# Paper review: Multi-temporal spaceborne SAR data for Urban change detection in China

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## 1 Background

Change detection using graph-based remote sensing analysis offers the possibility to access relevant information about image features on different hierarchical levels. In this paper, the authors sought to examine the effectiveness of unsupervised urban change detection algorithms using multi-temporal Synthetic Aperture Radar (SAR) data. The use of multi-temporal SAR offers a viable alternative to effectively tackle the challenge of cloud, haze and smog in multi-temporal optical images. The main weakness of using multitemporal SAR is the challenge of speckle noise, which could distort image information. To effectively tackle this, the authors proposed a modified change ratio operator that eliminates this speckle noise and simultaneously cluster the change and no-change class into a histogram of bin size L. Afterward, an unsupervised learning algorithm was used to separate the change and no-change classes and model the statistical properties of these individual classes using different probability density functions (PDF).

## 2 Problem studied

At the time of publishing this paper, it was highlighted that the Minimum Error Thresholding algorithm was the most used for unsupervised change detection. The minimum error thresholding algorithm utilizes a histogram fitting technique to estimate the unknown probability density functions given a normally distributed data. When faced with an unsupervised learning task for SAR images, three main challenges are observed: 1.) SAR images do not follow a gaussian distribution, 2.) some SAR image information are often distorted with speckle noise and 3.) the priors and PDFs of the data are not known in advance.

Hence, an algorithm and workflow that minimizes the effects of speckle noise and generate, simultaneously, the unknown probabilities parameters and an optimal threshold for estimating pixels in the change pixels into change and no change classes is needed. In this paper, the authors proposed a three-step workflow that achieves the workflow mentioned above in three steps – 1.) generating a change image using a modified image rationing operator (to eliminate speckle noise – assuming it is reproduced in repeat-pass images), 2.) automatic thresholding of the change image into change and no-change classes, and 3.) estimating the PDFs of the respective change classes.

### 2.1 Step 1: Modified ratio operator

The modified ratio operator compares two images acquired at time t1 and t2 on a pixel-by-pixel basis and clusters both positive and negative changes together in one side of the histogram to generate a change image. This one-side clustering of the change classes makes it easy to use a single-threshold approach to detect the peculiar classes of changes. The mathematical expression for the modified ratio operator is given by:

$$r_{i,j} = \frac{max(x_1^{i,j}, x_2^{i,j})}{min(x_1^{i,j}, x_2^{i,j})}$$

where,

$$X_1 = \left\{X_1^{i,j} : i : \ldots n, j : \ldots m\right\}$$

and

$$X_2 = \left\{X_2^{i,j} : i : \ldots n, j : \ldots m\right\}$$

are the images at time $t_1$ and $t_2$, respectively.

## 2.2 Step 2: Automatic thresholding using the Generalized Kittler-Illingworth algorithm

Since the data distribution of SAR data does not follow a gaussian distribution, a more generalized form of the Kittler-Illingworth algorithm was used to extract the change and no-change class in the generated change image. This algorithm simultaneously estimates the unknown probabilities parameters and an optimal threshold that can be used to classify each pixel into change and no change classes.

The statistical property of this change image is used to estimate an histogram, serving as a good approximation of the modified ratio image. The modified image ratio clusters both changes (positive and negative) in one side of the histogram, which later allows the definition of a single threshold to separate between change and no change. After identifying the changed areas, the distinction between change and no change is done by comparing the original amplitudes.

Considering that this histogram is a combination of change and no change classes, it is possible to estimate the unknown probabilities using each of these histogram sections, given an arbitrary selected threshold from all possible threshold values (T extends from 1 to L) that separates the histogram into two classes. The likelihood of classification error is minimized at the threshold that minimizes the criterion function.

## 2.3 Step 3: Estimating the probability density functions

Since the assumption of a Gaussian distribution does not hold for SAR images, the minimum error thresholding algorithm was applied four different probability density functions: Log-normal distribution, Nakagami ratio model, Weibull ratio model, and Generalized Gaussian Model.

The result shows that when compared to the other density functions, the generalized Gaussian considerably overestimates the histogram of the change and non-change classes, resulting in poor outcomes. The log normal and Nakagami ratio models with the modified ratio image achieved the best results for detecting new built-up areas, because they have very high detection accuracies in positive change areas while also having low false alarm rates.

The algorithm did not do well when it came to detecting negative changes due to the low intensity of changes in places where backscatter has reduced vs the extremely high intensity of changes in locations where backscatter has grown. The authors conclude the best change results are obtained by using either log normal or Nakagami ratio, due to their property of fitting asymmetrical histograms. On the other hand, the main weakness of the model is its low accuracy in areas of negative change, which occurs mainly due to the low intensity of change in these areas.

## 2.4 Contribution

Overall, this methodology proposed by the authors of this paper combines the relative strength of the Generalized Kittler-Illingworth algorithm and the modified ratio operator. It reduces the computational cost by sticking to the one threshold step for splitting the class categories leveraging on the clusters of positive and negative changes provided by the modified ratio operator.

# 3 Relation of method to graph-based processing

The paper sheds light on an interesting approach to estimate change in SAR images, being particularly careful to the non-normally distributed nature of the data. In terms of a graph related approach, the authors use a modified image rationing in order to cluster the change (positive and negative) in one side of the histogram. Although not clearly mentioned as a graph operation, clustering can be understood as such once it groups similar pixels (nodes) based on its intensity response (linking similar pixels together).

# References

[1] Yifang Ban, Osama A. Yousif, and Kaj Sotala. "Multitemporal Spaceborne SAR Data for Urban Change Detection in China" IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 5. No 4, August 2012. `https://ieeexplore.ieee.org/document/6230616`