Texture Characterization based on Grey-Level Co-occurrence Matrix

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Abstract—**Texture, along with color, is one of the most important characteristics of a material defining the appearance of its surface. Different approaches to texture characterization can be considered. In this work texture is analyzed through second order statistical measurements based on the Grey-Level Co-occurrence Matrix proposed by Haralick. By this method is possible to compute, among others, 5 features which are intended to describe texture: Contrast, Homogeneity, Dissimilarity, Energy and Entropy. The aim of this paper is to analyze the dependency of the features with the displacement considered for their computation and explore the possibility of features invariant under changes of the distance between the sample and observation position.**

Keywords-Texture; Image Processing; Grey-Level Co-occurrence Matrix

I. Introduction

There are different ways to face the analysis of textures as for example the Texton theory, the Wavelet approach or even the Fourier approach. However, the simplest analysis is interesting as it is proven to be related to the way the human visual system perceives texture, which is the very first approach to texture analysis defined by Haralik [1] and it is still widely used in image segmentation. Many authors investigated the usability of the features proposed by Haralick (or derived from its work), where the focus is placed in object recognition in remote image analysis, used mainly for classification of defined datasets and texture extraction [2-7].

Then, we propose a texture characterization made through second order statistical measurements based on Grey-Level Co-occurrence Matrix (GLCM), as proposed Haralick [1]. Features computed from GLCM are based on the assumption that the texture information in an image is contained in the overall spatial relationship which grey levels of neighboring pixels have to one another. GLCM contains information about the frequency of occurrence of two neighboring pixel combination in an image. Although 22 features can be derived from GLCM, usually only 5 are considered as parameters of importance: Contrast, Homogeneity, Dissimilarity, Energy and Entropy, as highlighted in different papers [1,7,8]. By calculating this five texture features it is possible to see how they behave for different textures.

The goal of this work is to study if the values of the features describing a texture are the same or very similar when the scale of the texture change. It must be notice that scale refers as the distance between the image and the camera. For this purpose the displacement between neighbors pixels must be establish in the computation of the GLCM. Additionally, some considerations for the value of the displacement have been proposed.

II. Method

A. Samples

In this work two experiments were performed – testing of the effect of the scale on the texture features and the definition of the best displacement value. In both experiments texture images were selected from KTH-TIPS and KTH-TIPS2 databases [9,10].

Samples are available at 8 different scales, corresponding to the following distances between sample and camera. Scale 1 was removed from KTH-TIPS as it gives for some samples blurred images and Scale 10 was removed from KTH-TIPS2 as it does not have its corresponding scale in KTH-TIPS.

TABLE I. Sample – camera distances and their correspondance witht the scale number.

Scale number	Distance to camera (cm)
2	16.65
3	19.80
4	23.55
5	28.00
6	33.30
7	39.60
8	47.09
9	56.00

In the computations, the size of the samples 200x200px was used.

From these two dataset, firstly were removed the samples that do not have the required size for all the scales. Therefore in KTH-TIPS Brown bread, Orange peel and Cracker were neglected and the experiment was performed on all the other samples. In total we analyzed 168 samples from this dataset [7 types of texture x 24 images for each type (8 scales times 3 orientations)]. In KTH-TIPS2 the same problem appeared only for the Cracker a, b and d. Therefore these samples were neglected and the computation was performed on all the other samples. In total it makes 1312 samples [32 images per type (8 scales times 4 orientations) x 4 subtypes for each type x 10 types of texture + 32 images for the Cracker c]. Thus, a total of 1480 samples were used for the analysis of the effect of the scale in the texture features.

For the study of the optimal displacement value in the computation of the GLCM a smaller subset of 32 texture images was tested. These samples include all scales of samples 15d (Aluminium), 16c (Cork), 22b (Wool, type 1) and 22d (Wool, type 2).

B. Computation

For the computation of the GLCM not only the displacement but also the orientation between neighbor pixels must be established. The orientations can be horizontal (0º), vertical (90º) and two diagonal (45º and -45º). For this study we have considered only horizontal orientation.

Displacement of the GLCM is basically the distance, *d*, between two pixels whose repetition is examined. It can take values from one pixel up to any number inside a reasonable range. For example if we apply a huge displacement for a fine texture it can happen that we miss texture information because for that texture the information is in a small region. Chen [11] used displacement values *d*=1, 2, 3, 4, 8, 16, 32 and found that single displacement value cannot be deducted because it depends on the type of the texture that is being investigated. In [12] is showed that if a displacement is of the size of the texture element the image classification is better. Therefore we should check this parameter to see if it is possible to generalize any criterion for the selection of the displacement value for certain texture types. To decide the displacement an experiment was performed to find the value of the displacement that corresponds to the smallest number of pixels that will contain texture elements. Our hypothesis is that the best displacement is the one that gives the highest Contrast, which means that there is a big difference in Contrast between the two pixels selected to be neighbors. We will call this displacement Maximum Contrast Distance (MCD).

Computations were performed in MATLAB® for all texture samples in the CIELAB color space on the L^* channel. The L^* channel was selected because several works stated that the majority of texture information is located on this channel [13,14].

Below are described all the features used in the experiment and the meaning of each one in the actual texture analysis case is explained [1,7,8]. In all the formulas $p(i;j)$ stands for $(i;j)^{th}$ entry or value in a normalized GLCM.

1) Contrast

Contrast is a local grey level variation in the grey level co-occurrence matrix. It can be thought of as a linear dependency of grey levels of neighboring pixels [1].

$$Contrast = \sum_{i,j} |i-j|^2 \, p(i,j) \tag{1}$$

In (1) *i* and *j* are the horizontal and vertical cell coordinates and *p* is the cell value. If the neighboring pixels are very similar in their grey level values then the contrast in the image is very low. In case of texture, the grey level variations show the variation of texture itself. High contrast values are expected for heavy textures and low for smooth, soft textures. The range of Contrast is [0, (size (GLCM,1)-1)^2] where Contrast is 0 for a constant image.

2) Homogeneity

Homogeneity measures the uniformity of the non-zero entries in the GLCM [7]. It weights values by the inverse of contrast weight [8].

$$Homogeneity = \sum_{i,j} \frac{1}{1-(i-j)^2} \, p(i,j) \tag{2}$$

The GLCM homogeneity of any texture is high if GLCM concentrates along the diagonal, meaning that there are a lot of pixels with the same or very similar grey level value. The larger the changes in grey values, the lower the GLCM homogeneity making higher the GLCM contrast. The range of homogeneity is [0,1]. If the image has little variation then homogeneity is high and if there is no variation then homogeneity is equal to 1. Therefore, high homogeneity refers to textures that contain ideal repetitive structures, while low homogeneity refers to big variation in both, texture elements and their spatial arrangements. An 'inhomogeneous texture' refers to an image that has almost no repetition of texture elements and spatial similarity in it is absent.

3) Dissimilarity

Dissimilarity is a measure that defines the variation of grey level pairs in an image. It is the closest to Contrast with a difference in the weight – Contrast unlike Dissimilarity grows quadratically [8].

$$Dissimilarity = \sum_{i,j} |i-j| \, p(i,j) \tag{3}$$

It is expected that these two measures behave in the same way for the same texture because they calculate the same parameter with different weights. Contrast will always give slightly higher values than Dissimilarity. Dissimilarity ranges from [0,1] and obtain maximum when the grey level of the reference and neighbor pixel is at the extremes of the possible grey levels in the texture sample.

4) Entropy

Entropy in any system represents disorder, where in the case of texture analysis is a measure of its spatial disorder [1,8].

$$Entropy = -\sum_{i,j} p(i,j) \log\left(p(i,j)\right) \tag{4}$$

A completely random distribution would have very high entropy because it represents chaos. Solid tone image would have an entropy value of 0. This feature can be useful to tell us if entropy is bigger for heavy textures or for the smooth textures giving us information about which type of texture can be considered statistically more chaotic.

5) Energy

Energy is a measure of local homogeneity and therefore it represents the opposite of the Entropy. Basically this feature will tell us how uniform the texture is [1,8].

$$Energy = \sum_{i,j} p(i,j)^2 \qquad (5)$$

The higher the Energy value, the bigger the homogeneity of the texture. The range of Energy is [0,1], where Energy is 1 for a constant image.

All the features discussed are connected in certain manner. Contrast and Dissimilarity both calculate the variation of grey level pairs, but with a different weight. Homogeneity weights values by the inverse of Contrast weight, which means lower the homogeneity, higher the Contrast. Energy is actually local Homogeneity and Entropy is the opposite of Energy.

III. Results

As stated previously, for the study of the optimal displacement of the GLCM the samples 15d, 16c, 22b and 22d from database KTH-TIPS2 were used. These samples were selected because they appear to have a nice transition between different scales without any moving of the sample itself. By considering different scales it is possible to check the change of the features with scale.

For this samples, Contrast, Dissimilarity, Energy, Entropy and Homogeneity were calculated for 9 different displacements (2,4,6,8,10,12,14,16,18 pixels), as can be seen in Table 2 for samples 16c and 22b. Similar results are obtained for the other samples.

TABLE II. Features values for different GLCM displacement for two texture samples

Displacement	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**
Sample 16c									
Contrast	0.560	0.829	0.974	1.063	1.117	1.153	1.169	1.177	1.174
Dissimilarity	0.404	0.539	0.610	0.658	0.689	0.708	0.719	0.724	0.723
Energy	0.264	0.231	0.216	0.208	0.203	0.201	0.200	0.198	0.199
Entropy	1.913	2.023	2.059	2.076	2.084	2.087	2.089	2.090	2.089
Homogeneity	0.813	0.759	0.731	0.711	0.698	0.690	0.685	0.683	0.683
Sample 22b									
Contrast	0.432	0.840	1.170	1.343	1.360	1.261	1.103	0.983	0.968
Dissimilarity	0.409	0.662	0.814	0.885	0.880	0.833	0.776	0.735	0.724
Energy	0.177	0.139	0.133	0.134	0.135	0.135	0.135	0.135	0.136
Entropy	2.037	2.245	2.284	2.273	2.268	2.271	2.271	2.260	2.259
Homogeneity	0.798	0.687	0.628	0.603	0.608	0.626	0.645	0.658	0.663

Table 2 shows the five texture features computed for different values of displacement for the GLCM. In order to select the best values of the displacement we suggest using the one that gives the maximum contrast – maximum contrast distance (MCD). In future more analysis should be performed in order to state the applicability of this hypothesis in more cases. However, based on the references, MCD criterion seems to describe a texture element for every considered sample. Figure 1 shows visually the size of the area of the picture corresponding to the displacement value defined in the table. Note that the images are zoomed in.

Figure 1. Magnified area of the image enclosed by a certain distance from 2 to 18 pixels with step of 2 for sample 16c (scale2)

Fig. 1 shows that what visually seems to be a texture element (red rectangular) corresponds to the maximum contrast distance in Table 1 for sample 16c.

From Table 1 we can see that Contrast and Dissimilarity change a lot with displacement. This happens because these two features are computed in a same manner (if we refer to the formula) just with a different weighting factor, such that Contrast has slightly higher values. On the other hand the other three features seem to be constant and if they change they do slightly and only before the values of the maximum contrast. This could mean that the displacement does not affect these values and if it does it only affects them when the actual texture element is not formed. This suggests that it is not possible to pick any displacement for all samples because Contrast is not constant with the distance. But if we relate the values of the Contrast with the size of the texture element, as suggested by Dikshit [2], we can note that the value of the maximum Contrast actually gives the displacement that encloses one single texture element.

Using the criterion of displacement giving the maximum contrast we have compute features at different scales, from 2 to 9 (see Table 1).

Fig. 2 shows one example of samples used for this analysis.

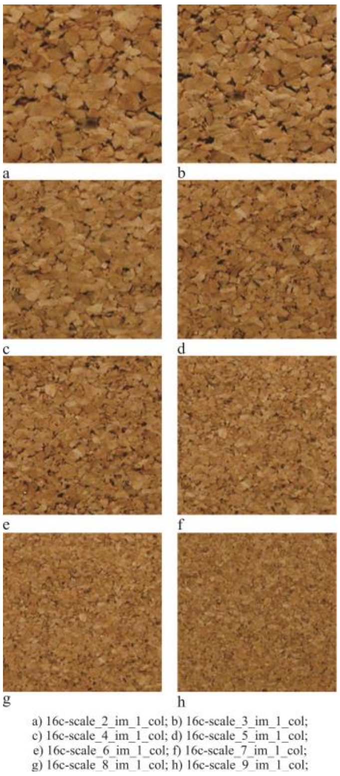

Figure 2. Example of one texture in differen scales.

Fig. 3 shows that quite constant values are obtained, independently of the scale for the texture features Dissimilarity, Homogeneity and Energy. For Entropy and Contrast small changes are obtained.

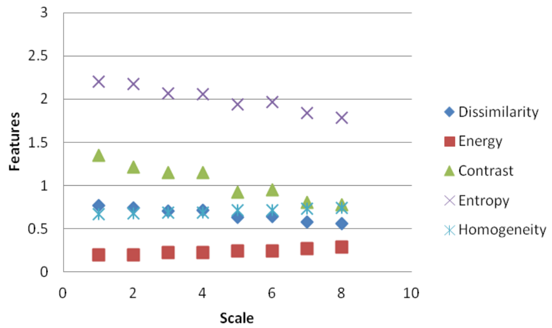

Figure 3. Texture features for sample 16c at different scales.

Thus, this finding suggests that MCD could be a good method to keep texture feature invariant under change of scale. Further studies are required.

IV. Conclusions

Three of the features, Energy, Entropy and Homogeneity do not exhibit a significant change with displacement while Contrast and Dissimilarity do. This concludes that for the first three the selection of any displacement in the computation of GLCM will not influence their performance suggesting that they could be good texture descriptors. However the other two suggest that not all texture features are displacement-invariant. We can suggest that the displacement giving the maximum Contrast (MCD) should be the best as it restricts the feature calculations to surely enclose only one texture element.

We have checked this criterion analyzing the behavior of the texture features with different scales, which give results close to ideal goal of features characterizing texture invariant under scale.

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