APPLICATION OF DSM THEORY FOR SAR IMAGE CHANGE DETECTION

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ABSTRACT

Synthetic Aperture Radar (SAR) data enables direct observation of land surface at repetitive intervals and therefore allows temporal detection and monitoring of land changes. However, the problem of radar automatic change detection is made more difficult, mainly with the presence of speckle noise. This paper presents a new method for SAR image change detection using the Dezert-Smarandache Theory (DSmT). First, a Gamma distribution function is used to characterize globally the radar texture data and allows mass assignment throw Kullback-Leibler distance. Then, local pixel measurements are introduced to refine the mass attribution and take into account the context information. Finally, DSmT is carried out by comparing the modelling results between temporal images. The originality of the proposed method is on the one hand, the use of DSmT which achieve a plausible and paradoxical reasoning comparing to classical Dempster-Shafer Theory (DST). On the other hand, the given approach characterizes the radar texture data with a Gamma distribution which allows a better representation of the speckle. The radar texture is being usually modeled by a Gaussian model in previous DST and DSmT fusion works.

***Index Terms*—** SAR image change detection, Kullback-Leibler distance, DST and DSmT fusion theories

1. INTRODUCTION

Change detection from images covering the same scene and taken at different times is of widespread interest for a large number of applications, especially in the remote sensing domain. SAR images are very useful tools to surface change detection especially in regions where optical data are rarely available. In many areas, more and more images are acquired on repeated orbits thanks to the repetitivity of radar satellites such as ERS 1, ERS 2 and Envisat. However, some difficulties are associated with SAR images change analysis: the speckle noise, which disturbs automatic change detection. Indeed, the speckle imposing a granular texture to radar images makes very difficult the use of these images even with slightly different acquisition angles. Nevertheless, despite the complexity of data processing, SAR sensors have important properties at an operational level, since they are able to acquire data in all weather conditions.

Recent works have proven that the statistics of SAR images can be well modelled by the probability distribution family known as Gamma distribution [1]. Other studies introduce some significant statistical measures for the change detection purpose [2]. In the same context, an interesting approach using statistical change measures between two SAR images have been introduced in [3]. The originality of this work is the fusion of change signatures computed on two SAR images using Dezert-Smarandache theory. This paper extends this work and proposes two main contributions. First, SAR texture is modelled by a Gamma distribution instead of a Gaussian one. Then, in addition to class distribution signatures we introduce local change attributes taking into account the context information.

The paper is organised as follows. Section 2 presents some pre-processing tools applied in order to estimate Gamma distribution parameters for each class of a temporal image. Section 3 exposes global and local measures introduced to characterize change signatures. In Section 4, a brief description of DST and DSmT is presented. The second part of this section shows the mass belief assignment used to compare two images for the change detection purpose. Section 5 presents experimental results obtained using two temporal Envisat images. Conclusions are given in Section 6.

2. DISTRIBUTION PARAMETERS ESTIMATION

This section provides an investigation to ascertain the most appropriate pre-processing tools which could be used for image classification in order to estimate Gamma distribution parameters. The temporal radar images are first filtered without altering SAR texture features and then classified. For each class of each image, the Gamma distribution parameters are estimated. We can notice here that the filtering process which is a delicate pre-processing step is used only for the classification purpose. Parameter estimation is applied on original images.

2.1. Gamma Distribution

In the case of radar images, previous works showed that the Gamma distribution is more accurate than the Gaussian distribution to model the real SAR intensity [4]. The Gamma distribution P_{Gamma} is given by:

$$P_{Gamma}(x;\alpha;\beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad (1)$$

where α is the shape parameter and β is the scale parameter and $\Gamma(z) = \int_0^{\infty} e^{-t} t^{z-1} dt, z > 0$ is the Gamma function. Then, each class will be characterized by the two Gamma distribution parameters α and β.

2.2. Parameter estimation

2.2.1. Pre-processing

Speckle, a form of multiplicative, locally correlated noise, plagues imaging applications. For images that contain speckle, a goal of enhancement is to remove the speckle without destroying important image features. The reducing filters have originated mainly from the synthetic aperture radar (SAR) community. The most widely cited and applied filters in this category include the Lee, Frost, Kuan, and Gamma MAP filters.

More recently, a new Partial Differential Equation (PDE) approach to speckle removal was introduced and called Speckle Reducing Anisotropic Diffusion (SRAD) [5]. The PDE-based speckle removal approach allows the generation of an image scale space (a set of filtered images that vary from fine to coarse) without bias due to filter window size and shape. SRAD not only preserves edges but also enhances them by inhibiting diffusion across edges and allowing diffusion on either side of the edge.

The aim of SRAD filtering is to ameliorate image classification results in order to perform a better Gamma distribution parameters estimation. After SAR image filtering, a K-means clustering technique is applied to classify the pixels into k and k' classes for both temporal images. The combination between the SRAD filter and the K-means algorithm provides a very sufficient classification.

2.2.2. ML-estimation

After applying pre-processing steps in order to carry out an appropriate classification image mask for both temporal images, we estimate statistical Gamma distribution parameters for each class. Maximum likelihood estimators are used to extract radar texture parameters.

3. CHANGE MEASURES

Most of the relevant change detection techniques are based on the difference or ratio operators when using radar images. In our case, we introduce two measures to characterize change signatures. The first one has a global behaviour since it operates on classes and the second one is calculated locally for a pixel neighbourhood.

3.1. Gamma Kullback-Leiber distance

The change detection algorithm is based on the modification of the statistics between the two acquisition dates of each pixel. A pixel will be considered as having changed if its statistical distribution changes from one image to the other. In order to quantify this change, we need a measure which maps the estimated statistical distributions for each pixel to a scalar index of change.

In this work, we choose the Gamma Kullback-Leibler divergence introduced in [6]. The proposed texture similarity measure between two Gamma distributions of two image I_1 and I_2 can then be given by:

$$D_{KLGamma}(I_1, I_2) = \log\Gamma(\alpha^{(I_1)}) + \alpha^{(I_1)} \log\beta^{(I_1)}$$
$$-\alpha^{(I_1)}(\Psi(\alpha^{(I_2)}) + \log\beta^{(I_2)}) + \frac{\alpha^{(I_2)}\beta^{(I_2)}}{\beta^{(I_1)}}. \quad (2)$$

For simplicity, the distribution value $I_k\,(i,j)$ for the pixel (i,j) of the image $I_k, k = 1,2$, is noted I_k in the above equation. The factors $\alpha^{(I_k)}$ and $\beta^{(I_k)}$, are the shape and the scale parameters associated with distribution $I_k, k = 1,2$.

3.2. Local pixel measures

The contrast measure takes care of the pixel realizations from a stochastic point of view. To highlight contrast information, the conventional Pixel by Pixel Ratio Measure (PPRM) between two SAR images is exploited. This detector is well-known and widely used in SAR imagery due to its ability to greatly reduce the speckle influence on the change map. The PPRM of a pixel between two image I_1 and I_2 is computed and normalized on a small window through a contrast measure $r(i,j)$ defined by:

$$r(i,j) = \log(\max(\frac{\sum_{(k,l)\in v} I_1(k,l)}{\sum_{(k,l)\in v} I_2(k,l)}, \frac{\sum_{(k,l)\in v} I_2(k,l)}{\sum_{(k,l)\in v} I_1(k,l)})) \quad (3)$$

where v is the pixel (i,j) neighborhood defined by a given window.

Moreover, we define a significance measure as a criteria dedicated to reduce the ambiguity of the pixel behaviour. The significance measure of a pixel (i,j) for images I_1 and I_2 may be defined by:

$$s(i,j) = \sum_{(k,l)\in v} I_1(k,l) * \sum_{(k,l)\in v} I_2(k,l) \quad (4)$$

We can notice that the contrast and the significance measures are calculated for a pixel neighbourhood and not for a class distribution. Besides, those measures characterize the evolution of each pixel and are not necessary linked to ground change but give potential candidates to ground evolution. That is why those indicators are to be considered into an evidential and paradoxical reasoning.

4. THE DEZERT-SMARANDACHE THEORY

The Dezert-Smarandache Theory (DSmT) [7] is a generalization of the classical Dempster-Shafer Theory (DST) [8], which allows formal combining of rational, uncertain and paradoxical sources. The DSmT is able to solve complex fusion problems where the DST usually fails, especially when conflicts between sources become large. In this section, we will first review the principle of the DST before discussing the fundamental aspects of the DSmT.

4.1. Dempster-Shafer Theory principle

The DST makes inferences from incomplete and uncertain knowledge by combining sources of confidence, even in the process of partially contradictory sensors. In the DST, there is a fixed set of mutually exclusive and exhaustive elements, called the frame of discernment, which is symbolized by the set of N elements potentially overlapped $\Theta = \{\theta_1, \theta_2, ..., \theta_N\}$. The frame of discernment Θ defines the propositions noted A_i for which the sources can provide confidence. Information sources can distribute mass values on subsets of the frame of discernment, $A_i \in 2^{\Theta}$. If an information source can not distinguish between two propositions A_i and A_j, it assigns a mass value to the set including both hypotheses $(A_i \cup A_j)$. The mass distribution for all hypotheses has to fulfill the following conditions

$i.$ $0 \leq m(A_i) \leq 1$.

$ii.$ $m(\emptyset) = 0$.

$iii.$ $\sum_{A_i \in 2^{\Theta}} m(A_i) = 1$.

Mass distributions from d different sources are combined with Dempster's orthogonal rule.

$$m(A) = (1-K)^{-1} \sum_{A_1 \cap \ldots \cap A_d = A} \prod_{i=1}^{d} m_i(A_i) \qquad (5)$$

where $K = \sum_{A_1 \cap \ldots \cap A_d = \emptyset} \prod_{i=1}^{d} m_i(A_i)$ is a normalization factor measuring the conflict between the sources. Two functions can be evaluated to characterize the uncertainty about the hypotheses. The belief function $Bel(A) = \sum_{A_i \subseteq A} m(A_i)$ measures the minimum uncertainty about A, whereas, the plausibility function $Pl(A) = \sum_{A_i \cap A \neq \emptyset} m(A_i)$ reflects the maximum uncertainty value.

4.2. The Dezert-Smarandache Theory (DSmT)

While the DST considers Θ as a set of exclusive elements, the DSmT relaxes this condition and allows for overlapping and intersecting hypotheses. This allows for quantifying the conflict that might arise between the different sources throughout the assignment of non-null confidence values to the intersection of distinct hypotheses.

4.2.1. Definition

Let $\Theta = \{\theta_1, \theta_2, ..., \theta_N\}$ be a set of N elements which can potentially overlap. We consider in our example $\Theta = \{\theta_{ch}, \theta_{no\_ch}\}$ involving only two elementary hypotheses 'change'and 'no change'. The hyper-power set D^{Θ} is defined as the set of all composite hypotheses obtained from Θ with $\cap$ and $\cup$ operators such that:

$i.$ $\emptyset, \theta_1, \theta_2, ..., \theta_N \in D^{\Theta}$

$ii.$ If $A, B \in D^{\Theta}$ $then$ $(A \cap B) \in D^{\Theta}$ and $(A \cup B) \in D^{\Theta}$.

$iii.$ No other elements belong to D^{Θ} except those defined in $i.$ and $ii.$

We define D^{Θ} in our example by $D^{\Theta} = \{\emptyset, \theta_{ch}, \theta_{no\_ch}, \theta_{ch} \cap \theta_{no\_ch}, \theta_{ch} \cup \theta_{no\_ch}\}$.
As in the DST, the DSmT defines a map $m(.) : D^{\Theta} \to [0, 1]$. This map defines the confidence level that each sensor associates with the element of D^{Θ}. This map supports paradoxical information and we have this condition:

$$\sum_{A \in D^{\Theta}} m(A) = 1. \qquad (6)$$

The belief and plausibility functions are defined in the same way as for the DST. The DSmT rule of combination of conflicting and uncertain sources is given by the above equation:

$$m(A) = \sum_{\substack{A_1, A_2, \ldots, A_d \in D^{\Theta} \\ A_1 \cap \ldots \cap A_d = A}} \prod_{i=1}^{d} m_i(A_i). \qquad (7)$$

4.2.2. Mass belief assignment

Changes may be expected for a pixel (i, j) when the Gamma Kullback-Leiber distance $D_{KLGamma}(I_1, I_2)$, the contrast measure $r(i, j)$ and the significance measure $s(i, j)$ become significant. Furthermore, the decision may be taken when there is a contradiction between the three indicators. Then, we propose in Table 1 the mass assignment which is done by an appropriate combination of change signatures. The decision is taken through the maximum of credibility with Belief on change $Bel(\theta_{ch})$.

Hypothesis	Mass belief assignment
$\emptyset$	0
θ_{ch}	$r(i,j) * D_{KLGamma}(I_1, I_2) * s(i,j)$
θ_{no_ch}	$(1 - r(i,j)) * (1 - D_{KLGamma}(I_1, I_2)) * (1 - s(i,j))$
$\theta_{ch} \cup \theta_{no\_ch}$	$r(i,j) * (1 - D_{KLGamma}(I_1, I_2)) * s(i,j)$
$\theta_{ch} \cap \theta_{no\_ch}$	$1 - (m(\emptyset) + m(\theta_{ch}) + m(\theta_{no\_ch}) + m(\theta_{ch} \cup \theta_{no\_ch}))$

Table 1. Mass Belief Assignement for image fusion.

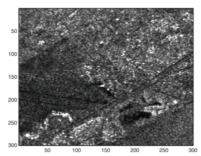

Fig. 1. Original Envisat SAR images.

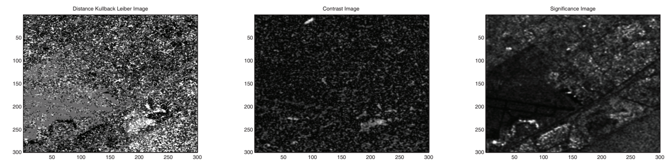

Fig. 2. Change measures results given respectively (from left to right) by Kullback-Leiber distance, contrast and significance measure.

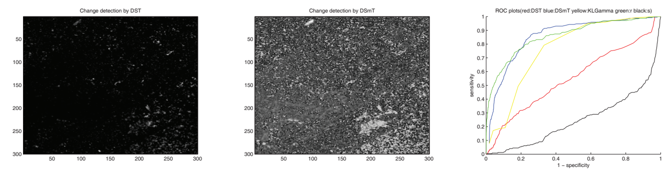

Fig. 3. Change detection results. (Left) DST Changes (Middle) DSmT Changes (Right) ROC plots comparison between Contrast, signifiance, KLGamma, DST and DSmT change detection measures.

5. RESULTS

The proposed method has been applied on two temporal Envisat SAR images covering the same region of Tunis City, North Africa (see Fig. 1). The first one is acquired in 2005 whereas the second one is acquired in 2007. A considerable amount of urban changes occurred between these two dates. These two images are already registered.

Fig. 2 shows a comparison between the change measures results obtained respectively with the KL distance, the contrast and the significance measures. As we can see, some change regions are highlighted by the three signatures. However, others are enhanced only by one or two measures which underline the complementarities of these attributes.

Fig. 3 shows decision results obtained by maximizing the belief change function exposed previously. Even if this method takes a strong decision, it is possible to analyse the belief response or the interval [credibility, plausibility] to introduce a confident interval into the decision. This decision is made under DST and DSmT.

Changes detected by DSmT processing (see Fig. 3 (Middle) shows that this approach provides better performances than the classical DST one (see Fig. 3 (Left)). Comparing these results to original images presented in Fig. 1, we can notice that the proposed method detects the most significant changes with a very few false alarms. So, taking into account conflict between the different sources enhances considerably the change detection results. Fig. 3 (Right) gives a quantitative evaluation (ROC plots) of the results using the ground truth. It shows the performances of all used measures and it confirms that DSmT (blue) is more accurate comparing to DST (red) and all the other indicators.

6. CONCLUSION

Change detection in multi-temporal SAR images requires the computation of specific measures which have to be sensitive to various kinds of changes and robust to speckle effects. Those measures are combined and used by DSmT to take into account conflicts between sources which enhance change detection results. The performance of the proposed technique is very suffcient comparing to DST results and original images. In future works, we can take the benefit from the DSmT hybrid model and introduce the multiscale information in the proposed change detection approach. This will allow detection of changes with various sizes.

7. REFERENCES

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