specific statistical properties. Through rigorous techniques of image capture, you can get a texture on a given surface that uniquely identifies its structure depending on the lighting and the intensity captured during acquisition. From this it's possible to extract characteristics or features that allow the actual image texture characterization, by means of an adequate mathematical formulation. In this experimental analysis we compare three types of statistical descriptors that define, although in a different way, the same features: coarseness, contrast and directionality according to Battiato's (Battiato et al., 2003) and Tamura's (Tamura et al., 1978) definitions and contrast, energy and entropy making use the co-occurrence matrices as defined by Haralick (Haralick, 1979). The analysis is achieved in two different phases: in the first one there is the features extraction through the descriptors calculation and in the second one the calculated data are classified using five classifiers: the Naive Bayes, the RBF, the k-Nearest Neighbor, the Random-Forest and Random-Tree. The classification is also performed using a feature selection process. The experimental study has been applied on the well-know database of Brodatz's album and on DDSM (Heath et al., 1998), a mammographic images database. The results obtained with this experimental analysis have led to obtain a high percentage of instances correctly classified if we use the descriptors all together, both with and without a feature selection, by using all the classification models. The rest of the paper is organized as follows: in section 2 the considered statistical descriptors are illustrated in details, in Section 3 we explain our comparison study, in Section 4 we illustrate the results obtained and, finally, in Section 5 we have the conclusions.

2 THREE BASIC STATISTICAL DESCRIPTORS

In literature there are several methods used for feature extraction from textured images, each of them based on a different type of texture (Rosenfeld, 1975) (van den Broek and Rikxoort, 2004) (Broek and Rikxoort, 2005). In Image Processing the term texture refers to any and repetitive geometric arrangement of the gray levels of an image (Broek and Rikxoort, 2005). The texture provides important information about the spatial arrangement of the gray levels and their relationship with the surrounding elements. The human visual system determines and easy recognizes different types of texture characterizing them in a subjective way but, even if for a human observer it is simple and intuitive to associate with a surface texture a particular concept, give a strict definition of what is very difficult (van Rikxoort et al., 2005). In fact, there is no general definition of texture and a methodology for

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Figure 1: Textured images examples: on the left Brodatz's image and on the right DDSM's image.

measuring the texture accepted by all. We can see examples of textured images in Fig. 1. Texture analysis has three fundamental aspects like classification, segmentation and shape from texture which determines regions of texture among different predefined classes of texture, the boundaries between regions with different textures and the reconstruction of the surface objects starting from different kind of texture, respectively. For texture analysis we can use a statistical approach which includes the statistics of the first, second and high order. Among the various methods for a statistical perceptual texture analysis we consider three simple and fast approaches (Prasad and Krishna, 2011). The first of these has been proposed by Tamura (Tamura et al., 1978) and explains how to calculate six texture features (coarseness, contrast, directionality, line-likeness, regularity and roughness) of which only the first three are actually being used. The latter in fact turn out to be redundant and not more discriminating than the former. The second one has been proposed by Battiato (Battiato et al., 2003) that gives a different definition of the same texture features of Tamura. The last one has been proposed by Haralick (Haralick, 1979) and we consider in particular three features among the fourteen defined: contrast, energy and entropy.

2.1 Tamura's Descriptors

Tamura's features are extracted from texture descriptors that correspond to human visual perception. Six features are extracted but only the first three are considered in subsequent studies because the last three do not add relevant information. The Tamura's features try to give a numerical value to each texture taken into consideration in order to relate the results with the human visual perception. The features extracted are: coarseness, contrast, directionality, line-likeness, regularity and roughness.

Coarseness: it is a fundamental texture feature and can be defined as the granularity. When two patterns differ only in the scale, the pattern appears larger coarse. If you have patterns with different structures, a coarse texture contains a small number of large elements, while a fine texture contains a large number of small elements. The higher coarseness value represents a fine texture. The essence of this method is to pick a large size as best when coarse texture is present even though micro-texture is also present but to pick a small size when only fine texture is present. To compute this feature it is possible to follow a procedure summarized in the following steps.

- **Step 1.** Take averages at every point over neighborhoods whose sizes are powers of two. The average over the neighborhood of size $2^k * 2^k$ at the point (*x*,*y*) is:

$$A_k(x,y) = \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j)/2^{2k} \tag{1}$$

  where $f(i,j)$ is the gray level at (*i*,*j*).

- **Step 2.** For each point, take differences between pairs of averages corresponding to pairs of non-overlapping neighborhoods just on opposite sides of the point in both horizontal and vertical orientations. For example, the difference in the horizontal case is

$$E_{k,h}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)| \tag{2}$$

- **Step 3.** At each point, pick the best size which gives the highest output value:

$$S_{best}(x,y) = 2^k \tag{3}$$

- **Step 4.** Finally, take the average of S_{best} over the picture to be a coarseness measure F_{crs}:

$$F_{crs} = \frac{1}{m*n} \sum_{i}^{m} \sum_{j}^{n} S_{best}(i,j) \tag{4}$$

  where $m*n$ is the image dimension.

Contrast: this feature is influenced by several factors: the range of gray levels, the relationship between black and white between the texture areas, the sharpness of the edges and the frequency of repetition of the plot. It can be said that the contrast is synonymous of image quality. To calculate the contrast we need the measure of kurtosis that can be defined as:

$$\alpha_4 = \frac{\mu_4}{\sigma^4} \tag{5}$$

where μ_4 is the fourth moment about the mean and σ^2 is the variance. Combining σ and α_4 we obtain the measure of contrast as follows:

$$F_{con} = \frac{\sigma}{(\alpha_4)^n} \tag{6}$$

where n is a positive number.

Directionality: it is a global property of the region of interest. Tamura measures the overall degree of directionality where the orientation of the pattern of the texture does not matter. Tamura uses a histogram of local edge against their directional angle. This histogram is sufficient to describe the overall characteristics of the input image as long lines and simple curves. The method uses the fact that the gradient is a vector and has both a magnitude and a direction. The approach proposed by Tamura is to sum the second moments around each pick from valley to valley, if multiple peaks are determined to exist. This measure can be defined as follows:

$$F_{dir} = 1 - r * n_p * \sum_{p}^{n_p} \sum_{\phi \in w_p} (\phi - \phi^2) * H_D(\phi) \quad (7)$$

where n_p is the number of peaks, r is a normalizing factor related to quantizing levels of ϕ and ϕ is a quantized direction code. H_D is the desired histogram defined as follows:

$$H_D(k) = N_\theta(k) / \sum_{i=0}^{n-1} N_\theta(i) \quad (8)$$

where $N_\theta(i)$ is the number of points and $k = 0, 1, ..., n-1$.

The other three features of Tamura are defined as follows.

Line-likeness is a feature that only affects the shape of the elements of the texture, it means all those elements which are composed of lines. In this case, when the direction of an edge and the direction of the neighbors edges are almost equal, it considers an edge points group as a line.

Regularity is calculated considering the variation of the elements. It is assumed, in fact, that the variations of the elements, especially in the case of natural texture, reduce the regularity in the complex. In addition, it can be said that a fine texture tends to be perceived as smooth. If any texture feature varies across the image, then the same is irregular.

Roughness indicates the roughness of a texture. It's a typical feature of tactile textures rather than visual. The effects of coarseness and contrast are emphasized and a measure of the roughness is approximated using these features.

2.2 Battiato's Descriptors

In (Battiato et al., 2003) Battiato proposes a variant to Tamura's features based on the calculation of the co-occurrence matrices. Battiato presents a visual system that starting from graphical cues representing relevant perceptual texture features, interactively looks more like those in a set of candidates belonging to the same space texture. Textures are described using mathematical models and purely statistical features that allow you to perform a classification both supervised and not supervised. The alternative approach is to identify and measure the features considered most relevant to human perception (van den Broek et al., 2006). The features proposed are the first three of Tamura: coarseness, contrast and directionality according to local properties. These features are used to produce a "perceptual space" where multi-dimensional textures are organized according to the axes of perception. The features calculated can be used to create a visual system for navigation and retrieval in large texture database. Then iconic representations are created and used to formulate a query to search for interactive visual texture through the human perceptual qualities. The three features proposed are defined as follows.

Coarseness: it is probably the most essential perceptual feature, in fact many times, the word "coarseness" coincides with "texture". The coarseness defines the granularity of the image. It is calculated using an algorithm that has four steps:

- **Step 1:** K images are created in which each element is the average of the intensities between the neighbors:

$$A_k(x,y) = \frac{1}{2^{2k}} * \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} f(i,j) \quad (9)$$

- **Step 2:** take the differences between the pairs of averages that correspond to the area that does not overlap either horizontally or vertically:

$$E_{k,horiz}(x,y) = |A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y)| \quad (10)$$

$$E_{k,vert}(x,y) = |A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1})| \quad (11)$$

- **Step 3:** for each pixel the maximum difference between adjacent regions is calculated:

$$S_{best}(x,y) = k \quad (12)$$

where k maximizes the differences:

$$E_k = max(E_{k,horiz}, E_{k,vert}) \quad (13)$$

- **Step 4:** calculate the value of the global coarseness:

$$coarseness = \frac{1}{m*n} \sum_{j=1}^{m} \sum_{i=1}^{n} S_{best}(i,j). \quad (14)$$

Contrast: this measure is based on the calculation of the local contrast defined for each pixel with the estimation of the local variation in the neighborhood of the neighbors. Local contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. Given a pixel $p = (i, j)$ and a neighbor mask $W * W$ of the pixel, local contrast is computed as:

$$local\_contrast(i, j) = \frac{max_{p \in W*W}(p) - min_{p \in W*W}(p)}{min_{p \in W*W}(p) + max_{p \in W*W}(p)} \quad (15)$$

The global contrast is defined as the global arithmetic mean of all the local contrast values over the image:

$$contrast = \frac{1}{m * n} * \sum_{j=1}^{m} \sum_{i=1}^{n} local\_contrast(i, j) \quad (16)$$

where $m * n$ is the image dimension.

Directionality: this measure is based on Haralick co-occurrence matrices. Their computation is focused on the calculation of the degree of confidence for a given orientation of the texture. In other words, instead of calculating a global value of directionality, is calculated a ”degree of confidence of significance” for a set of guidelines.

Let T be a texture of size $m*n*c$ colors and $\nu(x,y)$ an offset vector, the co-occurrence matrix $C(T,\nu)$ is a $c*c$ matrix defined in each point by:

$$C(T,\nu)_{i,j} = |(p,q) \text{ in } T*T: \ q = p+\nu, \\ L(p) = i, L(q) = j| \quad (17)$$

where $L(p)$ is the luminance value of the pixel p.

Then a point (i, j) in C contains the number of pixels pairs in T that have respectively gray level i and j and with displacement vector ν. The measure proposed in the paper is based on a simple idea: the plot of the main diagonal of a co-occurrence matrix with offset ν is closer to the histogram of the image as ν is relative to a relevant direction.

2.3 Haralick's Descriptors

In (Haralick, 1979) it has been implemented a method of content-based image retrieval (CBIR) for medical imaging, alternative and complementary to that based on the use of keywords. This system is based on the effective use of information of the texture of the images. The system is also part of the so-called computer-aided diagnosis systems (CAD) that help doctors make better decisions in the shortest possible time thus promoting early diagnosis. Three specific features are extracted: energy, contrast and entropy. These features are calculated using the co-occurrence matrices, computed for various angular relationships and distances between pairs of neighboring cells of the image.

Energy: it is also known as uniformity or angular second moment. It assumes the value of zero if the image is constant. Energy is defined as follows:

$$energy = \sum_i \sum_j c(i, j)^2 \quad (18)$$

where $c(i, j)$ is the value of co-occurrence matrix in (i, j).

Contrast: it is the weighted average of all diagonals parallel to the main one that rewards more and more remote from the latter. Its value is zero if the image is constant. Contrast is defined as follows:

$$contrast = \sum_{n=0}^{N_{g-1}} n^2 \{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} c(i, j) \} \quad (19)$$

where $|i - j| = n$.

Entropy: it expresses the measure of the entropy of the matrix in its entirety. Entropy is defined as follows:

$$entropy = -\sum_i \sum_j c(i, j) \log(c(i, j)). \quad (20)$$

3 OUR COMPARISON STUDY

In this work we compare the previous features descriptors for classification of textured images, taken from the Brodatz's album (Brodatz, 1966) and DDSM (Heath et al., 1998) and we analyze the goodness of classification obtained by combining them, too. The proposed comparison is developed in two main phases: in the first there is the texture features extraction, while in the second one there is the images classification by using the descriptors calculated in the previous phase. Various datasets are generated, each containing various combinations of descriptors: at the beginning the three types of descriptors are taken individually, then they are taken in pairs of two and finally combined all together. Before the classification phase a feature selection step has been introduced.

3.1 Feature Extraction

In this first phase the features for the three types of descriptors are calculated. We obtain a features vector that varies from a minimum of nine to a maximum of eighteen depending on the number of angles of the co-occurrences matrix that we decide to consider: three are related to Tamura's features (coarseness, contrast and directionality), three to Battiato's features (coarseness, contrast and directionality) and three to twelve are relative to Haralick's features (contrast, energy and entropy). In extracting Haralick's features, initially we calculate the co-occurrence matrix using only one angle, that of orientation 0° and with distance equal to one, thus obtaining only three features. Then we modify the offset for the calculation of co-occurrence matrix adding the other three angles of the upper part of the image: 0°, 45°, 90° and 135°. Finally, the offset has been modified further to include all the eight possible angles: 0°, 45°, 90°, 135°, 180°, 225°, 270° and 315°. After generating the co-occurrence matrix, we evaluate the properties related to it, going to keep only the energy, contrast and entropy to be used in the classification.

3.2 Feature Selection

This phase is carried out after an initial phase of classification to see if the results already obtained could be further improved. It is carried out a selection of attributes by ranking the positive values of the correlation with the class attribute in descending order. This phase has led to improvements of classification accuracy, even of 7-8%. However, in very few cases no attributes have been eliminated but a different ranking of them has produced a worsening of classification, as happened with the Random Forest classifier. Also during this phase, the more frequently discarded attribute is the Battiato's contrast.

3.3 Classification

The classification stage is the last of this experimental study. For this phase we use five different types of classifiers: Naive Bayes, RBF, k-NN, Random Forest and Random Tree. We decide to use the technique of ten fold cross-validation where the original dataset is divided into subsets each consisting of the same number of samples (ten in this case). The data are first classified by analyzing the original dataset (i.e. without feature selection) and then by applying the same classifiers after the feature selection step.

4 EXPERIMENTAL RESULTS

Now we present the numerical results obtained using the illustrated texture descriptors in classifying two different datasets: the well known Brodatz album and the DDSM (Heath et al., 1998). The DDSM contains a series of mammography screenings stored in four different categories: Normal, Cancer, Benign, Benign Without Callback. In both the experiments we show the accuracy values using the three descriptors individually, then combined in pairs and finally combined all together. A set of forty images taken from Brodatz's album is used, which has been divided into four non-overlapping portions of equal size; while for each category of DDSM we use twenty different images.

4.1 By Tamura's Descriptors on Brodatz Album

In Table 1 we present the results by using Tamura's features, with and without feature selection. In this case the highest accuracy value is achieved already before the feature selection with 81.5% of the RBF classifier, also confirmed after the feature selection.

Table 1: Results by using Tamura's features, with and without feature selection.

	No feature selection	Feature selection
NB	75.3%	81.5%
RBF	81.5%	81.5%
KNN	73.5%	73.5%
R-F	71.5%	71.5%
R-T	70.9%	70.9%

4.2 By Battiato's Descriptors on Brodatz Album

Let's see in Table 11 the results obtained by Battiato's features. By using the original dataset, the best accuracy is achieved with the RBF that goes up to 79.6% of instances correctly classified. After the feature selection the classification improves touching the threshold of 80.8% accuracy obtained with the KNN.

Table 2: Results by using Battiato's features, with and without feature selection.

	No feature selection	Feature selection
NB	78.8%	82.4%
RBF	79.6%	80.5%
KNN	63.6%	80.8%
R-F	61.4%	73%
R-T	68.7%	72.3%

4.3 By Haralick's Descriptors on Brodatz Album

Let's see now the results obtained with only one orientation angle in Table 3. The results obtained with these descriptors are good even without the feature selection, reaching 81.4% of instances correctly classified. After the feature selection the accuracy is slightly uphill coming up to 82.3% with Random Forest classifier.

Now let's see the classification using the four angles in Table 4. As we can see from the table the best result without feature selection is 89.5%, while this value after the feature selection comes down and the best is 88.8%. This is related to a different attributes ranking during the classification.

Table 3: Results by using Haralick's features with one angle, with and without feature selection.

	No feature selection	Feature selection
NB	77.1%	77.1%
RBF	68.7%	74.1%
KNN	77.8%	77.8%
R-F	81.4%	82.3%
R-T	76.7%	80%

Table 4: Results by using Haralick's features with four angles, with and without feature selection.

	No feature selection	Feature selection
NB	87.4%	87.4%
RBF	88.8%	88.8%
KNN	87%	87%
R-F	89.5%	77.5%
R-T	78.9%	85.7%

4.4 By Battiato's and Tamura's Descriptors on Brodatz Album

The first combination of descriptors is between the different definitions of Tamura's features.

Let's see the accuracy percentages obtained in Table 5. The accuracy is already high without feature selection with a peak of 92.2% achieved with KNN. After the attributes selection we still have the highest accuracy with the same classifier.

Table 5: Results by using Battiato's and Tamura's features, with and without feature selection.

	No feature selection	Feature selection
NB	89.3%	94%
RBF	88.4%	95.9%
KNN	92.2%	100%
R-F	80.5%	94.4%
R-T	69.5%	92.6%

4.5 By Battiato's and Haralick's Descriptors on Brodatz Album

In this experimentation we combine the features proposed by Battiato and those of Haralick using the co-occurrence matrix with the four corners of the upper part of the image.

Let's see the results in Table 6. Before the feature selection, the classifiers performing better are the Bayesian and the KNN, arriving both at 86.4% of instances correctly classified while after feature selection the best is always the KNN with an accuracy of 95.3%.

Table 6: Results by using Battiato's and Haralick's features, with and without feature selection.

	No feature selection	Feature selection
NB	86.4%	92.8%
RBF	86%	93.2%
KNN	86.4%	95.3%
R-F	84.5%	91.3%
R-T	79.4%	76.1%

4.6 By Tamura's and Haralick's Descriptors on Brodatz Album

The last combination of two types of descriptors is between Tamura's and Haralick's features.

The accuracy values obtained are showed in Table 7. Also in this case the feature selection does not affect the best result that, both before and after, is always 98.1% with KNN. In some cases, however, the ranking affects the accuracy of other classifiers causing them to deteriorate slightly as it happens for the Random Forest.

Table 7: Results by using Tamura's and Haralick's features, with and without feature selection.

	No feature selection	Feature selection
NB	95.8%	95.8%
RBF	94%	94%
KNN	98.1%	98.1%
R-F	91.6%	90.4%
R-T	89.6%	90%

4.7 By Battiato's, Haralick's and Tamura's Descriptors on Brodatz Album

In this last experimental analysis all the previous descriptors are combined together. Two classifications are conducted: the first uses the co-occurrence matrix calculated for a single corner and the second uses that for the four corners.

Let's see the results obtained with only one angle of co-occurrence matrix in Table 8. In this case, the satisfactory results already obtained before feature selection are further improved after the same leading them to achieve the highest classification accuracy with the KNN. The second classification, conducted with the co-occurrence matrix at the four angles, leads to the results in Table 9. Also in this case we have a very high value of accuracy: the percentage of 93.2% obtained without feature selection with the KNN, is increased to 100% with the same classifier after the attribute selection. The classification with all eight angles has the same results than that with four angles.

Table 8: Results by using all descriptors with one angle, with and without feature selection.

	No feature selection	Feature selection
NB	90.5%	96.9%
RBF	90.2%	98.1%
KNN	93.2%	100%
R-F	92.1%	98.1%
R-T	78.3%	79.5%

Table 9: Results by using all descriptors with four angles, with and without feature selection.

	No feature selection	Feature selection
NB	92.4%	96%
RBF	91.6%	98.1%
KNN	93.2%	100%
R-F	89.8%	94.4%
R-T	85.7%	82.1%

4.8 On DDSM Dataset Classification

We show now the results obtained on DDSM dataset. In this comparison, we use the same classifiers used in the previous classification. Also in this case we test the descriptors of Haralick (HA), Tamura (TA), Battiato (BA), Haralick-Tamura (HT), Haralick-Battiato (HB), Tamura-Battiato (TB) and Haralick-Tamura-Battiato (HTB). The results are resumed in Table 10 and Table 11. Also in this comparison, in fact, as it can be seen from the tables, the descriptors individually considered lead to a low accuracy level, while the percentage of instances correctly classified increases with the combination in pairs until reaching the maximum value when these three basic descriptors are used all together. In conclusions, the second experiment has confirmed the previous results.

Table 10: Results by using DDSM dataset without feature selection.

	NB	RBF	KNN	R-F	R-T
HA	49.1%	46.7%	49%	52.4%	48.8%
TA	48.7%	52.1%	48.7%	47.5%	47.1%
BA	44.9%	45.3%	39.4%	37.2%	40.3%
HT	55.3%	54%	56.6%	51.7%	59.6%
HB	56.4%	56%	56.4%	54.5%	49.4%
TB	59.1%	58.4%	62.2%	50.5%	42.5%
HTB	60.5%	60.2%	63.2%	62.1%	48.3%

Table 11: Results by using DDSM dataset with feature selection.

	NB	RBF	KNN	R-F	R-T
HA	49.1%	48.6%	49.6%	53.1%	51.7%
TA	52.6%	52.6%	48.7%	47.5%	47.1%
BA	48.1%	46%	46.3%	48.8%	51.4%
HT	65.8%	64%	66.5%	60.4%	60%
HB	62.8%	63.1%	64.2%	61.3%	46.1%
TB	64%	65.2%	66.7%	64.4%	62.6%
HTB	66.9%	68.1%	70%	68.1%	49.5%

5 CONCLUSIONS

The purpose of this work was to study which combination among the simple descriptors proposed by Tamura (Tamura et al., 1978), Battiato(Battiato et al., 2003) and Haralick(Haralick, 1979) leads to a better classification of images containing different texture. At the beginning, we tested the individual descriptors discussed above, obtaining an average accuracy value of about 74.5% by using Tamura's features, 77.8% by using Battiato's features and 78.2% by using Haralick's features (on Brodatz album). Already in this case, the accuracy value is high but we have decided to combine the descriptors to improve the percentage of instances correctly classfied. So we have combined in pairs these descriptors getting an average of accuracy of about 95.3% by using Battiato's and Tamura's features, 89.7% by using Battiato's and Haralick's features, 93.6% by using Tamura's and Haralick's features. Combining in pairs these descriptors we have a very high accuracy level. Finally, using all descriptors, we have an average of accuracy value about of 94.8%. The efficacy of the three basic descriptors combination is confirmed by the second experiment, even the accuracy level is not excellent but encouraging. In conclusions, since their easy and fast calculation, our future interest of course will be a possible integration of them with equally simple descriptors in a system for image retrieval, in particular for biomedical imaging where texture can be used to discriminate between healthy and diseased tissue.

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