MULTISPECTRAL REMOTE SENSING IMAGE CLASSIFICATION USING ADAPTIVE WAVELET PACKET

Aymen EL GHOUL, Ziad BELHADJ

URISA, Unité de recherche en imagerie satellitaire et ses applications
SupCom, Cité Technologique des Communications, Rte de Raoued Km 3,5 2083, Ariana Tunisie
ghoul.aymen@gmail.com, ziad.belhadj@supcom.rnu.tn.

ABSTRACT

In this paper, we propose a probabilistic approach for texture description using adaptive wavelet packet coefficients. The objective of this description is to extract features which characterize each texture class and thus for segmentation of multitextured images. Use standard dyadic wavelets is insufficient to analyse high frequency signals with narrow bandwidth and this type of decomposition is not translation invariant. So to remedy this insufficiency, we will use wavelet packet which are a generalization of standard wavelet and to describe texture accuracy we must adapt decomposition to each texture. To this end, we propose a probabilistic approach to select the best basis for a texture from all possibly partitions using Maximum A Posteriori estimate (MAP). We try to apply this method to classify multispectral images obtained from SPOT sensor.

1. INTRODUCTION

In many image processing applications, texture attribut is very important and wavelet packets have played an important role to describe texture [1]. To adapt wavelet packet for each texture, many methods are used to select the best basis that describe accuracy this texture. There is several choices of criterions in literature to define *best* and several *distances* to discriminate textures. Brady et al. [2] developed a probabilistic framework for adaptive texture description. Starting with a probability distribution on the space of infinite images, we compute a distribution on finite region by marginalization. For a gaussian distribution, the computational requirement of diagonalization leads naturally to adaptive wavelet packet models which capture the principle periodicities present in the textures and allow long-range correlations while preserving the independence of the wavelet packet coefficients. Several works mentioned that Gaussian distribution is a useful minimal assumption especially in the case of adaptive basis and coherent textures [3, 4]. Although many of subbands of the basis present a bimodal aspect and the remainder appear Gaussian and generalized Gaussian. The histograms of such subbands show the presence of maxima at non zero coefficient values thus proves existence of periodicity in texture class. In absence of this type of subbands, probably image of that texture are flat or untextured.

Remotely sensed images are very textured, so we have interest to adapt the approach given above and detailed in the rest of this paper to describe and discriminate texture class of multispectral images.

2. MAP ESTIMATE

The adaptive wavelet packet developed by Brady use Gaussian distribution assumption to model subbands of the best basis. Gaussian assumption is relaxed and extended to three models: each subband of the basis can take Gaussian form (G), Generalized Gaussian form (GG) or constrained mixture of Gaussian form (MoG). So, we use the adaptive probabilistic approach to consider several models for the distributions of the wavelet coefficients in each subband. Texture models are thus parameterized by the following data:

1. a wavelet packet basis, T, obtained by the giving of a mother wavelet,
2. a map $\mu : T \to M$, $M = \{G, GG, MoG\}$, selecting the subband model,
3. a map $\theta : T \to P$, P is the set of parameters for each model.

In the rest of this section, we detail MAP estimate for each above parameters, given a number of examples of a particular class of textures.

2.1. Bayesian methodology

We adopt MAP estimation to compute values of the above parameters. Given a number of training images $\{\phi_n : n \in \mathcal{N}\}$, we compute the following *a posteriori* probability:

$$Pr((\theta,\mu,T)|\{\phi_n\},A,\beta) \propto Pr(\{\phi_n\}|(\theta,\mu,T))* \\ Pr(\mu|T)Pr(\theta|\mu,T,A)Pr(T|\beta) \quad . (1)$$

where A and β are experimental parameters and take values respectively in $[0,20]$ and $[50,500]$ [5].

The first factor on the right-hand side represent the *likelihood* function of the training data which can be write like a product over the set T (we suppress the index n for legibility):

$$Pr(\phi|(\theta,\mu,T)) = \prod_{t\in T} Pr(\omega_t|\theta(t),\mu(t)), \quad (2)$$

where ω_t represent the set of wavelet packet coefficients in the subband t.

The second factor represent the probability of the model parameters. For each subband, all the parameters are uniformly distributed over a large range A. Thus it can be written as a product over the set T:

$$\begin{aligned} Pr(\theta|\mu,T,A) &= \prod_{t\in T} A^{-dim(\mu(t))} \\ &= \prod_{t\in T} e^{-dim(\mu(t))ln(A)}, \end{aligned} \quad (3)$$

The third factor represent *a priori* probability of model. We consider that all models are equally likely, with probability $1/3$, so we have:

$$Pr(\mu|T) = \prod_{t\in T} \frac{1}{3} = e^{-|T|ln(3)}, \quad (4)$$

where $|T|$ is the number of subbands which exist in the basis T.

The finally factor allow to penalize the depth of decomposition. It's given by:

$$Pr(T|\beta) = Z^{-1}(\beta)e^{-\beta|T|}, \quad (5)$$

where β is a complexity penalty and $Z^{-1}(\beta)$ is a normalization factor.

2.2. MAP estimation of μ^* and θ^*

These parameters depend only on the first two factors of equation 1, so we maximize the combination of equations 2 and 3 to estimate μ^* and θ^*. This quantity is given by:

$$Pr(\omega_t|\theta(t),\mu_t)e^{-dim(\mu(t))ln(A)}. \quad (6)$$

2.2.1. Gaussian model

In this case, we have this form of probability distribution:

$$Pr(\omega_t|\theta(t),\mu_t = G) = (f_t/\pi)^{\frac{N_t}{2}} e^{-f_t \sum_{i\in t}(\omega_{t,i}-\nu_t)^2} \quad (7)$$

The parameters of each subband are thus f_t, the inverse variance, and ν_t, the mean. This two parameters are then estimated by the following expression:

$$\nu_t^* = \begin{cases} \frac{\sum_{i\in t} w_{t,i}}{N_t} & \text{scaling coefficients ,} \\ 0 & \text{all other subbands ,} \end{cases}$$

$$f_t^* = \frac{N_t}{2\sum_{i\in t}(w_{t,i}-\nu_t^*)^2} \quad (8)$$

2.2.2. Generalized Gaussian model

Expression of this distribution model take the following form:

$$Pr(w_t|\theta(t),\mu(t) = \text{GG}) = Z^{-N_t}(f_t,s_t)e^{-f_t\sum_{i\in t}|w_{t,i}|^{s_t}} \quad (9)$$

where s_t is the *shape factor* and f_t control the width of the distribution; Z is a normalization factor that depends on f_t, s_t and the size of the subband. These parameters are estimated using the algorithm described by Do and Vetterli [3].

2.2.3. Constrained mixture of Gaussians model

To model the bimodal subbands, we use a constrained mixture of three Gaussians. Thus, likelihood probability is given by:

$$Pr(w_t|\theta(t),\mu(t) = \text{MoG}) = \prod_{i\in t}\left[\sum_{a=0}^{2}\frac{P_{t,a}}{(2\pi\sigma_{t,a}^2)^{\frac{1}{2}}}e^{-\frac{(w_{t,i}-\nu_{t,a})^2}{2\sigma_{t,a}^2}}\right] \quad (10)$$

where $a \in \{0,1,2\}$ is the index of mixture components. The mixture probability, $P_{t,a}$, the means $\nu_{t,a}$ and the variance $\sigma_{t,a}^2$ obey the following symmetry constraints: $P_{t,1} = P_{t,2}$, $\nu_{t,1} = -\nu_{t,2}$, $\sigma_{t,1} = \sigma_{t,2}$ and $\nu_{t,0} = 0$. Thus, the type of model has four parameters to estimate.

The estimation problem of these model parameters can be solved by the Expectation-Maximization (EM) algorithm because of the mixture of Gaussians [6, 7]. Constrained mixture of Gaussians model permit to detect principal periodicity which characterize such texture.

3. TEXTURED IMAGES SEGMENTATION

In the first section, we have developed a framework to describe texture class using adaptive wavelet packet coefficients. Therefore, for each texture class l, we assign a set of parameters denoted S_l which characterize it. In this paper, S_l can be written as:

$$S_l = \{T^*,\mu^*,\theta^*\}. \quad (11)$$

where $*$ means optimal for MAP estimates.

The process of classifying an image is carried out via *class map*, $\lambda : R \rightarrow \mathfrak{L}$ where R is the finite image region and $\mathfrak{L}$ is the label set of several entities existing in this image. So, λ assigns a label to each pixel in the finite image region R. Our goal now is to find the best class map, λ^*, that gives the best segmentation of the image. To do this, we must choose an optimisation criterion which is Maximum A Posteriori (MAP) estimate in our work. The probabilistic statement of the problem is thus to find λ^* that maximize the *posterior* probability, $Pr(\lambda|\phi,S)$. Using Bayes' theorem, we can reduce the form of this probability to the following expression:

$$Pr(\lambda|\phi,S) \propto Pr(\phi|\lambda,S)Pr(\lambda|B) \quad (12)$$

where the first factor represent the likelihood function of observed data and the second factor define the prior information on the class map λ.

To simplify the expression of likelihood function, we assume that:

- pixel values inside a region are independent of pixel values outside this region, this assumption is true only if the regions are illuminated from the same source and in segmentation process, independence assumption is often considered because dependency modeling is very difficult,
- the probability of the pixel values inside a region with a fixed label does not depend on the class map outside this region. This assumption sometimes ignores information about the scene but we accept this loss in the case of image segmentation.

The above assumptions simplifie the conditioning in the likelihood function to give:

$$Pr(\phi|\lambda, S) = \prod_{l \in \mathcal{L}} Pr(\phi_{R_l}|\lambda_{R_l}, S_l) \tag{13}$$

where ϕ_{R_l} represent the finite image restricted to the region labeled by l, λ_{R_l} is the label map restricted to R_l which is, by definition, constant and equal to l.

We choose a trivial prior on the class map which assumes independence between pixels in a region and assigns equal probability to each texture class. In addition to this, each pixel in the image must belong to one and only one texture class. Therefore, the prior probability on a class map can be written as:

$$Pr(\lambda|S) = \prod_{x \in \phi} \frac{1}{|\mathcal{L}|} \tag{14}$$

where x is a single pixel in the finite image ϕ.

Compute likelihood function is relatively simple procedure in the case of dyadic shape which can be viewed as three steps. We start by a training phase: we build the set B_l that contain the several parameters which characterize texture class such as the optimal wavelet packet decomposition and the corresponding parameters sets. The second step is apply the optimal decomposition to the dyadic-shaped finite region ϕ_{R_l}. Finally, we compute the likelihood function for the the region for each model: Gaussian, generalized Gaussian and mixture of three Gaussians given in the first part of this paper.

4. RESULTS AND DISCUSSION

We trained the different models given above on some texture extracted from remote sensing images. Texture is very important when analyzing remote sensing data, especially when high spatial resolution sensors are considered. Figure 1 shows patches of a remotely sensed images given by the first row which correspond respectively to flat soil, urbain and mountain texture class, and their optimal adaptive wavelet packet decomposition. These pieces are multispectral images obtained from SPOT4 satellite of 20 meters resolution. SPOT4 permit to obtain four spectral bands where each of them correspond to a wavelength band.

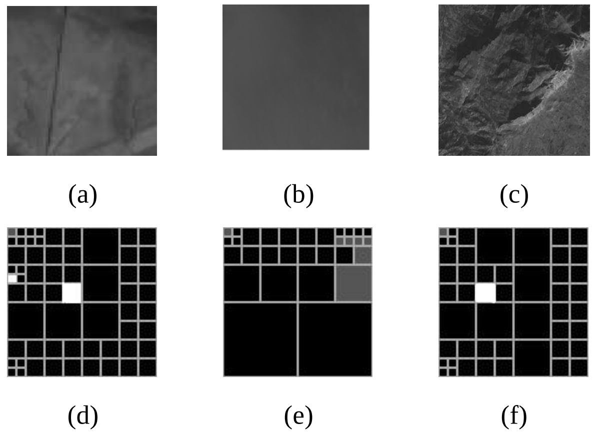


Figure 1. Examples of remotely sensed texture class: (a) flat soil, (b) water and (c) mountain, and their adaptive wavelet packet decompositions below. Different colors correspond to the different model automatically selected within each subband: black, gray, and white represent the GG model, the G model, and the MoG model respectively.

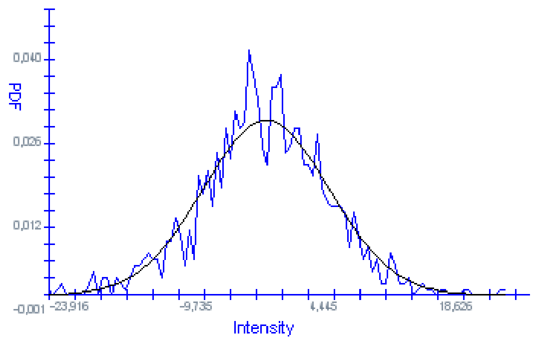
The resulting subband histograms and their fitted models are shown in figure 2. The first row, second row and third row of figure 2 show subband histograms and fitted model corresponding respectively to gaussian, generalized gaussian and mixture of gaussian model.

For all unimodal subbands, the most probable value of the wavelet packet coefficients is zero, i.e. the most probable image composed of these subbands is untextured like the water texture given in figure 1 (b). Clearly is unrealistic for a texture model. In contrast, even though the multimodal subbands have zero mean, the most probable value the coefficient is non-zero, and therefore textured. Since the multimodal subbands typically have narrow frequency support, we can think of them as capturing the principal periodicities in the texture.

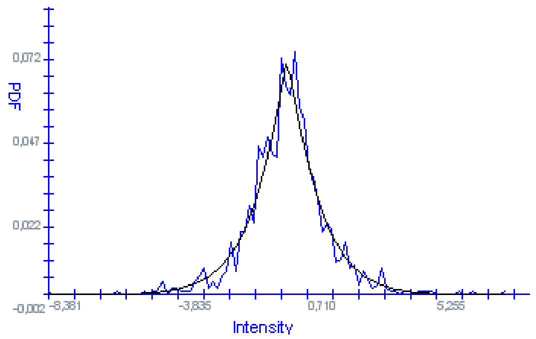
Now we aim to apply the segmentation approach given in section 3 to multispectral remote sensing image. Figure 3 (a) represent a band from multispectral image obtained by SPOT4 sensor of 20 meters resolution in April sixteen, 2000 which correspond to a region in Tunisia. This image contains three texture class : water, mountain and flat soil. Such texture is characterized by its signature obtained by optimal wavelet packet decomposition detailed in the precedent sections using all spectral bands which are four in our image example given in figure 3 (a), its optimal decomposition trees are given by figure 3 (a).

Figure 3 (b) shows the class map obtained by segmenting the multispectral remotely sensed image shown in figure 3 (a) using segmentation approach given in section 3. The black color, grey color and white color correspond respectively to mountain class, water class and flat soil class.

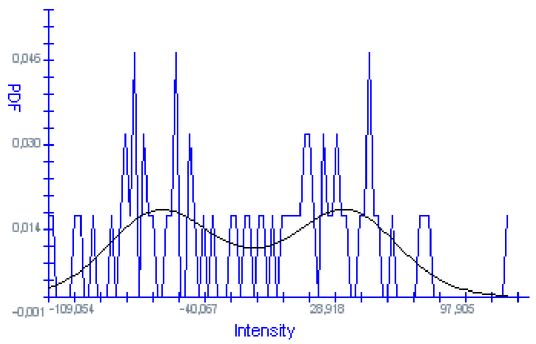
Psycovisually, we can said that the result of segmenta-



(a)



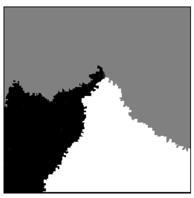
(b)



(c)

Figure 2. Examples of subband adaptive wavelet packet coefficient pdfs and their corresponding fitted model : (a) gaussian model, (b) generalized gaussian model, and (c) constrained mixture of gaussians model, selected from the optimal decomposition of mountain texture.

(a)



(b)

Figure 3. (a) Remote sensed image and its (b) segmented image.

tion is accurate but we try to evaluate it in the futur works using effective quantitative methods.

5. CONCLUSION

In this paper we have extended the adaptive Bayesian approach of Brady et al. [2] by considering information existing in all bands of multispectral remote sensing image to exploit correlation between several bands. Such type of image is very textured mostly at high resolution where we can have a problem to extract patch relative to each texture class.

Practically speaking, while the classification maps obtained for real remote sensing images are not as accurate as for synthetic images because the classification system could exploit multispectral information where the classes are spectrally overlapped or otherwise poorly separable to obtain a more accurate classification result.

References

[1] S. Livens, P. Scheunders, G. Van de Wouwer, and D. Van Dyck, ”Wavelets for texture analysis, an overview”, in *Proc. IEEE Int’l conf. Im. Proc. and its Applications*, Dublins, Ireland, July 1997, pp. 581-585.

[2] K. Brady, I. H. Jermyn, and J. Zerubia, ”Texture analysis: An adaptive probabilistic approach,” in *Proc. IEEE Int’l Conf. Image Processing*, Barcelona, Spain, September 2003.

[3] M. N. Do and M. Vetterli, ”Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Liebler distance ,” *IEEE Trans. Image Processing*, vol. 11, pp. 146-158, 2002, 2.

[4] K. Brady, I. H. Jermyn and J. Zerubia, ”A probabilistic framework for adaptive texture description,” Research Report 4920, INRIA, September 2003.

[5] R. Cossu, I. H. Jermyn, K. Brady and J. Zerubia,”Probabilistic models of the unimodal and multimodal statistics of adaptive wavelet packet coefficients,” Research report, INRIA, February 2003, To appear.

[6] A.P. Dempster, N.M. Laird, and D.B. Rubin. Maximum likelihood from incomplete data via EM algorithm. *Journal of Royal Statistical Society*,39:1-38, 1977.

[7] T.K. Moon. The expectation-maximization algorithm. *Signal Processing Magazine*, 13:47-60, 1996.