Use of Power Spectral Density Image to Support Early Forest Fire Direct Detection

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Abstract: In this work, we present a method for early forest fire detection from a satellite image using the power spectral density of a Gaussian white noise. To obtain the latter, we have considered each satellite image matrix line as a realization of a non stationary random process in the Thermal Infra-Red (TIR) spectral band, and then divided each line into very small intervals in which any random process can be, obviously, stationary. In addition the pixels of the satellite image are statically independent. Thus, any small interval of each line behaves as a white noise. As a consequence, we have calculated the power spectral densities (PSD) of these intervals and presented them in image form which has been magnified to fix a magnifying factor corresponding to the least hot pixel to appear for early visual fire detection.

Key-Words: - satellite image; power spectral densities (PSD) image; Thermal Infra-Red (TIR) spectral band; Gaussian model; stationary process; segmentation.

1 Introduction

Forest fire is one of the most important factors that affect the earth ecosystem and contribute to the global warming. Its early detection is, therefore, very important in order to limit any farther damage. Early detection is usually performed by surveillance either by human observers located at different places in the forest or by video systems. These kinds of surveillances are, however, not always efficient. Alternative surveillances which can be done by satellite were, therefore, proposed. In this case, many different methods, mostly based on radiometric analysis of the satellite image in the Thermal Infra-Red (TIR) spectral domain, have been suggested to improve its early detection. Analyzing directly the visual TIR satellite image does not, however, provide always good results. This is due to the fact that the image observation accuracy may be degraded by the clouds and humidity, in many dump regions of the globe, whereas in dry regions, such as in the north of Africa, the accuracy should be less degraded.

In this work, we suggest a method based on the power spectral density (PSD) of a white noise for fire detection. As it is well known, in any problem of modeling, the choice of the model is very important task. So it is important for the images to be characterized by a mathematical model in order to carry out any kind of processing. The image can be modeled by a classic mono-dimensional model, and consequently we can use all the tools and the mathematical analysis techniques of the mono-dimensional signals which are well developed in the literature. This mode of representation has been applied for the line by line processing of the images, in particular for the coding, the filtering and the storage [1]. In the first place we selected a type of model with reasonable results and can be applied to a possible large number of images. After many tests on several types of models, we have decided to choose the Gaussian model, mainly because of its simple computing and the good results obtained. In the following, we start our discussion by a highlight of random processes and how they are used for the image analysis. In our case, we apply a Gaussian white noise which is a stationary random process with non correlated samples.

2 Discussion

A random process is defined as an infinite number of curves of the same repeated event. The autocorrelation is, usually, used to compare two signals or two samples of the same process. Its value...
indicates how much two signals are correlated. For the random process, the auto-correlation is calculated by the inner product in Hilbert space using the mathematical expectation as follows

\[ \phi_{X}(i,j) = E[X_i X_j] \quad (1) \]

Where \( X_i \) and \( X_j \) are two vectors of the process at two different instants \( i \) and \( j \). If the elements of any parallel diagonal to the principal of the auto-correlation matrix are different then the process is non-stationary. An example of a non-stationary process may be represented by the curves (o, *, +) of fig.(1). We can see that the process in the intervals [0, 20] and [20,40] do not look the same; hence the auto-correlation is not constant for the same intervals. However, if we focus on a small space or on a small interval of the process(fig.2), then the curves may not vary too much and, thus, the auto-correlation could be considered as approximately constant for the same intervals. It is possible, therefore, to divide the process into many small stationary intervals. This is, particularly, illustrated in fig.(2) by the two small intervals [20, 25] and [45, 50]. Furthermore, the smaller these intervals the more stationary and ergodic they will be since their mean value calculated vertically can be the same as that obtained horizontally on any curve in these intervals. This mean value which can be calculated by the mathematical expectation is, therefore, almost constant \( E[X_i] = cte = m_x \). If, in addition, the ergodic process samples are independent, as in the satellite image case, then each small interval of any image matrix line behaves as a white noise and can be, thus, described by the following auto-correlation relation in Hilbert space;

\[ \phi_{w}(i,j) = \sigma^2 \delta_{ij} \quad (2) \]

In which \( \sigma^2 \) is constant representing the process variance or its power spectral density, and \( \delta_{ij} \) is the unit sample.

To obtain the mathematical model for the original image (fig.3), we have represented each small interval of each matrix line by a Gaussian white noise [7,...,10]. The choice of the number \( N_i \) of the intervals depends on the quality of the reconstructed image (fig.4). Once the adequate image model has been obtained, we have gathered the power spectral densities (PSD) of these white noises in a matrix form which was converted to a corresponding image for visualizing early forest fire detection (fig.5).
The good quality of the reconstructed image, obtained in figure (4) with Ni=200 after many tests, indicates that the power spectral density estimation shown in figure (5) is more accurate, and thus it has, approximately, the same intensity distribution as the real image in fig. (3). In our method for the detection, we have magnified the PSD image to obtain the image in fig.(5) by multiplying its matrix by a factor equals to 10 corresponding to the apparition of the least hot pixel representing the smallest fire that can be detected in the image. This procedure allows only the fires to appear in fig. (5), and the rest of the background remains dark. Figure (5) has, thus, the role as a filter detecting fires only. Indeed, by comparing the real image (fig.3) to that of the power spectral density fig. (5), we can say that the advantage of using the power spectral density for fire detection is that we can easily identify early fires in the dark background of the image (fig.5), while it is slightly confusing and difficult to distinguish them from the background of the real image (fig.3). Both images; the real satellite image and the spectral density image can, furthermore, be used to reduce the probability of false alarm.

3 Conclusion

We have estimated the spectral power densities (PSD) of the Gaussian white noises representing the real satellite image and presented them in image form. And then we have amplified this PSD image to determine an amplification threshold factor corresponding to the least hot pixel to appear for early visual fire detection. We have shown that the PSD image can be a fairly firm indication of fires existence, and thus it can be a good support to the direct observation of the real satellite image.

References: