An Investigation of the Textural Characteristics Associated with Gray Level Cooccurrence Matrix Statistical Parameters

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Abstract—The aim of this study was to investigate the statistical meaning of six GLCM (Gray Level Cooccurrence Matrix) parameters. This objective was mainly pursued by means of a self-consistent, theoretical assessment in order to remain independent from test image.

The six statistical parameters are energy, contrast, variance, correlation, entropy and inverse difference moment, which are considered the most relevant among the 14 originally proposed by Haralick et al.

The functional analysis supporting theoretical considerations was based on natural clustering in the feature space of segment texture values.

The results show that among the six GLCM statistical parameters, five different sets can be identified, each set featuring a specific textural meaning. The first set contains energy and entropy, while the four remaining parameters can be regarded as belonging to four different sets. Two parameters, energy and contrast, are considered to be the most efficient for discriminating different textural patterns.

A new GLCM statistical parameter, recursivity, is presented in order to replace energy which presents some degree of correlation with contrast.

It is demonstrated that in some cases it may be reasonable to replace the computation of GLCM with that of GLDH (Gray Level Difference Histogram), in order to benefit by a better compromise between texture measurement accuracy, computer storage and computation time.

I. INTRODUCTION

Texture is the visual effect which is produced by spatial distribution of tonal variations over relatively small areas. The concept of texture can be investigated through its relationship with tone; in fact, textural and tonal information can both be present in an image or either one can dominate the other. If texture is the dominant information in a small area, then this area has a wide variety of discrete tonal features [1], [2]. However, if the number of distinguishable tonal discrete features declines, then the tonal properties dominate.

In particular, the dominant information is gray tone when a small area presents little tonal variation; if the small area is homogeneous (i.e., there is a single discrete feature) it has tone but no textural content. Thus, the texture concept depends upon three variables:

- the size of the small area under investigation;
- the relative sizes of the discrete tonal features;
- the spatial distribution of distinguishable discrete tonal features.

A common technique in texture analysis involves the computation of GLCM [3] as a second-order texture measure. GLCM describes the frequency of one gray tone appearing in a specified spatial linear relationship with another gray tone, within the area under investigation. Several statistical parameters can be extracted from the GLCM. Some of these parameters are related to specific first-order statistical concepts, such as contrast and variance, and have a clear textural meaning (e.g., pixel pair repetition rate, spatial frequencies detection, etc.). Other parameters contain textural information but are associated with more than one specific textural meaning.

Six textural parameters are considered to be the most relevant [3] among the 14 originally proposed in [4]: energy, contrast, variance, correlation, entropy and inverse difference moment.

The aim of this study was to evaluate functional differences among these six parameters and to associate a textural meaning to each parameter, in order to perform an image-independent feature selection among them.

To reach this objective, the GLCM parameters assessment is first carried out on a theoretical basis. The reason for this choice is to overcome a common limit which affects several articles, appeared in the literature, dealing with the problem of the GLCM statistical parameters selection, where experimental results lack in general validity.

Numerical examples should be provided, whenever necessary, to support the theoretical conclusions. In this paper, no cluster plots in 2-dimensional space are used as a quantifiable description of different GLCM parameters sensitivity for different types of texture. This kind of analysis would have required the supervised selection of a combination of several texture parameters in order to stress some generic properties of the different texture parameters. This supervised procedure would have been very complex to implement. For this reason, an alternative strategy was developed to verify the theoretical considerations. First, a test image presenting a wide variety of texture types was selected. Second, cluster analysis, adopted as an unsupervised investigation tool, was applied to the test image for each texture parameter in order to reveal its numerical behavior. Third, a qualitative (visual) comparison between the texture types in the original image and the cluster output image should confirm the validity of the general properties provided by the theoretical considerations.

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The cluster approach allows a qualitative evaluation of:

- the distribution of each GLCM parameter in the feature space by changing the number of clusters;
- the textural meaning being associated with any GLCM parameter, by comparing the original image with the output of cluster analysis;
- the informational correlation between different GLCM parameters, by comparing their relative output products.

The functional assessment of these three points becomes the goal of this paper. In pursuing this goal, any decision involving texture analysis was taken while trying to reduce computation time. The paper is organized as follows: first, the GLCM computational approach is described; second, image segmentation and clustering algorithms are presented; third, experimental results are presented and discussed.

II. PROJECT PLANNING

A. Input Data

The informational utility of the six textural parameters was tested on an AVHRR image over Antarctica. In particular, an AVHRR channel 2 image of the area around Terra Nova Bay, 512 x 512 pixel size, for Dec. 6, 1990 (Fig. 1), was chosen as the basic test image for this study.

The choice of this image is based on its pictorial features. Few basic themes are present: low brightness water, clouds, sea ice and continental ice. These surface themes provide the test image with a wide variety of texture types. Textural rather than spectral informations characterize each surface class. High contrast areas (i.e., areas characterized by a relevant textural content due to spatial gathering of small-area homogeneous patches displaying strongly different spectral responses) appear to be the mountain zones which show a mixed snow over the shadow of the rock cover. Texture information is also present in clouds and sea ice areas. Large areas of the image appear to be homogeneous in tone, or characterized by very low spatial frequencies, regardless of their spectral signature (e.g., sea or continental ice).

B. GLCM Computational Variables

GLCM is computed over a segment, which is inspected by a displacement vector \( d \), defined by its amplitude \( b \) and its orientation \( \alpha \). The displacement vector \( d \) investigates the typical spatial frequencies of a generic cell area. Cell size choice results from a compromise between two contrasting requirements: 1) cell size reduction augments sensitivity to sensor noise and increases computation time; 2) cell size must be smaller than the smallest object to be mapped.

A visual inspection of the test image suggested a selection of a cell of \( 8 \times 8 \) pixel size, on the basis of former experience [5]. This choice allows the maintenance of the GLCM sensitivity to the smallest details of interest such as the mountain sites, while reducing noise effects and computation time.

In order to evaluate gray tone changes over small areas, and since it is not possible to find any typical orientation of small area patches in the test image (any value \( \alpha \) being good), the final choice for the displacement vector was \( b = 1 \) and \( \alpha = 0 \) [6]. The consequence of this choice is that only horizontally-oriented texture features will be captured. This choice, however, will not interfere with the purposes of the work presented here, since qualitative, rather than quantitative, and functional features of the GLCM parameters are investigated.

C. Hierarchical Classification Approach

The computation of GLCM’s requires an image partition stage. In order to reduce computation time, GLCM is assigned to the entire pixel block belonging to the GLCM computation segment and not to the individual pixel at the cell center. An initial image partition is made from \( 8 \times 8 \) pixel segments.

It must be stressed that GLCM computation must be performed within a realistic classification method. For instance, texture analysis should not be applied to those parts of the image that could be classified by a reliable nontextural (e.g., spectral) investigation.

Moreover, texture analysis should not be applied to every part of an image when a region-based classification approach is adopted. In a region-based method, spatial gathering of small homogeneous regions would point out the presence of image areas where texture information is relevant [7]. Pixels belonging to these areas should be investigated by means of a pixel-based classification approach that also takes spatial variations into consideration (e.g., GLCM computation associated with its central pixel). The region-based method is convenient in order to classify large features, while the pixel-based method is recommended to detect small details [8].

Following these considerations, any realistic texture investigation must be applied on an image logically divided into two parts: 1) a meaningful subset for texture analysis (Meaningful Texture subset, MFT); and 2) a meaningless subset for texture analysis (Meaningless Texture subset, MLT).
that has already been classified by means of nontextural (e.g.,
spectral, contextual, geometric) rules. An example of this
classification approach was presented in [9].

The first property featured by the MFT subset is that its
texture content is lower than or equal to that in the raw
image. Texturally significative image areas, liable to belong
to the MFT subset, are those in which gathering of small-
area homogeneous patches occurs. Among these patches, those
previously classified by means of nontextural rules belong to
the MLT. The second property of the MFT subset is that,
on a general basis, it is geometrically described by a set of
nonconnected regions of irregular shape.

In order to follow the proposed classification scheme, a
simple hierarchical classification model, using both spectral
and textural information, was used. The first classification
step detects low brightness pixels, as an example of reliable
spectral analysis. This module, when run on the monovariate
test image, extracts water and shadow pixels that constitute
the MLT subset and will be ignored by any further texture
investigations.

Since it was decided to reduce the texture computation
time performing the GLCM extraction from regular square
segments, a regular square grid must be superimposed to the
image under textural investigation. Because of the irregular
shape characterizing the MFT subset, some MFT border
regions, i.e., image segments not completely filled with MFT
pixels, can be found in the initial segmentation step. In order
to reduce the effect of segment size variations on textural
parameter computation, an iterative merging procedure applied
to the MFT border regions must be developed.

III. PROJECT IMPLEMENTATION

A. Image Segmentation and Merging Procedure

The original image is initially partitioned in a regular 8 ×
8 pixel grid. Each member of the partitioned image is defined
as an image segment.

Because of the presence of MFT border segments, a GLCM
cannot be extracted from each initial square segment as it may
contain a variable number of MFT pixels. Performing such a
computation would be analogous to computing a GLCM from
square segments filled with MFT pixels but of different sizes.
This size variation would affect the texture parameter domains.

At this stage, the requirements of texture analysis are
• respecting the edges of MFT, i.e., not considering any
MLT pixel in texture investigation;
• reducing the risk of texture parameters scattering due to
size variations among image segments.

A specific merging procedure was implemented to process
every MFT border segment.

Let us introduce two variables: 1) Each image segment is
characterized by a number, uppn (useful pixel pair number),
equal to the number of displacement vector positions involving
pairs of pixels that belong to both the image segment and the
MFT. The uppn can be considered to be the segment effective
area for texture investigation. Any image region can contain
both MFT and MLT pixels, these being randomly spread over
the image, but MLT pixels do not contribute to the effective
area value. 2) A threshold, $D_{\text{max}}$, is defined as the uppn of a
8 × 8 pixel cell filled with MFT pixels. For example, for an
8 × 8 pixel cell, if $\delta = 1$ and $\alpha = 0$, then $D_{\text{max}} = 56$.

The objective of the merging procedure is to obtain an image
partition in which each image segment featuring $\text{uppn} > 0$
(i.e., a segment including MFT pixel pairs) should also have
$\text{uppn}$ equal or close to $D_{\text{max}}$. Hence, any GLCM parameter
value extracted from an image segment featuring $\text{uppn} > 0$
should present little variations due to change in the segment
area, despite the fact that the MFT subset is characterized by
an irregular shape. The merging algorithm requires, as input,
both the raw data image and the binary image describing the
MFT and MLT subsets.

Thus, image segmentation is performed in two steps:

1) An initial segmentation step. The entire image is initially
divided into a regular grid of 8 × 8 pixel segments, each
segment being identified by a label. The $\text{uppn}$ value
characterizing each initial segment is computed. The
$D_{\text{max}}$ threshold is computed. This means that, for any
initial segment, the condition $\text{uppn} \leq D_{\text{max}}$ is always
satisfied.

2) An iterative merging procedure is applied to all MFT
border segments, i.e., the segments featuring the condition
$0 < \text{uppn} < D_{\text{max}}$. The iterative merging process
produces an output image made of segments that are not
necessarily square, but are built by square blocks.

The currently implemented merging procedure is not pre-
sented in details.

The result of the image segmentation step is shown in Fig.
2 where image segment contours are white, black pixels are
those belonging to MLT. MFT pixels within each segment are
displayed with a randomly selected gray tone.

The merging procedure produces image segments charac-
terized by different effective area values, despite the fact that
most segments should present $\text{uppn}$ values equal or close

Fig. 2. Result of the segmentation step as applied to Fig. 1.
to $D_{\text{max}}$. To reduce the risk of GLCM parameter domain variation due to change in the effective area of image segments, only segments having:

$$0.95 \cdot D_{\text{max}} \leq u_{\text{ppn}} \leq 1.05 \cdot D_{\text{max}}$$

are texturally investigated.

Since the initial partition of the image in square cells has been arbitrary, segments in the final segmentation output may not be "pure" (monothematic) in their informational content.

The suggested characterization of image segments involved in the GLCM computation by means of a $u_{\text{ppn}}$ value can be extended to any neighbor involved in the GLCM computation associated to its central pixel.

For instance, let us consider the central pixel in Table I as belonging to MFT. Its neighbor area involved in the GLCM computation would grow with increasing distances from the center (computed with the chamfer 3-4 transformation [10]) until the desired $u_{\text{ppn}}$ value characterizes the connected neighborhood made of MFT pixels.

B. Cluster Analysis

The basic ISODATA clustering algorithm [11] was adopted for cluster analysis. This algorithm is appropriate when the clusters form compact gatherings which are well separated from each other, and when there are small differences in the number of vectors belonging to different natural groups [11], [12].
The main characteristics of the basic ISODATA procedure are

• it requires the number of clusters as input data;
• it is applied in parallel, i.e., it waits until all vectors are clustered before updating the cluster center;
• it is applied iteratively;
• it optimizes the sum of squared errors (SSE).

In particular, in the tests described in Section III, ISODATA clustering was performed with input clusters \( n = 5 \) and 10.

IV. RESULTS

What follows is a detailed description of the discriminating efficiency of the six GLCM statistical parameters, with ISODATA clustering performed with clusters equal to 5 and 10 on the test image of Fig. 1. For each parameter the different results are indicated by three letters followed by the number 5 or 10 relative to the number of clusters utilized. A randomly chosen color is associated with each cluster in each output image.

When considering the results, the following definitions, relating different texture types to image surface themes, are given (see also Fig. 1):

1) very high texture = mountains
2) high/medium texture = sea ice with floes
3) low texture = clouds
4) no texture = continental ice

For the mathematical symbols used in the following paragraphs see the Appendix at the end of the paper. The name of the GLCM statistical parameters are written in italics.
A. Energy

\[ \text{ene} = \sum_{i=0}^{N_x-1} \sum_{j=0}^{N_y-1} g^2(i, j) \]

Theoretical Description: This parameter is also called Angular Second Moment [13] and Uniformity in [6], [14], [15]. Energy measures textural uniformity, i.e., pixel pairs repetitions; when the image patch under consideration is homogeneous (only similar gray level pixels are present) or when it is texturally uniform (the vector displacement always falls on the same \((i, j)\) gray level pair), a few (possibly only one) elements of GLCM will be greater than 0 and close to 1, while many elements will be close to 0. In this case energy reaches values close to its maximum, equal to 1. Thus, high energy values occur when the gray level distribution over the window has either a constant or a periodic form [15]. This result means that energy is strongly uncorrelated to first order statistical variables such as contrast and variance. Indeed, energy may reach its maximum either with maximum or no variance and contrast values.

Visual Description: ene5: clusters are gathering in the zones of very high homogeneity, while all other parts of the image with high, medium, and low textural content assemble in one cluster. This assembly indicates that textural values of strongly homogeneous regions (close to 1) turn out to be statistically separated from textural values (close to 0) of other zones. Furthermore, the cluster analysis stresses an important
behavior of energy: its rate of variation is considerably higher at the smooth-texture end than at the rough-texture end [15].

**B. Entropy**

\[
\text{ent} = - \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} g(i, j) \cdot \log(g(i, j))
\]

**Theoretical Description:** This parameter measures the disorder of an image. When the image is not texturally uniform, many GLCM elements have very small values, which implies that entropy is very large. As an example, consider a window with completely random values of gray level pixel values (white noise). The histogram for such a window is a constant function, i.e., all \(g(i, j)\) are the same, and the entropy parameter reaches its maximum [15]. From a conceptual point of view, entropy is strongly, but inversely, correlated to GLCM energy. Theoretically, similar results are expected for energy and entropy clustering. An advantage in using energy rather than entropy lies in the fact that the former has a normalized range.

**Visual Description:** ent5: all medium and low heterogeneity regions appear associated with the same background cluster, while highly homogeneous regions are shared among different clusters. This result implies that low and medium homogeneity areas are very well separated from the other clusters. ent10: the results show smaller sensibility compared with ent5, the new clusters appearing mainly distributed over the medium and low homogeneity regions.

**C. Contrast**

\[
\text{con} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 \cdot g(i, j) = \Delta_{\text{con}}
\]

where

\[
\Delta_{\text{con}} = (i - j)^2
\]

**Theoretical Description:** Spatial frequency is the difference between the highest and the lowest values of a contiguous set of pixels. This definition holds for the GLCM contrast expression as well, in particular when the module of the displacement vector is equal to one. This implies that a low contrast image is not necessarily characterized by a narrow gray level distribution, i.e., it does not necessarily present a low variance value, but the low contrast image certainly features low spatial frequencies. The conclusion is that the GLCM contrast tends to be highly correlated with spatial frequencies while the module of the displacement vector tends to one. With regard to the GLCM variance and contrast pair, the only condition that relates these two parameters to each other is the following: a sufficient, but not necessary, condition to keep contrast low is to maintain variance low (while the vice versa is not true). A low contrast image presents a GLCM concentration term around the principal diagonal and, consequently, a low value of the GLCM contrast. This result means that high contrast values imply high contrast texture, i.e., first-order statistics contrast and GLCM contrast are strongly related. GLCM contrast and variance were also found to be highly correlated with the first order statistic standard deviation [13], but this condition, according to the theoretical discussion presented above, must be considered as a particular case for the contrast parameter.

**Visual Description:** con5: the result is opposite to that of ent5, while energy assembled clusters starting from very high homogeneous regions, contrast gathers clusters starting from strongly contrasted areas; low and medium contrast regions are associated with the same background cluster. con10: a large part of the new clusters gather in higher contrast areas. Large low contrast image regions, e.g., continental ice and large clouds, still result associated with the main cluster. This result means that these regions are associated with textural contrast values that are strongly separated from the values of higher contrast areas.

**D. Variance**

\[
\text{var} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - \mu)^2 \cdot g(i, j) = \Delta_{\text{var}}
\]

where

\[
\Delta_{\text{var}} = (i - \mu)^2
\]

**Theoretical Description:** GLCM variance is a measure of heterogeneity and is strongly correlated to first order statistical variables such as standard deviation [13]. In particular, when a square image area is under textural investigation, the first order statistical variance is equal to the GLCM variance if the GLCM vector displacement is equal to 1 and if its investigation angle is equal to 0° or 90°. Variance increases when the gray level values differ from their mean. Variance is not dependent on the GLCM parameter contrast, in particular when the module of the displacement vector tends to one, since a region may have low spatial frequencies and a low contrast value while its variance may have either a high or a low value (see
the theoretical description of the GLCM contrast). Besides, variance requires more computation time than contrast.

Visual Description: var$^5$: clusters are concentrated in high heterogeneous areas. The result looks very similar to con$^5$, but variance is also able to discriminate between image areas characterized by low spatial frequencies, according to the theoretical discussion. This result points out that variance and contrast holds similar results in many practical situations. var$^{10}$: same considerations as for con$^{10}$.

E. Correlation

$$
\text{cor} = \sum_{i=0}^{N_i-1} \sum_{j=0}^{N_j-1} (i-\mu)(j-\mu) \cdot g(i,j)/g^2 = \frac{\Delta_{\text{cor}}}{g^2}
$$

where

$$
\Delta_{\text{cor}} = (i-\mu)(j-\mu).
$$

Theoretical Description: GLCM correlation is expressed by the correlation coefficient between two random variables $i$ and $j$, where $i$ represents the possible outcomes in gray tone measurement for the first element of the displacement vector, while similarly $j$ is associated with gray tones of the second element of the displacement vector. Correlation is a measure of gray tone linear-dependencies in the image [3], in particular, the direction under investigation is the same as vector displacement. High correlation values (close to 1) imply a linear relationship between the gray levels of pixel pairs. Thus, GLCM correlation is uncorrelated with GLCM energy and entropy, i.e., to pixel pairs repetitions. Correlation reaches its maximum regardless of pixel pair occurrence, as high correlation can be measured either in low or high energy situations. GLCM correlation is also uncorrelated to GLCM contrast, as high predictability of the gray level of one pixel from the second one in a pixel pair is completely independent from contrast. As a limiting case of linear-dependency a completely homogeneous area may be considered, for which correlation is equal to 1.

Visual Description: cor$^5$: since the test image does not show any linear structure, correlation will assume low values around homogeneous region edges, where uncorrelated scene noise is present (unfocused edges, produced by mixed pixels). This observation applies to image regions where there are large flocs but not, unexpectedly, to mountain sites. The background cluster is associated with medium-high correlation values which are typical of homogeneous areas like continental ice. This result means that in an image without probable linear-dependencies, correlation is efficient in statistically discriminating homogeneous areas, and areas having low textural content. cor$^{10}$: with the introduction of new clusters, an erosion of image regions associated with the main cluster is observed. This result means that image segments with increasing textural contents are associated with the new clusters. Homogeneous areas that are not affected by the new clusters show their strong separation in the feature space.

F. Inverse Difference Moment

$$
idm = \sum_{i=0}^{N_i-1} \sum_{j=0}^{N_j-1} [1/(1 + (i-j)^2)]g(i,j) = \Delta_{\text{idm}}
$$

where

$$
\Delta_{\text{idm}} = \frac{1}{1 + (i-j)^2}.
$$

Theoretical Description: This expression is called homogeneity in [14]. This parameter measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. Therefore, the parameter is more sensitive to the presence of near diagonal elements in the GLCM, i.e., to low contrast, organized texture structures [15]. It is easy to understand that GLCM contrast and idm are strongly, but inversely, correlated. However, this is necessarily true only in terms of equivalent distribution in the pixel pairs population. In other words, idm decreases if contrast increases while energy is kept constant. On the other hand, idm decreases if energy increases while contrast is kept constant. This means that idm is inversely related to both contrast and energy. These considerations can be easily derived from experimental observations (see Table II).

Cases (a) and (b) in Table II reveal that idm is inversely related to energy while contrast is almost unchanged. Cases (b) and (c) reveal that idm is inversely related to contrast while energy remains constant. Cases (b) and (d) show that an increase in contrast and a decrease in energy keep idm almost unchanged.

In [13], [14] experimental results reveal that GLCM idm can be more correlated to energy than to contrast. Table II shows that, on a general basis, idm can not be considered as highly correlated either to energy or to contrast, but it is dependent on their combination.

Visual Description: idm$^5$: image segments showing similar homogeneity values to visual inspection are distributed over different clusters. This result means that the cluster number is too high with respect to vector grouping, or that there are great differences in the number of vectors belonging to different natural groups. idm$^{10}$: the new clusters confirm that idm values do not produce well separated vector grouping, with respect to the different textural contents that can be recognized by a human photointerpreter in the test image.
V. DISCUSSION AND CONCLUSIONS

Several papers have appeared in the literature in recent years regarding the use of texture analysis in satellite image classification. Some observations about GLCM computation can be made:

- In [13]-[15] an isotropic GLCM is computed for each pixel. With this method GLCM information does not present a directional bias which is a recommended feature in a classification context. This method, however, increases computation time with consequent discouragement of GLCM investigation in real-time classification. Computation time can be considerably reduced by storing GLCM in a linked list as suggested in [16], due to the presence of a large number of zero elements in a typical GLCM.

- In [15] a normalized form for GLCM contrast and idm is presented. The first advantage is that these GLCM parameters become invariant to linear gray scale transformation. The second advantage is that the normalized form allows comparison between the values of the same GLCM parameter computed using different combinations of the GLCM computational variables. These two properties are already shared by GLCM features which do not present gray tone term in their expression. Summarizing, by means of the normalized form all GLCM parameters show a more universal nature than gray tone [15]. Due to the invariant character of the GLCM measures under monotonic gray tone transformations, these parameters reduce the need for an absolute radiometric calibration or a linear transformation of the input image. Thus, the normalized form is strongly recommended in order to clearly separate the concept of texture features with respect to gray tone parameters. The advantage of having uncorrelated texture and gray tone parameters is stressed in [13] and [15], where supervised classifiers are trained in a feature space which is both spectral and textural.

- A first order statistic like standard deviation is highly correlated to variance, it requires less computation time and can be successfully used as texture measure in classification [13]. On the other hand, in many practical cases GLCM variance and contrast are highly correlated, while the normalized form of contrast presents the advantages listed in the previous paragraph and requires less computation time than variance.

In this paper, the definition of effective area or uppn in GLCM computation has been introduced. Its aim is to allow GLCM computation for pixels belonging to a MFT subset which is characterized by irregular shape. The concept of MFT subset is strongly related to the necessity of a hierarchical classification approach to texture analysis. A basic scheme of a classification process that applies texture analysis within a hierarchical organization can be as follows:

- First classification level: low spatial variability image area classification. In this module, the first step is the detection of the image subsets characterized by low and high spatial variability. For example, this partition can be pursued my means of: 1) image segmentation in spectrally homogeneous regions, e.g., by means of spectral clustering; and 2) extraction of the image areas where small segments are gathered together (MFT areas). The image subsets dominated by spectral information, i.e., presenting low spatial variability (MLT areas), are better classified employing a region-based approach, since this approach is more convenient for classifying large features.

- Second classification level: high spatial variability image area classification. In this module, the first step is the extraction of texture information from the MFT areas. This step should be suited to a pixel-by-pixel classification approach that exploits contextual information, since this approach is more convenient to detect small image details. For example, each pixel belonging to the MFT subset is characterized by a feature vector presenting some GLCM parameter values beside the pixel gray level values.

Six textural parameters, extracted from GLCM's, have been functionally investigated by means of cluster analysis. Five parameter sets, each one characterized by a specific functional and textural meaning, have been identified. The first set contains energy and entropy, while each one of the parameters contrast, variance, idm and correlation forms a set on its own. Parameters belonging to different sets may present high correlation values in particular cases. This is true, in particular, for the parameters contrast and variance, which showed similar clustering results over the variety of texture types presented in the test image. The selection of the most valuable parameters is based on the following considerations:

- Energy is preferred to entropy since its values belong to a normalized range. The elements in this set measure a texture concept which is very different from those assessed by contrast and variance.

- Contrast and variance measure different texture concepts, the former being associated with the average gray level difference between neighbor pixels, the latter with the average gray level difference between pixels and their mean. The clustering results of these two parameters are very similar. This means that contrast and variance present a very similar behavior in the detection of many different texture types, i.e., in many practical situations contrast and variance are very correlated. Contrast is preferred to variance because of its reduced computational load and its effectiveness as a spatial frequency measure. This second property is extremely relevant, since in many application fields (e.g., satellite image segmentation) the texture information level increases when spatial frequencies (rather than variance) increase.

- Idm is a texture parameter affected by both textural frequency and contrast. This means that idm is a combination of the textural effects characterizing both energy and contrast. Since these two effects are conceptually and numerically distinguishable, the use of idm is not recommended. This conclusion is also supported by the unsatisfactory experimental results obtained applying cluster analysis to idm values.

- When the pixels under investigation present linear gray level dependencies, the parameter correlation may be-
come valuable, otherwise correlation separates in a binary form spectrally homogeneous segments (whose correlation value is very close or equal to 1) from segments presenting some degree of texture. This means that in many practical situations, whenever pixel linear dependencies are not expected, the use of correlation is discouraged (because of its heavy computational load as well).

The conclusion is that two parameters, energy and contrast, are the most significant, in terms of visual assessment and computational load, to discriminate between different textural patterns. The GLCM energy and contrast parameters are associated with a specific textural meaning, i.e., they are uncorrelated. In particular, energy increases with the frequency of primitive patterns, while contrast increases with higher contrast values of primitive patterns. This means that, despite the characteristics of the sensor, the surface types and the classification method, the combination of the GLCM energy and normalized contrast is recommended, even though a specific feature selection may be applied to the presented sets of GLCM parameters for particular applications. These conclusions compare well with those described in [13], where the three less correlated features were energy, contrast and correlation, and where the best texture parameters were energy and first order statistic standard deviation (that is highly correlated to contrast in many practical situations). In both [13], [14] idm showed high correlation properties with respect to the parameters belonging to the first set, to contrast and variance. In [15], idm was chosen as the most effective textural parameter and this conclusion is not consistent with the results of this paper.

Some additional questions regarding the relationship between energy and contrast are discussed. Indeed, the presence of periodic structure and local contrast are independent textural concepts. Nonetheless, energy and contrast, which were selected to measure these two textural features, are related in some way. In fact, energy is sensitive to the presence of contrast. This is clearly shown by the following example. If a gray level pair (i, j) does exist so that g(i, j) = 1, this necessarily means that i = j, due to the symmetric structure of the GLCM. In this case, energy = 1 and contrast = 0. For a situation in which i ≠ j, the maximum probabilities associated to this pair are g(i, j) = g(j, i) = 0.5. In this case, energy = 0.5 and contrast > 0. This means that the (overall) frequency of a gray level pair (i, j), given by g(i, j) + g(j, i), provides an (overall) contribution to energy that is reduced by a factor of 2 if i ≠ j (i.e., (i, j) does not lie on the GLCM principal diagonal). This effect is also stressed by considering that each primitive pattern frequency lying over the GLCM principal diagonal contributes to energy with a term ranging from 0 to 1, while each symmetric pair of off-diagonal frequencies gives a contribution to energy that falls in the range from 0 to 0.5. The different weights that diagonal elements and off-diagonal symmetrical pairs have in energy computation are responsible, in part, for the higher sensitivity that this parameter has experimentally shown at the smooth-end of the texture scale. Similar observations can be made for entropy. In this case, each primitive pattern frequency lying over the

GLCM principal diagonal contributes to entropy with a term ranging from 0 to +∞, while each symmetric pair of off-diagonal frequencies gives a contribution to entropy that falls in the range from −log(0.5) to +∞.

It should be pursued that no correlation exists between contrast and both energy and entropy. The off-diagonal and on-diagonal (i, j) situations described above should be measured as being equivalent by a GLCM parameter that actually evaluates the pixel pairs recursivity (i.e., the presence of periodic structure). A GLCM parameter, recursivity, is introduced to replace energy (a similar expression can be used to replace entropy). Recursivity accounts for the symmetric form of the GLCM by working only on the upper triangular part of the matrix and has the following expression:

\[
rec = \sum_{i=0}^{N_x-1} \sum_{j=i+1}^{N_y-1} (2 \cdot g(i, j))^2 + \sum_{i=0}^{N_x-1} (g(i, i))^2.
\]

To replace entropy the parameter inverse recursivity is introduced:

\[
invrec = -\sum_{i=0}^{N_x-1} \sum_{j=i+1}^{N_y-1} 2 \cdot g(i, j) \cdot \log(2g(i, j)) - \sum_{i=0}^{N_x-1} g(i, i) \cdot \log(g(i, i)).
\]

These parameters are fully independent from the presence of contrast, since the contribution of contrast to their higher rate of variation at the smooth-end of the texture scale is removed. However, rec and invrec are still more sensitive to the smooth-end of the texture scale. This can be seen in Table III, which was adapted from [15].

An additional advantage in the exploitation of the proposed combination of the recursivity and contrast parameters is the possibility of processing the GLCM as an upper triangular matrix. During the GLCM computation stage, whenever two pixel values (i, j) are encountered by the displacement vector, they are sorted out to make i ≤ j and hence the GLCM element correspondent to the (i, j) entry is incremented by a unitary value. During the texture parameter computation, the recursivity and contrast parameters are extracted from the upper triangular part of the GLCM matrix.

As a future development, a new GLCM parameter measuring the frequency of primitive patterns, and less sensitive to the smooth-end of the texture scale, should be designed. A final observation can be presented about the possibility of using the Gray Level Difference Histogram (GLDH) [17] in place of the GLCM. A recent work outlines that the one dimensional GLDH yields similar results to those extracted from the second-order statistics GLCM [18]. In relation to the GLCM parameters recursivity and contrast presented above, some considerations follow:

- The contrast value computed from the GLCM is equal to the contrast statistical parameter extracted from the correspondent GLDH.
- The GLCM recursivity is related to the GLDH energy parameter since they both assess the presence of periodic
structures. However, while the GLCM recursivity measures the repetition rate, or periodic presence, of pixel pair gray level combinations, the GLDH energy measures the repetition rate of pixel pair differential values. The conclusion is that these two statistics relate to quite different visual concepts, even though in some images they may provide highly correlated results. In terms of texture assessment accuracy, the GLDH energy decreases with the presence of nonperiodic textural structures which are a "subset" of those detected by the GLCM recursivity. This property can be expressed in mathematical terms by the following relationship, which is always true:

\[ \text{GLDH energy} \geq \text{GLCM recursivity} \]

This relationship stresses the fact that the GLDH energy is less sensitive than the GLCM recursivity.

- Both the GLCM recursivity and the GLDH energy present a very interesting property: they are logically uncorrelated to the contrast measure, i.e., they do not depend upon the presence of spatial frequencies.

- Both the GLCM recursivity and the GLDH energy minimum values are greater than zero. This situation occurs when entropy is maximum, i.e., when all the elements in the probability matrix present the same probability value. Let us call \( N_c \) the total number of cells in the probability matrix. For GLDH: \( N_c = N_g \), while for the upper triangular GLCM: \( N_c = \sum_{i=0}^{N_g-1} (N_g-i) \). The GLDH energy minimum value is equal to

\[ e_{\text{ene}} = \frac{N_g-1}{N_c-1} \]

It is easy to demonstrate that the minimum value of the GLCM recursivity is also equal to \( 1/N_c \). In order to expand its output range to the [0,1] interval, the GLCM recursivity must be transformed in its \( f \text{inal recursivity (frec) value} \) by means of the following equation:

\[ \text{frec} = (\text{rec} - N_c^{-1}) \cdot \frac{1}{1 - N_c^{-1}} = \frac{N_c \cdot \text{rec} - 1}{N_c - 1} \]

An analogous expression can be employed to expand the range of the GLDH energy from 0 to 1. Similar observations can be applied to the original GLCM energy.

We conclude that it may be reasonable to use the GLDH instead of the GLCM, in order to obtain a better compromise between texture assessment accuracy, computer storage and computation time.

VI. APPENDIX

A brief description of the mathematical symbols used in the paper is given below:

1) \[ g(i, j) = p(i, j) \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} p(i, j) \]

where \( g(i, j) \) is the \((i, j)\)th entry in GLCM, \( p(i, j) \) is the occurrence of gray levels \( i \) and \( j \), measured at two pixels separated by a given displacement vector, and \( N_g \) is the number of gray levels of the image.

2) \[ \mu = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} i \cdot g(i, j) \]

3) \[ \sigma^2 = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i - \mu)^2 \cdot g(i, j) \]

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