Analysis and Comparison of Functional Dependencies of Multiscale Textural Features on Monospectral Infrared Images

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***Abstract*— In this paper, we deal with the problem of extracting meaningful textural features leading to good segmentations on satellite images of natural environments. Standard texture features using graylevel co-occurrence matrices have been widely applied on remote sensed images but they impose limitations (due to finite window sizes) as poor spatial localization. We have generalized the definition of texture features using a multiscale framework, in order to take advantage of multiscale properties of natural images. The new definition improves spatial localization and the relevance of the parameters. We then investigate the dependencies among different features for classification purposes. An unsupervised scheme of classification was performed on different satellite infrared images. We see that natural, chaotic images should be treated with a different methodology.**

I. Introduction

Texture segmentation is one of the central problems in image processing and has given rise to an abundant scientific literature [11]. Techniques which use textural (combined with spectral) information are among the methods which have given the best results in satellite imagery [12].The main problem in the segmentation of natural environment images is the large variability of texture characteristics over them.

Segmentation of images is usually performed in two stages [9]. In a first stage, features characterizing the texture are calculated. In a second stage, those features are used to determine uniform regions over the image. The main purpose of texture feature extraction is to find relations among pixels belonging to a similar texture. As satellite images display fine-grained textures, a statistical approach is often adopted for remotely sensed data: statistical measures of the spatial distribution of graylevels are computed. The most common method consists in computing local co-occurrence matrices representing joint probabilities of graylevel pairs [8] and from that to derive some statistical measures [13]. Classification schemes based on those methods provide good results in cloud classification [13] [7] or land cover segmentation [5], and show also good performance on benchmark images [11].

In this paper, we focus on the use of multiscale textural features for the segmentation of infrared images of natural environments. We show the limitation of a classification scheme on meteorological images, as the features appear to be mutually functionally dependent. In the next section, we introduce the concept of multiscale textural features which generalize the classical definition. In section III, we present measures of functional correlation between features computed on Landsat, Spot and MeteoSat infrared images. We perform then a classical K-Means classification on those data in section IV and we interpret the different results in section V.

II. Multiscale textural features

Information in a natural image is not contained at only one scale: multiple objects of different real and apparent sizes appear intervowed in a complicated mesh. It is thus necessary to relate somehow information from the different scales of resolution. Approaches based on co-occurrence matrices, generally obtained over fixed size windows, need to be extended in order to acquire textural features at several scales [10].

We propose to generalize co-occurrence in a multiscale framework by introducing a non-uniform, scale-invariant weighting function in the computation of spatial distribution of grey-levels variations. The standard way for the evaluation of gray-level distribution consists in defining small (overlapping or not) windows of predefined size around each pixel, then computing the relative frequency of the observed pairwise graylevels and finally calculating a representative feature (GLCM approach [13]). In our approach, instead of defining a small window around the pixel x, we consider a rather large window $W(x)$ but each pair of graylevels is assigned a weight so that pairs of pixels further and further away will contribute less and less. In such a way, a good localization is obtained, even for large windows. We define the multiscale joint probability $p_{ij}^W(x)$ of a graylevel pair (i,j) by: $p_{ij}^W(x) \propto \sum_{y,y' \in W(x) | I(y)=i, I(y')=j} |x-(y+y')/2|^{-\alpha}$. We choose the exponent $\alpha = 2$. Due to the scale invariant character of this weight function, the result does not in principle depend on the size of the window [6], although we limit the calculations to a 21×21 window to avoid divergences and to fasten calculations. For that reason, the computation of the features [13] does not depend either on any fixed scale: it is scale invariant. This

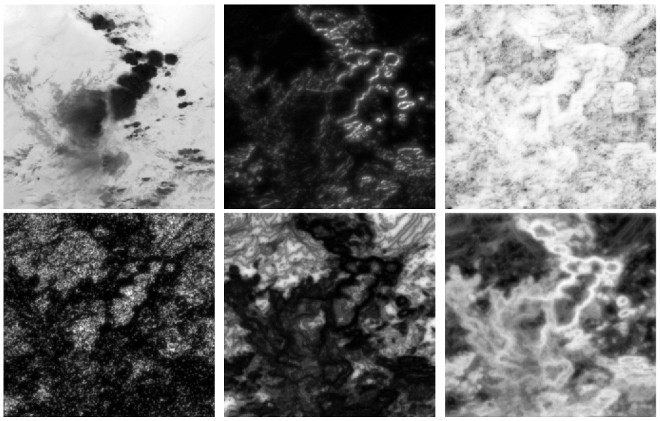


Fig. 1. Examples of multiscale textural features computed on an infrared MeteoSat image. From top to bottom, from left to right: original image, contrast, correlation, homogeneity, energy and entropy.

method provides a better spatial localization than the classical methods and reduces the overestimation in feature (Fig. 1). Moreover, for some features (like entropy, energy or contrast), assuming statistical translational invariance, it is possible to consider marginal probabilities $p_i^W(x) \propto \sum_{y:I(y)=i} |x-y|^{-\alpha}$ (GLV approach [2]) instead of joint probabilities, what leads to features attaining a better performance in spatial localization, significancy, computer storage and computation time.

III. Correlation in feature space

By calculating many features, we form a multidimensional classification space which helps to determine the class each pixel belongs to. Deciding which features are the most relevant has been the focus of many research efforts [12]. A selection process is usually applied on the feature space, which consists in determining the most discriminant textural features [7] [4]. It reduces the cost of classification by reducing the number of features that need to be collected and provides a better classification accuracy.

However, these conventional methods treat the different features as independent ones. The selection of uncorrelated features is necessary to perform efficient segmentation. In [1], the authors conclude that energy and contrast are the most efficient in terms of visual assesment, and, hence, they recommend the combined use of those parameters for discriminating textures. Other studies [5] show that energy, contrast and correlation are the less correlated parameters and that energy is the best texture parameter. In [12], homogeneity is chosen as the most effective textural parameter.

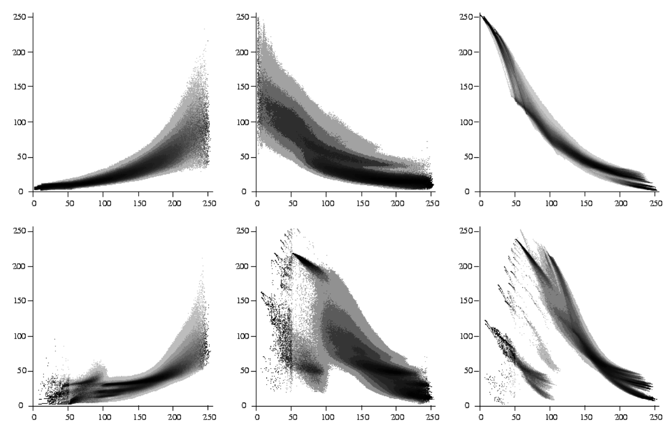
We investigate here the statistical meaning of six textural features: entropy, energy, contrast, variance, homogeneity and correlation [8]. We measure their mutual dependencies in order to exclude redundant, less significant features. For any couple of features $\mathcal{F}, \mathcal{F}'$ we will calculate the mutual information $I_1(\mathcal{F}, \mathcal{F}')$ (which is a measure of the independency of both variables) and the correlation ratio $I_2(\mathcal{F}, \mathcal{F}')$ (which measures their functional correlation) [3]:

$$\left\{ \begin{array}{l} I_1(\mathcal{F}, \mathcal{F}') = H(\mathcal{F}) - H(\mathcal{F} \mid \mathcal{F}') \\ I_2(\mathcal{F}, \mathcal{F}') = V(E[\mathcal{F} \mid \mathcal{F}'])/V(\mathcal{F}) \end{array} \right. \tag{1}$$

where the functions H, E and V stand for entropy, expectation and variance and where the symbol $\mid$ denotes conditioning. The closer I_1 and I_2 are to their maximum values ($H(\mathcal{F})$ in the case of I_1, 1 in the case of I_2) the more dependent the features are, while values of I_1 and I_2 close to zero imply independency of the features.

features $\mathcal{F}$		**cont.**	**homo.**	**corr.**	**ener.**	**var.**
MeteoSat data:	$\mathbf{I}_1$	1.416	0.987	0.280	2.621	1.533
	$\mathbf{I}_2$	0.756	0.668	0.331	0.899	0.744
Spot data:	$\mathbf{I}_1$	0.812	0.517	0.236	1.622	1.104
	$\mathbf{I}_2$	0.402	0.389	0.202	0.680	0.533

(a) Mutual information I_1 (in bits) and correlation ratio I_2 of different features $\mathcal{F}$ with respect to the entropy.



(b) Conditional distributions of features with respect to entropy for MeteoSat (top) and Spot data (bottom). **Left**: contrast; **Middle**: homogeneity; **Right**: energy.

Fig. 2. Functional correlation between features, computed on samples of MeteoSat (20 1350×460 images) and Spot data (20 1000×1000 images).

These measures are performed for different kinds of infrared images: Spot NIR images (TOC channel 3, 0.79μm-0.89μm), Landsat NIR images (band 4, 0.76μm $-$ 0.90μm) and also MeteoSat thermal IR images (10.5μm-12.5μm). In Figure 2, we present the values of I_1 and I_2 for some features computed on large samples of such images and the corresponding conditional distributions. The dependence between homogeneity, contrast, variance energy and entropy turns out to be stronger for MeteoSat data than for Spot data. For Spot data, this dependence is multivalued. Correlation and entropy are the less mutually dependent features; however correlation is not very significant as it poorly locates structures (Fig. 1).

IV. Interpretation for classification purpose

Using sets of computed textural features, we can perform a segmentation of infrared images with a classical K-Means method [9]. The results of the segmentations on land-cover images can be compared with those based on all spectral channels (Fig. 3); textural features allow to characterize some well textured regions (fields and water) but have difficulty to extract small textured areas (cities). For MeteoSat images, the segmentations are not so good, and they are not improved when new features are included in the classification procedure (Fig. 4).

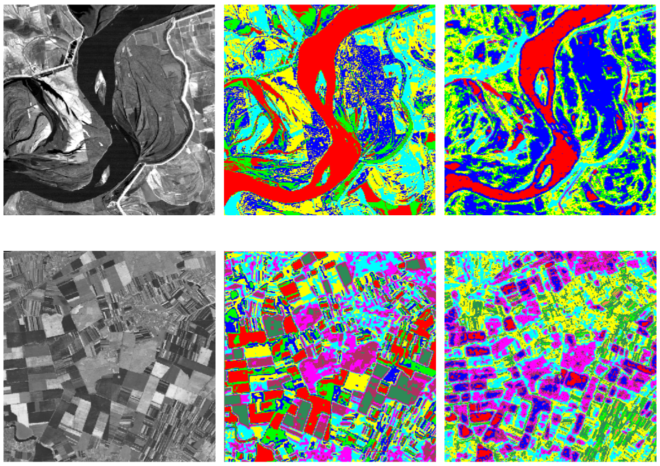


Fig. 3. **Left**: Landsat (left) and Spot NIR land-cover images. **Middle**: K-Means Classification with spectral features. **Rigth**: K-Means Classification with textural features.

V. Discussion and conclusion

We have investigated the mutual dependencies of multiscale features when computed on two types of infrared images: land cover images (from Spot and LandSat satellites) and higher atmosphere temperature images (from MeteoSat). We see that for land-cover images the different textural features are dependent on the underlying region, what allows to classify those regions by applying standard algorithms (as K-means) in the feature space. This dependence of the features on the spatial region is evidenced by the weak functional dependence among features (measured by the mutual information and correlation ratio) and by the multi-valued character of the conditional distributions (as different textures are represented by different clusters in feature space).

On the contrary, segmentation methods based on texture extraction do not work when applied to MeteoSat IR data, a fact already pointed out by Gu [7] and Ebert [4] in the classification of clouds. One of the reasons of this failure lies in the fact that those methods assume regularity conditions that are not satisfied by MeteoSat images (those images are related to thermodynamical properties of a turbulent, chaotic flow). A more detailed analysis of the features shows a remarkable degree of mutual dependency among features, together with narrow, uni-valued conditional distributions of pairs of features. This dependency means that all the features are sensitive to the same property of images and multiple feature classification does not provide new meaningful features. Henceforth, the segmentation has to be carried out by means which take into account the properties of the flow, as for instance performing multiscale singularity analysis [6].

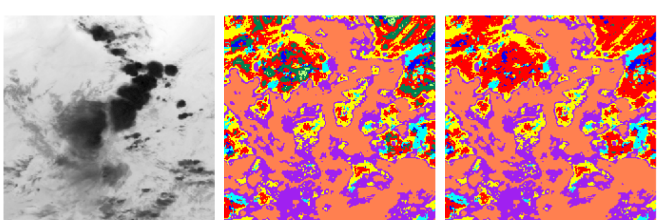


Fig. 4. **Left**: infrared MeteoSat image. **Middle**: K-Means Classification with textural features. **Right**: Segmentation obtained with entropy feature only.

To conclude, the results shown so far means that, unlike what is discussed in [1], there is not an image-independent methodology for feature selection, and in particular classification techniques on multi-feature spaces do not work efficiently for every kind of data disregarding inherent structure of images. Methodologies which are related to the properties of the object of study, specially in the case of natural, chaotic images, should be considered.

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