UNSUPERVISED CHANGE DETECTION IN SAR IMAGES USING A MULTICOMPONENT HMC MODEL

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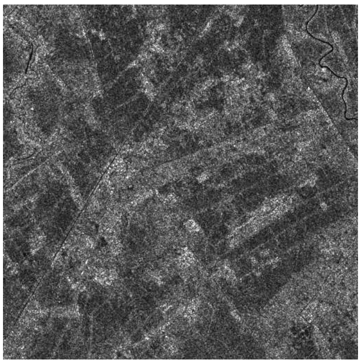
In this work, we propose to use the Hidden Markov Chain (HMC) model for fully automatic change detection in a temporal set of Synthetic Aperture Radar (SAR) images. First, it is shown that this model can be used as an alternative to the Hidden Markov Random Field (HMRF) model in the *image differencing* context. We then propose a novel approach, called *joint characterization*, whose principle is to consider that the 'before' and 'after' images are a unique realization of a bi-dimensional process. Parameters estimation is performed from a multicomponent extension of the HMC model and thematic change can be detected according to the joint statistics of the classes in the images. Preliminary experiments show promising results.

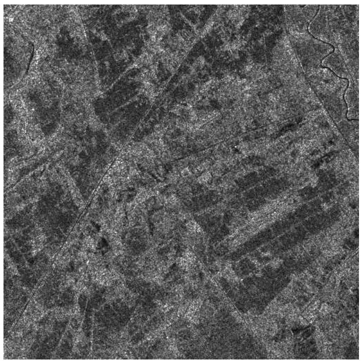
1 Introduction

The recent developments in satellites and remote sensors, together with the necessity for an efficient control of the environment (management of natural resources, risk assessment, damage mapping, land use monitoring, ...), offer new challenging applications. Multitemporal change detection is one of them and a number of methods has been designed the last few years (e.g. [1–3]). Basically, change detection techniques rely on some clustering schemes that identify the coordinates of pixels that have changed between two dates. In this work, we are concerned with SAR images and we assume that the images have been geometrically corrected and co-registered.

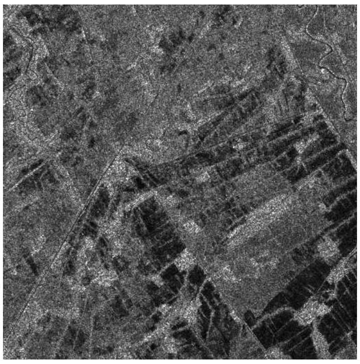
An exemple is given with the three SAR images in figure 1. They show a rice plantation in Semarang (Java Island) with mainly early rice, late rice and other



(a) I_{t_1} - Feb. 6, 1994



(b) I_{t_2} - Feb. 16, 1994



(c) I_{t_3} - Mar. 6, 1994

Figure 1. Three co-registered ERS-1 images of a rice plantation in Java Island, Indonesia (size: 512×512). A flood can be observed in the bottom-right part of the (c) image.

fields. The change that has to be automatically detected concerns the impact of the flood in image I_{t_3}. These images contain major difficulties: (i) speckle induced by the backscattering mechanisms is really strong; (ii) errors from the geometric registrations can be expected; (iii) reflectivity of plantations have been modified during the period of observation; (iv) a flood appears on the second image and covers a part of the observed scene.

There is loosely two main methods in the literature to detect changes in a set of images : the *image differencing* and the *post-classification comparison* techniques :

- In the *image differencing* methods [3], the corresponding pixel values are subtracted to produce a new image (noted DI for 'Difference Image') that represents the radiometric change between the image before (Y_b) and the image after (Y_a). Pixel exhibiting a significant radiometric change can be expected to lie in the tail of the DI histogram, whereas the remaining pixels should be grouped around the mean. Hence, the histogram of a DI can be considered as a mixture of two classes representing ω_c='change' and $\overline{\omega_c}$='no change'. The change detection challenge becomes a classification problem whose result can be directly interpreted as a change detection map. Other representations than the DI can be used, e.g. image ratioing which is considered more robust in case of SAR images [4] or an image of mutual information [5].
- The principle of the *post-classification comparison* methods [2] is to, first, classify independently the Y_a and Y_b images with a fixed number of classes and, second, compare the class labels to detect and localize changes. The class labels can be compared using hard or fuzzy logics. One difficulty is to automatically determine the number of classes for the two images.

In both kind of methods, the accuracy of change detection highly depends on the classification strategy adopted, and a number of methods are available. In this work, we propose to use the HMC model [6, 7] for fully automatic change detection in a temporal set of SAR images. Section 2 starts with a presentation of the model and gives some detection results in the image differencing context. We then propose in section 3 a novel approach, called *joint characterization*, whose principle is to consider that Y_b and Y_a are a unique realization of a bi-dimensional process. Parameters estimation is performed from a multicomponent extension of the HMC model [8] and thematic change can be detected according to the joint statistics of the classes in the images. Preliminary results on the images in figure 1 are presented. Conclusion and perspectives are drawn in section 4.

2 Scalar HMC based change detection method

As underlined in the introduction, the change detection problem can often be considered as a classification challenge. Per-pixels methods, such as the k-means, the fuzzy c-means or, in a Bayesian context, the blind Estimation-Maximization (EM) algorithm, are often inefficient due to the large amount of, possibly correlated, speckle in SAR images. Hence, spatial context sensitive methods (contextual and global) seems to be more suitable since they make use of the information about the neighborhood of each pixel. Bayesian restoration in the framework of the Hidden Markov Models (HMMs) is among the best known statistical methods.

This success is mainly due to the fact that when the unobservable process X can be modeled by a finite Markov model, then X can be recovered from the observed process Y using different Bayesian classification criteria like Iterated Conditional Mode (ICM), Maximum A Posteriori (MAP) or Maximum Posterior Mode (MPM). In an unsupervised context, the statistical properties of the classes are unknown and must first be estimated. Iterative methods such as EM, Stochastic Estimation-Maximisation (SEM) or Iterative Conditional Estimation (ICE) [9] can be used.

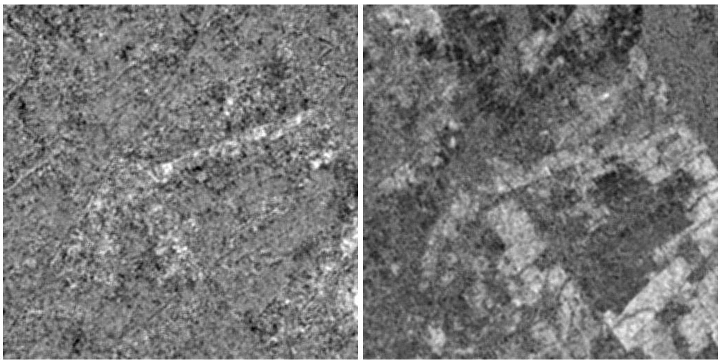
In the image differencing context, Bruzzone et al. [10, 3] report change detection results based on the HMRF model, the EM estimation procedure and the ICM criterion. However, the regularity parameters, that control the homogeneity of the class ω_c (and so the false and missed detection rates), were set to a particular value fixed from experiments. These parameters can also be estimated using the stochastic gradient algorithm proposed by Younes [11]. But, according to our experience in RS image segmentation, this algorithm can sometimes have difficulties to converge.

A substantially quicker and sometimes competitive alternative to the HMRF model in SAR image segmentation is the HMC model. This model can be adapted to a 2D analysis through a Hilbert-Peano scan of the image [6, 7, 12]. In that model, the homogeneity of classes are tuned by a stationary transition matrix whose estimation is much more robust than the estimation of the regularity parameters in a HMRF model. Figure 2 reports the change detection maps obtained from the DIs $\mathrm{I}_{t_1-t_2}$ and $\mathrm{I}_{t_2-t_3}$, with the ICE estimation and the MPM criterion. Clearly, $\mathrm{S}_{t_1-t_2}$ shows only small changed areas (0.5% of pixels) whereas $\mathrm{S}_{t_2-t_3}$ shows large ones (25% of pixels), which seems consistent (no ground-truth map is available).

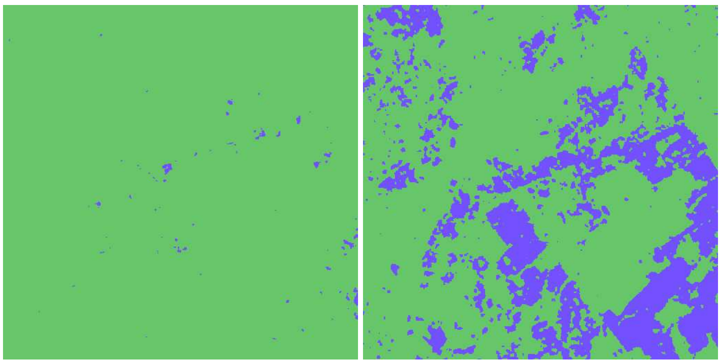
In radar images, the distribution of noise is generally not Gaussian and the mixture between the classes ω_c and $\overline{\omega_c}$ was estimated within the Pearson' system of distributions [13, 14]. This system consists of mainly eight families of distributions with mono-modal and possibly non symmetrical shapes (Gaussian, Gamma, Exponential and Beta distributions among others). Each distribution in the Pearson' system is uniquely determined by its four first moments μ_1, ..., μ_4. Table 1 reports, for the two DIs, the distributions selected after 70 ICE iterations.

3 Vectorial HMC based change detection method

When change detection is applied to SAR images, several behavior can be expected:



(a) $\mathrm{I}_{t_1-t_2}$ (b) $\mathrm{I}_{t_2-t_3}$



(c) $\mathrm{S}_{t_1-t_2}$ (d) $\mathrm{S}_{t_2-t_3}$

Figure 2. Two classes segmentation results $\mathrm{S}_{t_1-t_2}$ and $\mathrm{S}_{t_2-t_3}$ of the DIs $\mathrm{I}_{t_1-t_2}$ and $\mathrm{I}_{t_2-t_3}$. In order to reduce the impact of the speckle and the geometric registration errors, the value of each pixel in a DI is the difference between the mean values computed on a small window centered on the pixel. The width of the window was set to 5.

– When the captors are different, the speckle noise does not have the same behavior. Then, statistical parameterizations of noise may differ from Y_b and Y_a.
– When the captors are identical, a difference of viewpoint (ascending or descending orbit, several incidences, ...) yields a specific response for the same area. Then, change detection has to be invariant from captor modality.

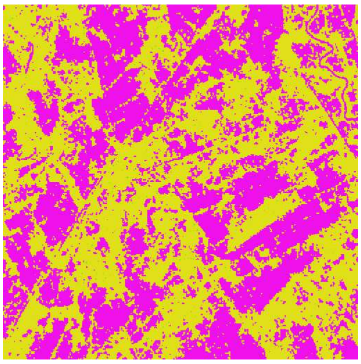
Those remarks are prohibitive for DI-based approaches since a difference of speckle characteristics may be interpreted as a change. We now propose a novel approach , called *joint characterization,* whose principle is to consider that Y_b and Y_a are a unique realization of a bi-dimensional process $\mathbf{Y}_{b,a} = \{\mathrm{Y}_b, \mathrm{Y}_a\}$.

Parameters estimation and classification can be performed from the multi-component extension of the HMC model we have proposed recently in [8]. The main difference between the 'scalar' and the 'vectorial' HMC models lies in the estimation of a multidimensional mixture[1], composed by the multidimensional densities $f_{\omega_1}(y_a, y_b)$, ..., $f_{\omega_K}(y_a, y_b)$, with K the number of classes. In fact, the multicomponent HMC model takes into consideration the difference of modalities between Y_b and Y_a by means of the multidimensional statistical characteristics of the classes. But non-Gaussian multidimensional densities can be difficult to estimate. One solution is to use the two marginal densities $f_{\omega_k}(y_b)$ and $f_{\omega_k}(y_a)$ of $f_{\omega_k}(y_b, y_a)$. Several strategies are possible. If independence between the layers is assumed then $f_{\omega_k}(y_a, y_b)$ is the direct product of the marginals. However, in the change detection context, such assumption is totally wrong. In order to take care of the link between the 'before' and 'after' images, the solution we have adopted consists in combining the ICE estimation with an Independent Component Analysis (ICA) approach.

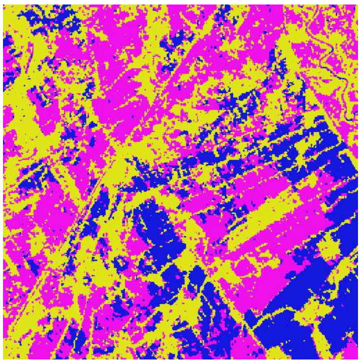
Figure 3 reports the joint classifications S_{t_1,t_2}, S_{t_2,t_3} and S_{t_1,t_2,t_3} obtained from the vectorial HMC model, with three classes (ω_1='light gray', ω_2='dark gray' and ω_3='black'). Note that the third result is an example of a change detection with two 'before' and one 'after' image. The flooded area is represented by the ω_3 class in figures 3(b) and 3(c); such a class can not be seen in figure 3(a). This class represents respectively 0.1%, 22.1% and 21.8% of the total number of pixels (to be compared with the results obtained on the DIs in section 2).

The classes representing a thematic change can be detected according to the shape and the parameters of the marginal densities (each of them belongs to the Pearson' system of distributions). Indeed, one can expect that a change modifies the shape of marginals considerably, so that different families of distributions are

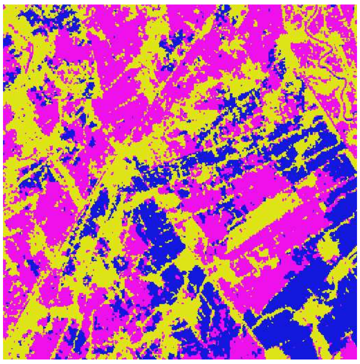
[1] The dimension of the mixture equals the number of images in the multicomponent process, e.g. two for a 'simple' (Y_b, Y_a) change detection problem.



(a) S_{t_1,t_2}



(b) S_{t_2,t_3}



(c) S_{t_1,t_2,t_3}

Figure 3. Images S_{t_1,t_2}, S_{t_2,t_3} and S_{t_1,t_2,t_3} were respectively obtained from the joint classification of images I_{t_1}, I_{t_2} and I_{t_3}, with three classes.

selected. The computation of a distance between distributions (e.g. the Kullback-Leibler divergence) can help to automatically detect these modifications. Such a study has not been performed yet and remains an interesting issue.

4 Conclusion

Change detection in multitemporal SAR images is a challenging problem since thematic changes that have to be detected are hidden by several sensor-inherent and application-dependent factors such as ascending or descending orbit, several incidences, strong speckle noise, ... In this work, the *'joint characterization'* method do not consider pixel-based changes, but rather thematic changes as a modification of both spatial and temporal distributions of classes in the images. The proposed solution is founded on the recent multicomponent HMC model and the ICE parameter estimation procedure. The results we obtained are encouraging and the method should be further tested by using data sets with ground truth data in order to estimate the false and missed detection rates. We also plan to analyze the families and the shapes of selected densities inside the Pearson' system. It is important to note that this technique remains valid for multidate (i.e. more than two dates) change detection problems, and can even help to automatically decide when the change occurs in a sequence of 'before' and 'after' images.

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Table 1. Estimated noise parameters for the two DIs in Fig. 2.

Image	Four first moments					
	Law		μ_1	μ_2	μ_3	μ_4
$\mathrm{I}_{t_1-t_2}$	$f_{\overline{\omega_c}}(y)$	Student't	-4.3	187.9	-89.7	125245
	$f_{\omega_c}(y)$	Beta 1	50.6	63.7	555.0	14958
$\mathrm{I}_{t_2-t_3}$	$f_{\overline{\omega_c}}(y)$	Beta 1	-7.1	257.6	-2035.8	200021
	$f_{\omega_c}(y)$	Beta 1	42.1	267.5	3510.7	226925