# NORMALIZED COMPRESSION DISTANCE FOR SAR IMAGE CHANGE DETECTION

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## ABSTRACT

With a continuous increase in multi-temporal synthetic aperture radar (SAR) images, leading to enable mapping applications for Earth environmental observation, the number of algorithms for detection of different types of terrain changes has greatly expanded. In this paper, a SAR image change detection method based on normalized compression distance (NCD) is proposed. The procedure mainly consists in dividing two time series images in patches, computing a collection of similarities corresponding to each pair of patches and generating the change map with a histogram-based threshold. The experimental results were computed using 2 Sentinel 1A images over the city of Bucharest, Romania and 2 TerraSAR-X images over the Elbe River and its surrounding area, Germany.

***Index Terms***— NCD, satellite image time series (SITS), Change detection, SAR

## 1. INTRODUCTION

Various processes like seasons, natural disasters, climate, human activities and urban development are constantly affecting the Earth's surface, thus describing why the study of its surface transformations is one immediate issues in the field of remote sensing imagery processing. Monitoring the land cover evolution is essential for comprehension of environmental changes and complex land dynamics identifiable over different periods of time. A number of images containing a region at different moments of time is identified as satellite image time series (SITS) that can provide significant knowledge about the Earth's surface dynamics.

Using the content of a SITS acquired during long periods of time (seasonal-years), one can observe the evolution of domains like agriculture, forestry or hydrology. The dynamic of a scene can be analyzed considering only two images and computing how alike they are. This could be extremely helpful for finding specific details about the transformations that a certain area had suffered at a specific moment of time. In order to identify those transformations, change detection algorithms may be applied on image pairs depicting the same region at different moments of time, before and after a certain event. Similarity measures are generally used to estimate the degree of variation between the pixels or windows of pixels (patches) of two images.

There are multiple types of similarity measures that employ linear dependences, statistical measures and spatial relationships to compute radiometric, spectral and texture changes that offer a description for the multi-temporal behavior of the SITS. There are well known similarity measures that highlight radiometric changes, emphasize the changes associated to the spectral features of the compared scenes and distinguish the changes related to the images' texture. The changes related to the images' texture are captured when computing the normalized compression distance (NCD) [1].

Usually, in classical machine learning, the formulated mathematical hypothesis or models are tested by feeding data into it and see how it behaves. In Normalized Compression Distance (NCD), a mathematical model is not created in advance, but in practical terms, the incoming data is characterized by a compressor and a format [2]. By changing the format, the investigator can control what information the compressor can see by emphasizing certain aspects.

This paper analyses the land cover dynamic evolution in a parallel manner by comparing a classical change detection technique with a change detection method based on similarities generated by NCD. By measuring how similar each patch was to every other, the plotted results consist in a tree-shaped pattern, in which similar pieces cluster together on the same branch. Based on that, we want to get to two decisional clusters that contain changed and unchanged patches from both images of the data set.

The rest of this paper is structured as follows. Section II presents the theoretical analysis employed, while in Section III the methodology is applied to spaceborne SAR data. The conclusions are drawn in Section IV.

## 2. THEORETICAL ANALYSIS

The similarity measure from Normalized Compression Distance is a general and robust measure that aims to encompass all similarity measures like Levenshtein

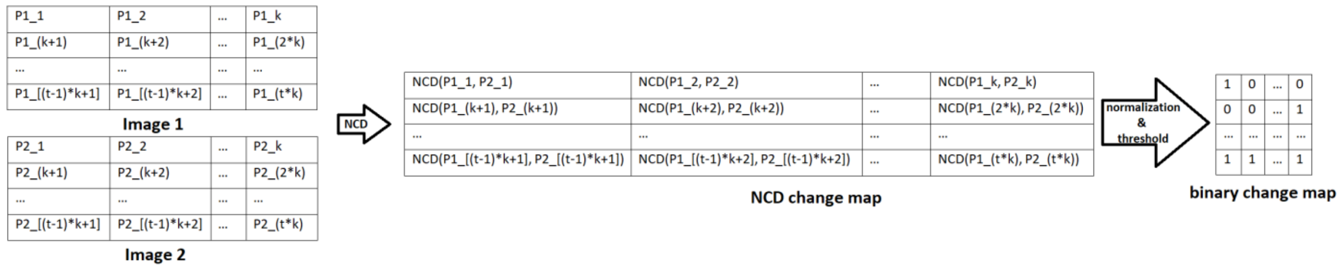


**Fig. 1**. Flowcart for the proposed change detection approach.

distance, edit distance and entropy distance [3]. NCD is a universal parametric free metric successfully applied as a similarity measure to unstructured data in various domains such as text corpora, computer programs, genomes or images. The NCD considers the length of the shortest binary program used to transform two items into each other [1]. Its main idea is based on the Kolmogorov complexity, a non-computable notion that needs to be approximated using a compressor (i.e. bzlib, zlib). Two objects are deemed close if we can significantly "compress" one given the information in the other, the idea being that if two pieces are more similar, then we can more succinctly describe one given the other.

The NCD is obtained by employing the following equation:

$$NCD(x,y) = \frac{C(xy) - \min\{C(x), C(y)\}}{\max\{C(x), C(y)\}} \qquad (1)$$

where $C$ is the compressor, *(x,y)* the pairwise of patches in the first and second image, respectively, $xy$ is the concatenation of objects $x$ and $y$, and $C(x)$ denotes the length of the object $x$ compressed using some compression algorithm which asymptotically reaches the entropy of $x$, when the length of $x$ tends to infinity. The $NCD(x,y)$ between $x$ and $y$ is expressed as the ratio between the bit-wise length of the two compressed versions, compressing $y$ using $x$ as previously compressed "data base" and compressing $y$ from scratch [2]. The result of $NCD(x,y)$ is a nonnegative number $0 < r < 1 + e$ representing how different the two images are. Therefore, smaller numbers, which correspond to a low gray level represent more similar parts in the map of changes. The error $e$ in the upper bound occurs for two reasons: imperfections in the compression technique and the expected effect of the too noisy content of the object $y$ relative to the object $x$ [4].

In order to perform a change detection analysis, we employ a non-overlapping sliding window, used here as patch term, which simultaneously covers the same area from both images. Since the NCD similarity measure extracts the salient properties of the data, the dimension of the patch is constrained on both the image spatial resolution and the type of the analyzed change.

Starting from equation (1) we defined a simple rule to generate a collection of similarities for each pair of patches from both images, in order to identify both spectral and texture transformations. In Figure 1 is depicted the above process, in which are implicated several phases. First phase includes the split of both images in patches, where $i$ and $j$ inside the pattern *Pi_j* describe the index of the image, respectively the index of the patch inside the image. The second phase encloses the generation of the *NCD change map*, where a matrix of similarities is obtained based on (1). The third phase contains a normalization of the matrix resulted from the previous phase, which generates a gray level image with the intensity of the pixel defining the degree of change. Finally, in the last phase a threshold is applied, which generates a *binary change map*. The threshold value is applied by finding the inflection point of the histogram of the gray level image, obtained in the third phase. Both 2D images *Image 1, Image 2* have the same size and the parameters $k$ and $t$ represent the division result of the number of columns of the image to the dimension of the patch, respectively the division result of the number of rows of the image to the dimension of the patch, taking in consideration that patches are always quadratic. The result of the process described will be a matrix with $t$ rows and $k$ columns.

Essentially, when applied to a single set of patches, the scope of NCD is to generate a distance matrix that contains similarity grades between pairwise objects. The values contained in matrix are slightly above 0 when comparing an object to itself, slightly above 1 when the objects cannot compress together, leading to expansion instead of compression and below 1 otherwise [2]. Based on this assumption, we generate an NCD distance matrix on a unified set of patches from both images, but just for a subarea of interest.

The CompLearn Toolkit [5] is an open source suite of simple utilities that one can use to apply compression techniques to the process of discovering and learning patterns in completely different domains. In fact, this method is so general that it requires no background knowledge about any particular subject area. There are no domain-specific parameters to set, and only a handful of general settings.

SAR image change detection is a challenge issue due to the existence of speckle noise, being a more difficult task than the optical image change detection. A promising SAR image change detection technique is described in [6] where

**Table 1** Acquisition dates of the SAR images

| | *Image 1* | *Image 2* |
|---|---|---|
| *TerraSAR-X* | 2008/06/26 | 2013/06/15 |
| *Sentinel 1A* | 2015/07/17 | 2017/01/07 |

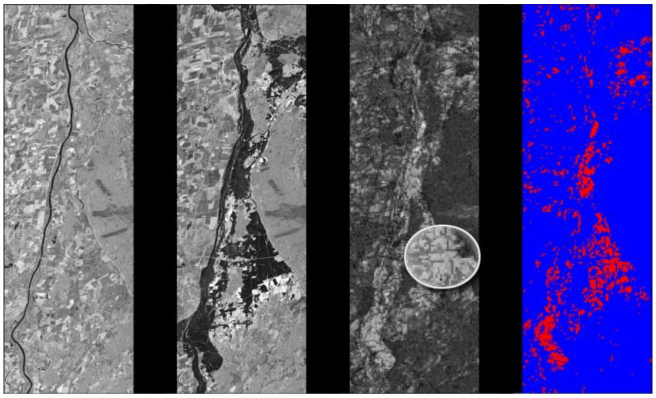

**Fig. 2**. TerraSAR-X image collection. The first two (from left to right) represent the pre-disaster and post-disaster images. The third contains a gray-level image obtained at phase three from the process depicted in Fig. 1. The fourth one is the binary change map.

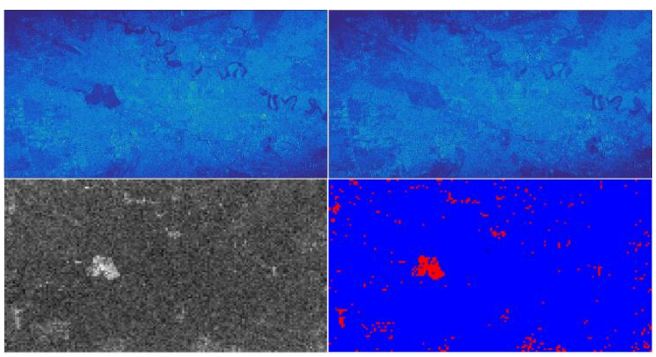

**Fig. 3**. Sentinel 1A image collection. The two top images (from left to right) represent the city of Bucharest in summer, respectively winter [Table 1]. The third (bottom left) contains a gray-level image obtained at phase three from the process depicted in Fig. 1. The fourth one is the binary change map.

the authors propose to obtain a stable and clear change detection map. Their algorithm involves usage of Gauss-log ratio and log-ratio difference operators applied on small patches, which imply robustness to calibration and radiometric errors. Additionally, mechanisms like discrete wavelet transform (DWT)-based fusion difference images and non-subsampled contourlet transform (NSCT) de-noising are employed to suppress the noise of the difference image and keep the shape of the changed portion. The feature extraction is performed via compressed projection to take full advantage of spatial neighborhood information and finally, a simple k-means clustering is applied to obtain the change detection map. The scope of this paper is to compare the relevance of the results obtained through a least biased method like NCD and the results obtained through a state-of-the-art algorithm [6] based on relatively classical tools for change detection in SAR images.

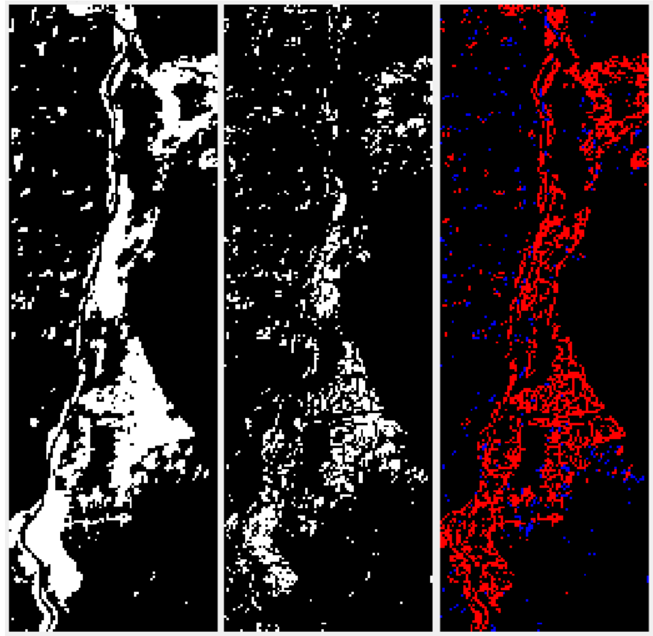

**Fig. 4**. Change map for two methods. First image (from left to right) is the output of the algorithm described in [6] with a sliding window parameter of 64x64 pixels. The second image is the output of the proposed method. The third image is the difference between the two change maps. In red are highlighted the pixels that are marked as changed in first map and unchanged in the second one. For the blue ones is vice-versa.

## 3. EXPERIMENTAL EVALUATION

The proposed processing chain implies the study of two sets of SAR data, one from the TerraSAR-X satellite and the second from the Sentinel 1A satellite. First dataset consists of two image products: a TerraSAR-X image acquired prior to the flooding on June 26, 2008 as a pre-disaster image [Fig. 2, first from the left part] and a TerraSAR-X image acquired after the flooding on June 15, 2013 as a post-disaster image [Fig. 2, second from the left part]. In the second dataset, the images are closer in time [Table 1]. The first set contains images with dimensions 17280x5760 (rows x columns) and the second one 5952x9984 (rows x columns).

Considering the process described in Fig. 1, we included in Fig. 2, in the right most two images the results of the last two phases. The third image (from left to right) is a gray level image obtained from a normalization applied to the collections of similarities (normalized from 0 to 255). The collection of similarities is obtained by applying the formula from (1) on each pair of patches, generated with a non-overlapping sliding window that simultaneously covers the same area from both images. Considering the employed data, a 64 x 64 pixel sliding window was selected experimentally as a compromise between the data features and accuracy of the results. The fourth image represents a binary map in which, the red pixels depict the changed area. The threshold value used to make the difference between change and unchanged pixels was chosen 130. This value is obtained as an inflection point on the histogram of the gray level image.

In Fig. 3, the same process is applied for Sentinel 1A data. The size of the patch used for the change detection map remains the same, 64 x 64 pixels. Here, the value of the threshold was also selected experimentally, by analyzing the histogram. In the fourth image (bottom right) a value of 120 is used as a limit for changed and unchanged pixels. An interesting fact is that on January 7 2017, the outside temperature was -10 °C, which produces a difference in the backscatter from frozen water areas than the one from normal water areas.

As can be mentioned, smaller sliding windows increase the sensitivity to local changes. Since NCD is used for detecting transformations of the land cover texture, the modified areas can be detected from several points of view. For example, an area that is crossed by a railway or by a road that remains unchanged between the two images, influence the resulted similarity of NCD for the pair of patches. As can be seen in Fig. 2, the zoomed area from the third image highlights the fact that the patches that have no background texture, but have a common feature that remains unchanged (railway) are classified into an unchanged patch. The relevance of this method came from the fact that not only the background texture of compared objects matters, but also the feature of the classes inside.

Both sets of data were also used as input for the methodology described in [6]. Because we used a relatively large patch of 64x64 pixels, some steps of the original algorithm (e.g., difference image fusion or NSCT-based de-noising) had a minor contribution to the final result. In Fig. 4 are included two different change maps generated with the two different methodologies, where the first one (state-of-the-art) is focused on spatial neighborhood information and the second one is just detecting transformations of the land cover texture. Even if there are singular unchanged areas within some changed areas, the state-of-the-art method will consider the isolated unchanged areas as irrelevant. On the other hand, our method will take into account the relevance of each feature content as is highlighted in the zoomed area inside the third image, in Fig 2. There are flooded areas separated by railway or roads that appear also separated in change map. Indeed there are flooded areas that are not detected as changed by our method because of its properties. The similarity of a random pair of patches is independent of another since the generation of the change map by our method is linked with the value of the threshold. In the third image inside Fig. 4 is a difference between the change maps obtained with the two methods. It can be noticed that the pattern generated by the red pixels corresponds to roads, or other obstacles that do not let the water settle down. Another aspect between the two methods is the computation time, which is much smaller for our method. To generate a collection of similarities for 14 508 pairs it takes 1 minute and 27 seconds on a desktop with 3.4 GHz quad-core CPU and 16 GB of RAM. To iterate with the same amount of data through the methodology described in [6] it is need at least one order of magnitude more, since it involves more computationally demanding processing steps.

## 4. CONCLUSIONS AND FUTURE WORK

Being a totally unsupervised and feature-free method, our approach is able to distill an accurate semantic information. The relevance of our method is defined as maintaining the relevant common feature between two random structures at two random times. The second method for change detection analysis is based on spatial neighborhood information, being less relevant for the feature content. Future work will focus on finding other relevant methods in discrimination of the unchanged isolated areas inside the changed area.

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