

# URBAN CHANGE DETECTION IN SAR IMAGES BY INTERACTIVE LEARNING

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## ABSTRACT

This paper focuses on finding changes in an urban environment (new or demolished buildings, activity monitoring) using Synthetic Aperture Radar (SAR) imagery. We propose a novel approach to characterize changes between two registered images. First, “what is a change” is learned interactively using user-provided examples in order to adapt the detection to the query context. Second, we propose the Change-Index Histogram of Oriented Gradients (CI-HOG), a new change descriptor that captures local statistics of change indices. We assess our system on TerraSAR-X data captured over challenging locations.

## 1. INTRODUCTION

For years now, remote sensing has been a powerful tool for land cover monitoring which allows to gather informations without field surveys and for a huge zone at once. For planning and management, experts need to know how the land use and the socio-economic activity evolve. Change detection between multi-temporal data captures provides them with indicators for their studies. Synthetic Aperture Radar (SAR) data are particularly suitable for such tasks. Though difficult to visually interpret with no specific training, SAR images lay emphasis on geometric and metallic structures which are often linked with human activity and perform well in all weather conditions.

Automatic change detection has a long history [1, 2, 3]. Twenty years ago, White and Oliver [1] stated that the “two major difficulties associated with SAR image change detection are [...] the removal of speckle noise and the registration of information between image”. In the scope of this paper we will assume that some solutions have been proposed for these purposes, and will focus on a third difficulty: the characterization of change between two registered images. Several change indices have already been proposed for estimating the change of appearance at two identical locations, from simple image difference or ratio [2] to more elaborated statistics such as the Generalized-Likelihood Ratio Test (GLRT) [4] or the local Kullback-Leibler divergence [5].

Dealing with an urban environment raises new problems.

Structures of interest are far more numerous than in the countryside and they often have overlapping SAR signatures due to the variability of building heights. Moreover, because of layover and registration errors or image noise, standard automatic techniques result in plenty of confusing alarms (true or false). To offer a finer representation of change, we propose a new supervised-learning-based change detector, the key features of which are:

- Defining what is a change from examples of real changes proposed online by the image analyst. Such relevance feedback is a powerful way to capture what the analyst’s mind sees in an image [6, 7].
- Using boosting or kernel methods for learning the most discriminant features among local statistics of the change indices.

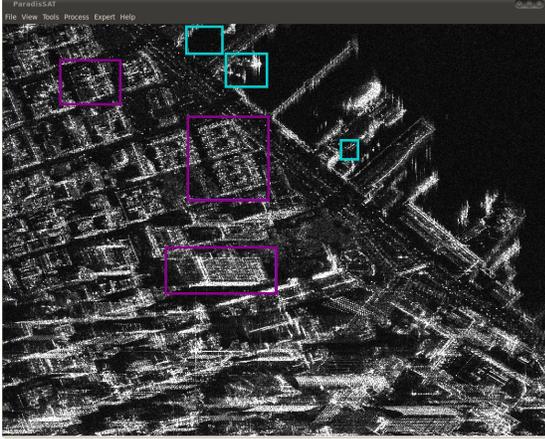
This paper is structured as follows. The new descriptor used for measuring the change between two locations is defined in part 2. Part 3 details the interactive learning approach we use for building a classification rule. In part 4 we present experimental results on TerraSAR-X images in a challenging urban environment that we discuss finally in part 5.

## 2. LOCAL STATISTICS OF CHANGE INDICES AS FEATURES

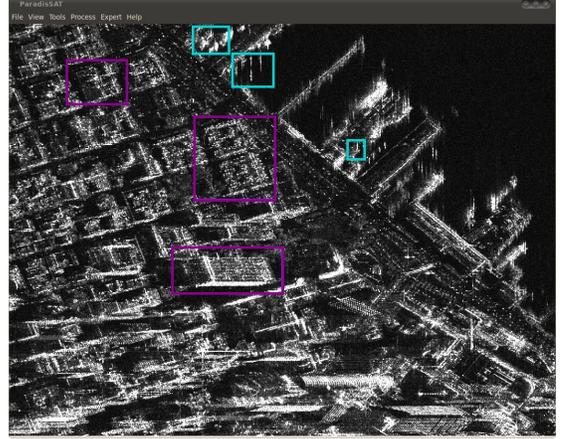
First, various standard change indices are computed on the couple of SAR images (denoted by  $\{I^i, I^j\}$  with real-valued pixels  $I_{x,y}^i \in [0; 1]$ ).

- Image difference was one of the first straightforward approaches to compare multitemporal images and has been widely studied [8]. It is defined at pixel-level by:  
 $C_{x,y}^{\text{diff}} = |I_{x,y}^i - I_{x,y}^j|$ .
- An alternative method consists in computing image ratio [2] or log-ratio.

$$C_{x,y}^{\text{ratio}} = 1 - \min \left( \frac{I_{x,y}^i}{I_{x,y}^j}, \frac{I_{x,y}^j}{I_{x,y}^i} \right)$$



(2007)



(2011)

**Fig. 1.** Interactive change detection between two dates (2007) and (2011) over San Francisco Financial District: obvious changes due to shipping movements were selected in the harbour area (clear cyan boxes) along with visually-unchanged urban examples (dark magenta boxes). CI-HOG are then extracted from these examples to train an Online Gradient-Boost algorithm that delivers a classification rule to detect changes between two images (cf. Fig 2).

- The Generalized-Likelihood Ratio Test (GLRT) [4] is a more statistically-grounded measure defined by:

$$C_{x,y}^{\text{GLRT}} = 1 - \frac{\sqrt{I_{x,y}^i * I_{x,y}^j}}{\frac{I_{x,y}^i + I_{x,y}^j}{2}}$$

Moreover, image analysts often resort to the colored composition (the mapping of the images to various channels of a color image as in [9]) to get an immediate and intuitive visualisation of the changes. The best results shown in section 4 are obtained with the GLRT change map.

Second, we estimate the local geometric statistics of the change map using Histograms of Oriented Gradients (HOG) [10]. The process consists in computing HOG over small neighbourhoods at various locations of the change map. This new descriptor is called Change Index HOG (CI-HOG).

The objective is two-fold. On the one hand, this allows to capture local information of the spatial neighbourhood and not only pixel-based information. On the other hand, we want to be able to differentiate real changes from regularities of the change index due to the geographic context (e.g. street orientations) or data acquisition (e.g. registration errors due to different aspect angles to ground).

### 3. ONLINE LEARNING

The interactive learning process follows a geographical-information-system-based approach [11]. The analyst selects regions that seem unchanged (label  $y = -1$ ) and regions of identified changes (label  $y = 1$ ) over SAR images

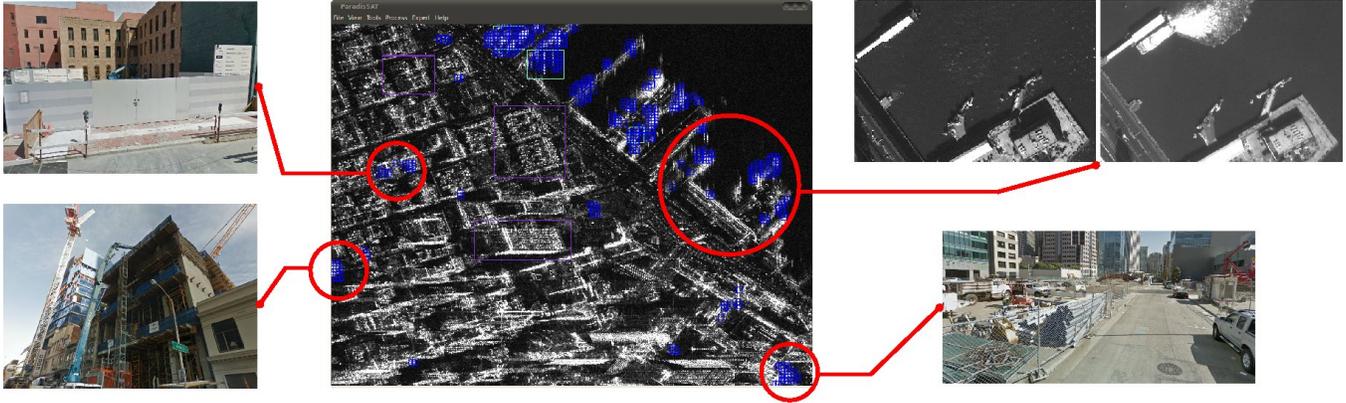
at two different dates (cf. Fig 1). For each region, CI-HOGs ( $d$ -dimensional vectors denoted by  $x_k$ ) are computed at regularly-sampled locations to describe the local neighbourhood. Along with their associated label, they constitute the training set  $\{(x_k, y_k)_{1 \leq k \leq N}, x_k \in \mathbb{R}^d, y_k \in \{-1, 1\}\}$  of the learning algorithms.

The aim of supervised learning is to build a function  $f : \mathbb{R}^d \rightarrow \{-1, 1\}$  able to predict the label of an unknown CI-HOG descriptor. In practice, it minimizes the misclassification risk  $R(f) = \frac{1}{N} \sum_k L(y_k, f(x_k))$  where  $L$  is a loss-function. In our application, building training sets on the fly raises two major problems. First, the interactive selection may lead to mislabeled training data (e.g. if a region larger than the target is drawn). Second, positive and negative sets are unbalanced since it is more likely to have much fewer changes than stable areas. We propose two flavours of standard learning techniques that can deal with these problems.

#### 3.1. Boosting

Online GradientBoost [12] is an incremental variant of Boosting that allows to use non-convex loss functions  $L$  that are less sensitive to mislabelings [13] such that the DoomII function. Moreover, to deal with unbalanced data sets, weights of classification errors in the iterative minimization of risk are modified according to the priors of each class. Consequently, the modified DoomII loss is expressed by:

$$L(y, f(x)) = \frac{1 - \tanh(y \cdot f(x))}{p(y)} \quad (1)$$



**Fig. 2.** Resulting change detections over San Francisco Financial District (cf. training areas on Fig. 1) are shown by blue square boxes, mainly located in the harbour area along the docks and in various locations downtown. Detections can be assessed either by comparing more easy-to-interpret optical images at the same dates or by field survey using street views that show that urban detections correspond to recent construction sites.

### 3.2. Support-Vector Machines

Support-Vector Machines (SVM) are a popular kernel method for minimizing risk. By setting an appropriate cost parameter, it yields in a soft margin that permits some misclassifications due to mislabeling. Unbalanced data is handled in the same way as in boosting, by weighting different costs for each class according to their prior. Moreover, SVM are particularly suitable for fast implementation on Graphics Process Unit (GPU) [14] that allows fast user interactions.

## 4. RESULTS AND EXPERIMENTS

The DataSet used for validation consists of 3 couples of TerraSAR-X images and one couple of optical images (Quick-Bird & WorldWiew-2) captured over San Francisco (SF) in 2007 and 2011.

### 4.1. Detection in images

Fig. 2 shows the detection results over SF Financial District using interactive learning. Training sets for defining what is a change are the areas drawn in Fig. 1. We assessed the validity of the detections by comparing the DTFC optical images and by looking what was going on at these locations using street views. Most detections are located in the harbour and correspond to regular shipping movements (for example in the ferry terminal). Urban changes correspond to construction sites of new buildings or urban multi-lane motorways.

### 4.2. Change measure comparison

Fig. 5 presents area-based detections obtained by online classification of CI-HOG features for comparison with pixel-based change indices: ratio map in Fig. 4 or color composition in Fig. 3. In an urban environment, pixel-based

detections give numerous alarms that can be contradictory depending on the target (for example the ratio map is able to detect the playground construction site in the park while the colored map is not). Interactive learning allows to implicitly select the change measures that are appropriate to the kind of changes that is looked for.

## 5. CONCLUSION

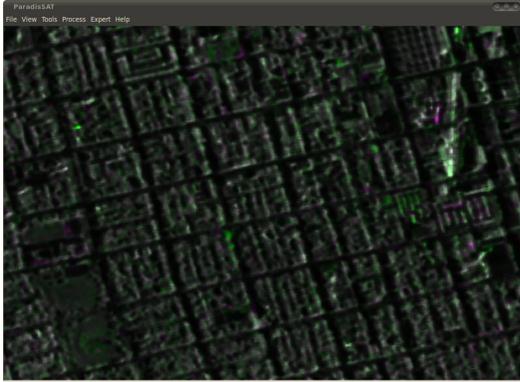
Online learning of change can identify automatically which change measures are relevant and complementary for a given task. We also proposed in this paper the CI-HOG feature that captures both the intensity and the spatial distribution of local changes. Moreover, it is generic enough to make possible the addition of new change indices. The resulting framework allows to build precise and complex requests that can adapt to changes that are not predictable and may depend on a particular context, for example post-earthquake damages or urban monitoring

## 6. ACKNOWLEDGEMENTS

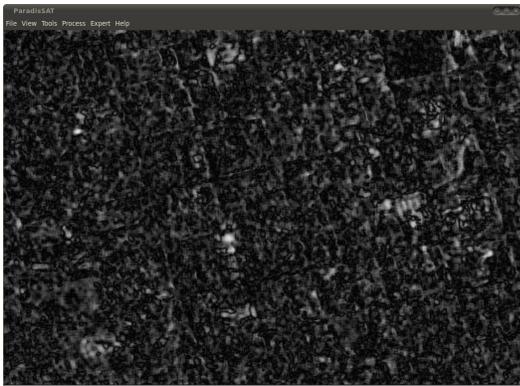
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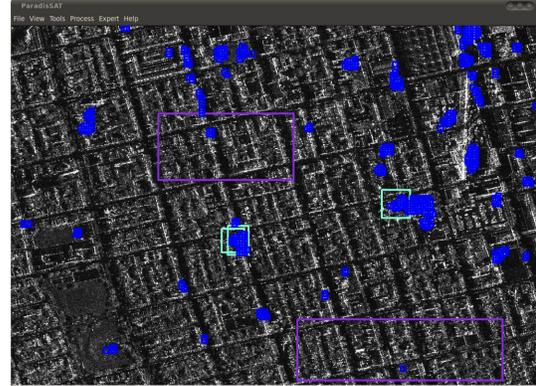
**Fig. 3.** Change detection over SF Mission District by color composition.



**Fig. 4.** Change detection over SF Mission District by ratio map.

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**Fig. 5.** Change detections over SF Mission District: classification by Online Gradient Boost on local statistics of change index CI-HOG (detections are marked by blue squares). The training set contains two modified buildings (cyan boxes) and areas that look similar when switching between the two images (magenta boxes). In comparison with Fig. 3 and Fig. 4, alarms are more precisely located on real urban modifications (new buildings, modified playgrounds, new solar panels, etc.).

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