SAR IMAGE AUTOMATED DETECTION OF DUNE AREA

Dr. Christophe Gouinaud, Atteib Ibrahim Doutoum, Pascale Gouinaud, Dr Mamadou Kaba Traore

LIMOS -Clermont University
ISIMA - Campus des Cézeaux
63173 Aubière - FRANCE

ABSTRACT

Detecting changes in desert areas is an important challenge for remote sensing images. This may concern the immediate security (when looking for lost people, for example), but also the measurements of environmental changes. In this paper we will develop a new method, based on a multi-user approach, for automatic classification of SAR images which can be used to detect dunes areas in the desert. This will provide a new approach for detecting changes.

We will show here that only methods based on shape criteria can give good results, which justifies our choice. Our method is mainly based on multi-scale correlation between two images with two different acquisition dates, so that we can get better benefits of textures information, and minimize the effects due to the building of SAR images. We have selected an area corresponding to a part of the Tibesti (Sahara Desert), west from Faya-Larjeau, Chad. This region of study is providing various landscapes which represents a great interest for applying our algorithm : we can find there sand areas, with a diffuse backscattering, and areas with a lot of stone blocks that are generating specular backscattering.

As a result, we show differences in accuracy by applying those works to a couple of Envisat images in our area of interest in Chad.

***Index Terms*—** SAR, desert area, change detection, dune

1. INTRODUCTION

The study of desert areas and especially areas with dunes is interesting for environmental surveys, but also it may have a lot of applications for the exploration of other planetary systems [1].

As we began to work on this study, we realized that detecting changes on those areas was difficult because of the temporal and geometrical variabilities of the soil surface.

The areas with hard soil surface do not change a lot, but they show geometrical distortions due to erosion because of ancient rains. On the other hand, areas made of sand have more regular shapes, but with lots of changes over time. As the dunes move, they change their shape at the same time, and this adds difficulties in tracking changes. That is why, in a first step, we decided to define the different kinds of landscape, to allow us to identify methods for monitoring changes for each type of area.

We present here this first step divided into three parts : the first one is devoted to an argumentation to define the most interesting characteristics of sandy areas and rocks areas in mineral deserts. The second one exposes our method for detecting dunes areas and the last step presents the results of this study applied to the Tibesti desert, Chad.

2. CONTEXT

The areas in dry deserts are characterized by a mineral land surface we can consider without any vegetation. They present two major kind of landscape : one with sand organized in dunes, and the other with rocks surfaces. The discrimination of those two types of desert land is necessary before any study of variation over time using SAR images. If we try to search for local targets in SAR images, the detection methods will be radically different depending on the kind of soil we are examining, and because the studies of dune movements have no sense in rocks areas.

There are many different algorithms for radar images classification and the use of those methods on desert areas [2] shows that it is difficult to discriminate the different types of soil with good results, using only one image and computing statistics with radiometric measure. The areas with blocks of rocks and the sandy areas are backscattering signals with quite the same value of mean, even if the source of the power backscattered is different.

The backscatter from sandy areas is mainly due to the shape of the dunes and ripples that appear on them because of the sand carried away by the wind. As those regions have very constant wind regime, the most frequent dunes are the barchans [3] : crescent-shaped dunes with tines pointing in the direction of wind. We also meet degenerated forms of this family of dunes. Because of those shapes, there is automatically a part of the dune facing the radar, with a slope of 30 degrees. So the probability to get a signal giving a brilliant point in the image is high. The image of such an area has alternatively bright and dark parts, sprinkled with brilliant spots. The scale of this alternation is only related to the

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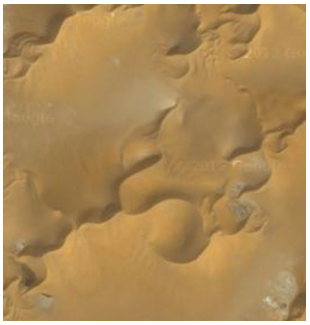
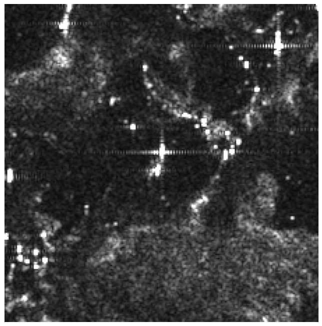
dunes dimensions.



(a) Google Map view of dunes



(b) Sar view of dunes

Fig. 1. Example of dunes area in Chad

The signal backscattered by rocks areas presents a background made of speckle generated by a rough soil, dotted with blocks generating very bright spots when they show a surface big enough with a good orientation to the radar sensor.

Image simulations computed with a large number of random configurations, with a 30 meters resolution, show us that, regarding to the configuration, the value of the backscattered signal appears not to depend on the type of the area (blocks of rocks against sand). We have counted the brilliant pixels present in uniform plots built by photo-interpretation, and their number is not specific to the zone type.

So, it is difficult to perform a classification from SAR images based on the backscattered signal power and it is much more difficult to automatically detect test spots to compute a machine learning for that kind of area.

The only opportunity that remains is then to use variations of the ground shape to characterize the differences between areas made of rocks, and sandy areas. A very detailed observation of the desert images has shown that the dunes areas are characterized by sequences of bright faces oriented to the radar and dark faces in the shadow of the radar. The rocks areas are fully chaotic, excepted when they are crossed by a fossil waterway. Then it is possible to characterize the dune areas by the regularity of the perturbation they produce in the images.

The dunes lines consist of sequences of dunes with similar dimensions. This means that it is possible to observe the frequency of the global changes in the images by characterizing sets of adjacent pixels. This kind of study uses usually tools from Fourier Analysis ([4]), or even uses methods coming from radarclinometry ([5]) to study shapes. It provides quite good results for recognizing dunes areas, but the differences we get for rocks areas are not significant, especially when using Fourier analysis. There are several other methods that are able to produce a solution for this problematic, but the tests we applied on those images were not conclusive because of the effects of speckle, or because of the presence of specular reflectors that give too high values for their response to the sensor.

This survey shows that solving this problem needs to introduce some more informations and that the solution will use the shape of the dunes, even if it is affected by noise inducted by the SAR image geometry. So, we have chosen images acquired at two different dates so that the sandy areas have changed independently from the others. Because of the wind effects that created them, the dunes are eroding themselves which create their displacement along the major wind directions. According to the dunes, those displacements are quite fast and we can then be certain that rocks areas don't change so quickly.

So, our problem became then "how to locate changes between two images ?" where changes are in fact displacements of bright and dark spots to the scale of dunes. We then wanted to use correlation of two related images with a multi-scale approach, which allows us to forget the effective size of the dunes.

3. CLASSIFICATION METHODOLOGY

Our method is based on computing the correlation on windows between the two images acquired at two dates separated by at least one year. To get rid of the effective size of the dunes, we use windows with growing size and we observe the transitions of the maximum of the correlation on one area.

The correlation between an image I_0 and an image I_1 at the pixel with coordinates x, y is computed in a usual way :

$$C = \sum_{i=-n,j=-n}^{i=n,j=n} \frac{I_0(x+i,y+j)I_1(x+i,y+j) - E_0E_1}{\sigma_0\sigma_1}$$

where : E_a and σ_a are the mean and the standard deviation of the image I_a.

We proceed the following way :

- We take two images (1 and 2), superimposable, corresponding to a desert area;
- For each pixel in the image 1, we compute the correlation with the image 2, over a window 5 x 5 pixels;
- We increase the size of the window till 30x30, corresponding to a surface with 900 x 900 meters for example with Envisat images.

Observing for each pixel the sequence of its values, we can notice that the more we increase the size of the window, the more the correlation values increase on the spots corresponding to dunes, while they only have small variations on spots with blocks.

This can be explained by the fact that, with small size of window, the speckle decreases the values of the correlation of the spots where the shapes of the ground are not changing with time. Then, the correlation values decreases in a very small way, with values near the values we find when we have full speckle. This effect increase as the size of the correlation window grows. On the contrary, with dunes areas, the correlation will increase as the size of the windows will grow. This is because as dunes are moving, their shape influences the signal in the same way, and the process "dune" is organizing the signal.

In the following table, we have collected mean values of correlation computed on some learning spots for different areas.

Windows width	5	10	15	20	25	30
Rocks areas	0.1	0.09	0.08	0.08	0.08	0.07
Dunes areas	0.1	0.2	0.3	0.4	0.5	0.6

We then compute a classification of the images, so we need a learning method and a classification algorithm. The observation of the histograms of the maximum of the correlation shows us that as the size of the correlation window increases, the distribution of the values of the correlation is cut of into two independent sets. Our method of learning machine is based on the calculation of two local maxima as distant as possible in all the histograms of the correlation images.

We proceed to a supervised classification with a gaussian Markov random field modeling where the input datas are the set of correlation images computed with window size from 5 pixels to 30 pixels on ENVISAT images.

The results of this test are shown near Faya-Larjaud, Chad, for a couple of ENVISAT ASAR images acquired in 2005 and 2007.

4. RESULTS IN TIBESTI

On the figure 2, we show extracts of 2048x2048 pixels from two images ENVISAT acquired in June 2005 and June 2007. On the image with a 30 meters resolution, we can clearly observe different dunes areas separated by rocks areas with hard soil. Those images are a good example for understanding that it is not possible to discriminate the two types of areas (sand/rocks) only with brilliant pixels and also that usual statistics are not significant to separate the two classes we are studying.

On the figure 3, we expose the correlation between the two images of the figure 2 with different sizes of windows. On these images, we can notice that the more the size of the window increase, the more the dunes areas appear with high correlation values. To determinate from which size of window the correlation is useful, we have computed statistics on photo-interpretated spots. They show that the values of correlation we get using windows smaller than 9 by 9 pixels, in this particular case, can not be used for the classification, because they are not discriminative enough.

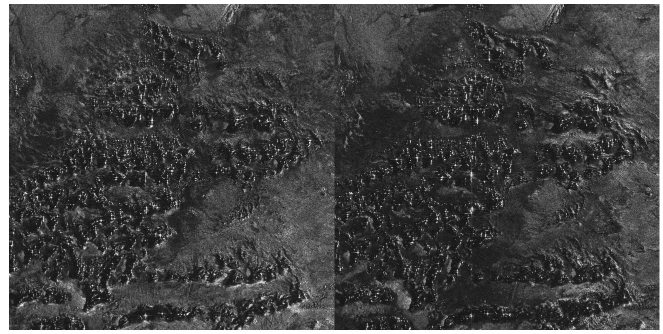


Image year 2005 Image year 2007

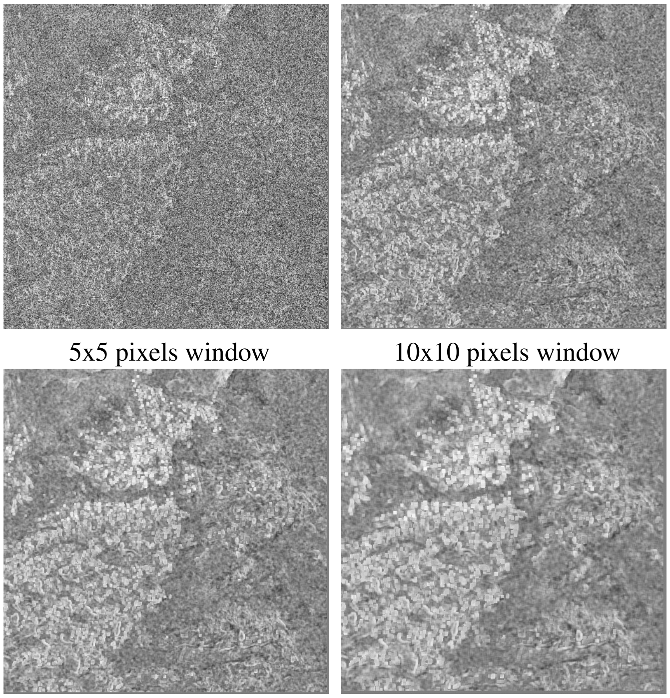
Fig. 2. Example of Tibesti desert,Chad - ASAR ENVISAT images.

On the figure 4, we present, on the left, the result of a Markovian classification based on classical textural index (mean, standard deviation, skewness) and on the right, the result on the correlation images of the figure 3. For those two cases, the same classical classification is computed, and using a linear relation with the distance to the mean of the classes, optimized by simulated annealing. This result shows that our method discriminate properly dunes areas from rocks areas, and this whatever the size of the studied spots. On the contrary, we notice that, in spite of the regularization imposed in the classification, the classical indices, even if they are computed on the two images, do not give the same discrimination. The confusion matrix calculated between our classification and photo-interprated areas on the entire ENVISAT image provides a good classification rate of 92 percent, with a false-recognition rate of 5 percent. With programs properly optimized, this result is obtained in few minutes, using a laptop with 4 Go of RAM and a 2GHz Pentium processor.

5. CONCLUSIONS

This work reached its objective : we succeed in discriminating areas with dunes from areas made of rocks or hard ground. This method provides reliable results on the Tibesti desert and allows us to work for the next steps : the research for displacement of dunes et the research of local changes in the other kinds of areas in the desert. But, the inconvenience of this method leads in the fact that two images are needed and that the acquisition dates of those two data should be distant enough, and that is not always possible, depending on the aim of the study : if looking for lost people, or following displacements on a short period like in case of storm on a local area, for example.

Then, the next step of our study will be the introduction of a stochastic landscape model combined with image simulations to prevent from needing a second image for our method. This simulation will be calculated using a compass card com-



5x5 pixels window | 10x10 pixels window
15x15 pixels window | 20x20 pixels window

Fig. 3. Correlation between the two images of figure 2 with different window sizes.

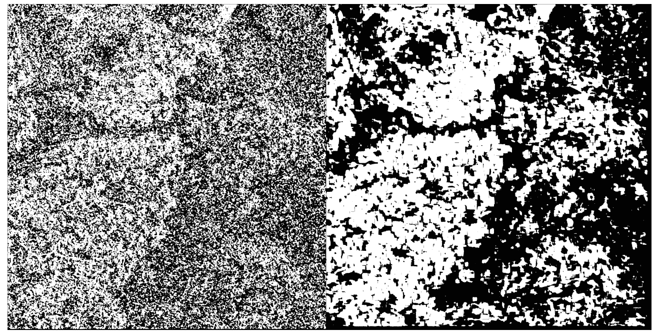


Fig. 4. Results of classification in figure 2 image. On the left, input statistical image, on the right correlation indice like in figure 3.

puted from meteorological models. We would also like to study the association of SAR images with optical images to make our detection more reliable.

In an another direction, for studying dunes changes, we are investigating the use of models issued from frequency transforms and radarclinometry that may provide cartography of deserts, even not on Earth.

6. REFERENCES

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