RELEVANCE FEEDBACK FOR SATELLITE IMAGE CHANGE DETECTION

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ABSTRACT

Due to the exponential growth of satellite image collections, there is an increasing need for automatic solutions that assist operators in different applications. Automatic change detection is one of these applications that received an increasing attention during the last years. Nevertheless, fully automatic solutions reach their limitation; on the one hand, it is difficult to build general decision criteria able to select area of changes for different images, and on the other hand, the relevance of changes may differ from one user to another.

In this paper, we introduce an alternative change detection method based on relevance feedback. The proposed algorithm is iterative and based on a query and answer (Q&A) model that (i) asks the user the most informative questions about the relevance of his targeted changes, and (ii) according to these answers updates change detection results. Experiments conducted on large satellite images, show that indeed the approach is effective and allows the user to retrieve almost all his targeted changes while discarding the untargeted ones, with a negligible interaction effort.

***Index Terms*—** Relevance Feedback, Change Detection, Satellite Images, Kernel Machines, Image Retrieval.

1. INTRODUCTION

Change detection is the process of finding occurrences of *targeted* changes into a scene at a given instant t_1 w.r.t the same scene, acquired at instant $t_0 < t_1$. In remote sensing, acquisitions may be of different natures (such as satellite images) and applications are numerous ranging from studying environmental variations (melting glacier, deforestation, etc.), to assessing damaged areas after catastrophe (flooding, earth-quakes, fires, etc.) [1, 2], to video surveillance and cartography. Early change detection algorithms were introduced during the 70's and were initially based on simple comparisons of multi-temporal signals, via image differences and thresholding, using vegetation indices, principal component analysis and change vector analysis (see for instance [3, 4, 5, 6]).

Depending on use-cases, one may identify *relevant* changes (appearance or disappearance of entities or objects into scenes) and many *irrelevant* changes (due to sensor motion, viewpoints, registration errors, radiometric changes, atmospheric variations, occlusions, shadows, parallaxes, insignificant local motions of objects like waving trees, etc.). Existing methods (see for instance [7, 8, 9, 10]) rely on a preliminary preprocessing step that removes irrelevant changes, by finding parameters of sensors for registration as well as correcting radiometric effects, occlusions and shadows. Other methods [11, 12, 13, 14, 15, 16] either ignore irrelevant changes or consider them as a part of appearance model design and are able to detect relevant changes while being resilient to irrelevant ones.

In spite of their relative success, the aforementioned techniques are highly limited by the huge variability due to the presence of irrelevant changes and are often subject to many false alarms and missing detections. These errors either result from the limitation of preprocessing techniques or from the difficulty to learn a general decision criterion[1] as the frontier between relevant and irrelevant changes is sometimes narrow and may differ from one user to another. Thus, it is preferable to first let users designate few positive and negative examples of relevant and irrelevant changes, according to their intentions, and then automatically update change decision criteria. This process, when repeated iteratively, is known as relevance feedback (RF). The latter makes it possible - not only - to enhance quality of detection criteria, by adapting them to input images but also provides a natural way of interaction, with users, without systematic and tedious parsing of large satellite images. That's why relevance feedback should be preferred.

In this paper, we propose a change detection algorithm, for satellite images, based on relevance feedback. The method is interactive and based on Q&A model that helps the user expressing his intention and finding his targeted changes in few iterations. Relevance feedback has been previously studied mainly for image retrieval [17, 18, 19, 20, 21, 22, 23] and foreground/background segmentation [24, 25, 26], but our work is the first comprehensive study of relevance feedback for satellite image change detection, and includes at least three contributions

- The application of RF to change detection rises many new issues compared to the known RF for single category image retrieval (for instance [27, 28, 29, 30]). On the one hand, learning how to detect changes in "images including *many* categories of objects" is clearly more challenging than learning how to find "a *single* category in image retrieval". On the other hand, images in change detection are also subject to many irrelevant changes that make the problem even harder.
- The building blocks of our relevance feedback method include learning and display models. The learning model is built with user's answers *to the most informative questions* which are suggested by the display model.
- Finally, comparisons with related baseline methods, show the substantial gain of our interactive RF method, that allows the user to find his targeted changes, in few iterations.

The remainder of this paper is organized as follows. Section 2 discusses the steps of our relevance feedback algorithm, and Section 3, presents the design of these steps and mainly strategies for the Q&A model. Section 4, shows the evaluation of our interactive change detection method on satellite images and comparison w.r.t different baselines. Finally, Section 5 concludes and provides possible extensions for a future work.

[1]This results from the difficulty to get representative training sets, including sufficient amount of relevant and irrelevant changes.

2. RELEVANCE FEEDBACK-BASED CHANGE DETECTION

Let $\mathcal{I}_r = \{\mathbf{p}_1, \dots, \mathbf{p}_n\}$, $\mathcal{I}_t = \{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ be two satellite images captured at two different instants t_0 and t_1 with $t_0 < t_1$. $\mathcal{I}_r$, $\mathcal{I}_t$, referred to as reference and test images respectively, are defined as the union of patches $\{\mathbf{p}_1, \dots, \mathbf{p}_n\}$, $\{\mathbf{q}_1, \dots, \mathbf{q}_m\}$, with $\mathbf{p}_i, \mathbf{q}_i \in \mathbb{R}^d$ (here $d = 30 \times 30 \times 3$ in practice, see experiments). Without loss of generality, we assume these two sets registered, i.e., pixels in pairs $\{(\mathbf{p}_i, \mathbf{q}_i)\}_i$ correspond to the same locations. Now, we define $\mathcal{I} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$, with $\mathbf{x}_i = (\mathbf{p}_i, \mathbf{q}_i)$, and $\mathcal{Y} = \{\mathbf{y}_1, \dots, \mathbf{y}_n\}$ the underlying unknown labels. Our goal is to design a change detection algorithm based on relevance feedback[2] in order to predict the unknown labels $\{\mathbf{y}_i\}_i$ with $\mathbf{y}_i = +1$ if the test patch $\mathbf{q}_i \in \mathcal{I}_t$ corresponds to a "change" w.r.t its reference patch $\mathbf{p}_i \in \mathcal{I}_r$; and $\mathbf{y}_i = -1$ otherwise. As "changes" are scarce, it is very reasonable to assume that $|\{\mathbf{x}_i : \mathbf{y}_i = +1\}| \ll |\{\mathbf{x}_i : \mathbf{y}_i = -1\}|$.

2.1. Overview of our change detection algorithm

Let $\mathcal{D}_t \subset \mathcal{I}$ be a subset of patch pairs (also referred to as *display*) shown to an oracle (user) at iteration t and let $\mathcal{Y}_t$ be the unknown labels of $\mathcal{D}_t$; in practice $|\mathcal{D}_t|$ is fixed to $16 \ll |\mathcal{I}|$. We build our RF algorithm by asking the user "questions" about the relevance of changes in $\mathcal{D}_t$ according to the following steps

Display zero. Select a display $\mathcal{D}_0$ including the most representative samples in $\mathcal{I}$. This is achieved using an effective and also efficient algorithm, called "max-min", described in Section 2.2.

Run following steps for $t = 0, \dots, T-1$ (In practice, $T = 10$)

-User model. Label display $\mathcal{D}_t$ with an oracle function (denoted $\mathcal{C}(.)$) and assign $\mathcal{C}(\mathcal{D}_t)$ to $\mathcal{Y}_t$. In this work, $\mathcal{C}$, also referred to as the user model is assumed deterministic and *known-only-by-the-user* so the user's answers are assumed coherent and objective otherwise $\mathcal{C}(.)$ should be stochastic [31]. In this work, and since our change detection ground-truth is objective, we assume deterministic user models only.

-Learning model. Train a decision function $f_t(.)$ on data labeled, so far, $\cup_{k=0}^{t}(\mathcal{D}_k, \mathcal{Y}_k)$ and use it to predict the unknown labels in $\mathcal{I} - \cup_{k=0}^{t}\mathcal{D}_k$ depending on $\text{sign}[f_t(.)]$. As will be shown in Section 3.1, we use balanced support vector machines (SVMs) to build $f_t(.)$ at each iteration t.

-Display model. Select the next display $\mathcal{D}_{t+1} \subset \mathcal{I} - \cup_{k=0}^{t}\mathcal{D}_k$ to show to the user. We choose this display using two strategies, closely related to active learning (see for instance [32, 33]): (i) exploration and (ii) exploitation. The former aims to select data in order to discover new modes of $f_{t+1}(.)$ while the latter seeks to locally refine the decision boundary of $f_{t+1}(.)$. Details about these two strategies and their combination, are shown in Section 3.2, and constitute the main contribution of this work.

2.2. Display Zero

Initial display selection, also referred to as the "display zero" problem, consists in finding an initial set of patch pairs which are sufficiently different and representative of $\mathcal{I}$. This allows us to cover a few possible relevant changes (resulting from different types of appearances or disappearances of objects) and irrelevant ones (due to illumination, occlusion, etc.); see Fig. 1.
We propose to select this display as

$$\mathcal{D}_0 \leftarrow \arg\max_{\mathcal{D} \subset \mathcal{I}} \sum_{\mathbf{x} \in \mathcal{D}} \min_{\mathbf{x}' \in \mathcal{D} - \{\mathbf{x}\}} \left\|\mathbf{x} - \mathbf{x}'\right\|_2, \qquad (1)$$

here $\|.\|_2$ denotes the L_2 norm. As this problem is combinatorial (with a huge search space including $C_n^{|\mathcal{D}_0|}$ configurations) we consider instead a greedy version described in Algorithm 1, called max-min. It is clear that the solution (display) found by this algorithm is sub-optimal and depends on the initial setting of the first element in $\mathcal{D}_0$ (see comment in Algorithm 1). Nevertheless, as show in experiments (see Fig 2, top-left), this procedure is effective compared to random selection while being efficient (its complexity is $O(n)$). This procedure is also more appropriate than usual clustering algorithms (for instance k-means) as it explicitly seeks to maximize diversity of samples in $\mathcal{D}_0$.

Algorithm 1: Display Zero

Input: The union of all patch pairs in $\mathcal{I}$.
Output: Display $\mathcal{D}_0 \subset \mathcal{I}$ of size $m = 16 \ll n$.

```
D_0 ← ∅
for i := 1 to n do
    d_{x_i} ← ∞
x ← x_r ;            // r is randomly picked in {1, ..., n}
for j := 1 to m do
    D_0 ← D_0 ∪ {x}
    for i := 1 to n do
        d_{x_i} ← min{d_{x_i}, ||x_i − x||_2}
    x ← arg max_{x_i} d_{x_i}
```

3. LEARNING AND DISPLAY MODELS

3.1. Learning Model

Considering the union of displays and their labels $\cup_{k=0}^{t}(\mathcal{D}_k, \mathcal{Y}_k)$, the goal of this model is to learn to distinguish between relevant changes and irrelevant ones as well as no changes. For that purpose we train a decision criterion f_t for each iteration t, based on SVMs, and we use it to predict labels of patch pairs in $\mathcal{I} - \cup_{k=0}^{t}\mathcal{D}_k$.
Given a training set $\{(\mathbf{x}_j, \mathbf{y}_j)\}_j \subseteq \cup_{k=0}^{t}(\mathcal{D}_k, \mathcal{Y}_k)$, SVM learning consists in finding a vector of training parameters $\{\alpha_j\}_j$ and a scalar b that reduce an empirical loss while maximizing the margin between the positive and the negative data in $\{(\mathbf{x}_j, \mathbf{y}_j)\}_j$ [34]. Given a test data $\mathbf{x}$, its label $\mathbf{y}$ is set to $\text{sign}[\sum_j \alpha_j \mathbf{y}_j \kappa(\mathbf{x}, \mathbf{x}_j) + b]$; here κ is a symmetric, continuous and positive definite function, also known as kernel [34]. In practice, we use the laplacian kernel defined as $\kappa(\mathbf{x}, \mathbf{x}') = \exp(-\|\mathbf{x} - \mathbf{x}'\|_2/\sigma)$, with $\sigma = \text{E}_{\{\mathbf{x},\mathbf{x}':\|\mathbf{x}-\mathbf{x}'\|_2 \le \delta\}}\|\mathbf{x} - \mathbf{x}'\|_2$, and E being the expectation. This kernel choice is motivated by the good performance of SVMs, in different tasks including relevance feedback, w.r.t the use of many other kernels.

As positive and negative training classes in $\cup_{k=0}^{t}(\mathcal{D}_k, \mathcal{Y}_k)$ are very unbalanced (due to scarceness of relevant changes), we use randomization to train many SVM classifiers (denoted $\{g_\ell\}_\ell$); we

[2] In this process, the user has to label an infinitesimal fraction of data in order to build the change detection algorithm.

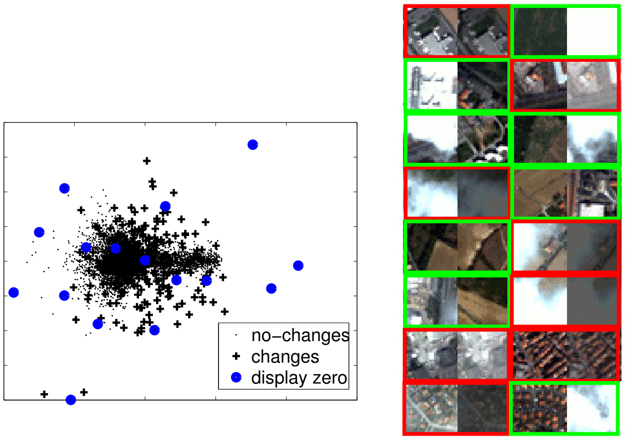

Fig. 1. (Left) This figure shows examples of "changes" and "no changes" taken from a particular ground truth (see experiments) as well as their "display zero". These points correspond to $\{\psi(\mathbf{q}_i) - \psi(\mathbf{p}_i)\}_i$ with $\psi(\mathbf{p}_i)$, $\psi(\mathbf{q}_i)$ being the projections of a reference patch $\mathbf{p}_i$ and a test patch $\mathbf{q}_i$ on the two principal components of PCA (again see experiments). For ease of visualization, only a subset of changes and no-changes were displayed among $53,550$ patch pairs. (Right) This figure shows patch pairs of display zero. Red rectangles stand for no-changes while green rectangles correspond to changes, according to the oracle.

train each classifier g_ℓ with the same number of positive and negative examples which are randomly taken from $\mathcal{I}$. Then, we predict the unknown label $\mathbf{y}_i$ of a given test data $\mathbf{x}_i$ using voting, i.e., $\mathbf{y}_i \leftarrow \text{sign}[f_t(\mathbf{x}_i)]$ with $f_t(\mathbf{x}_i) = \sum_\ell \text{sign}[g_\ell(\mathbf{x}_i)]$; and this makes the final decision criterion f_t unbiased towards the dominant class (i.e., no-changes). Note that this process is extremely fast as training[3] the SVMs $\{g_\ell\}_\ell$ involves subsets, in $\cup_{k=0}^t(\mathcal{D}_k, \mathcal{Y}_k)$, with very small cardinalities.

3.2. Display Model

At each iteration t, the goal of the display model is to select a display $\mathcal{D}_{t+1} \subset \mathcal{I} - \cup_{k=0}^t \mathcal{D}_k$ that minimizes the generalization error of the next decision criterion f_{t+1} and hopefully reaches the actual decision boundary. It is clear that a brute force strategy that (i) enumerates all the possible displays $\mathcal{D} \subset \mathcal{I} - \cup_{k=0}^t \mathcal{D}_k$, (ii) builds a decision function on $\cup_{k=0}^t \mathcal{D}_k \cup \mathcal{D}$ and (iii) estimates their generalization power, is out of hand; we consider instead heuristics. Display selection heuristics are usually related to active learning but one should be cautious in using these heuristics since many of them, which have nevertheless led to advances in several applications, can perform worse than the basic display strategy consisting in choosing uniformly randomly data of the display (see [32] and references within for a more detailed discussion).
As discussed earlier, our heuristics select the display in order to refine the current estimate of the decision function and also to find uncharted spaces in which the actual decision boundary exists. The first strategy, *exploits* our knowledge about the location of the decision boundary while the second one, *explores* new locations of that boundary. As will be shown through this section, our display selection strategy, seeks to find the good balance between exploration and exploitation.

We consider five display strategies which either discover and/or locally refine modes of decision criteria. A good strategy is the one which displays many ambiguous data, close to the decision boundary that could be misclassified by the subsequent classifier f_{t+1}.

Strategy-1 (Only Exploration). Data in display $\mathcal{D}_{t+1}$ are selected using a search strategy similar to display zero, i.e., by maximizing the dissimilarity between data in $\mathcal{D}_{t+1}$ and $\cup_{k=0}^t \mathcal{D}_k$ resulting into a new display $\mathcal{D}_{t+1}$ including representatives of $\text{span}(\mathcal{I})$. This strategy is efficient when modes of decision boundary are spread.

Strategy-2 (Only Exploitation). Again we use the same display strategy as display zero but we restrict $\mathcal{D}_{t+1} \subset \{\mathbf{x} : f_t(\mathbf{x}) \geq 0\}$. This strategy suggests data which are usually close to the decision boundary (i.e., ambiguous) and it is efficient when the class of targeted changes includes a single mode.

Strategy-3 (Explorations followed by Exploitations). Displays are selected by applying k explorations followed by $T - k$ exploitations (In practice $k = 5$).

Strategy-4 (Exploitations followed by Explorations). Displays are selected by applying k exploitations followed by $T - k$ explorations (In practice $k = 5$).

Strategy-5 (Adaptive Explorations/Exploitations). At $t = 0$, we apply exploration, then at each iteration $t \geq 1$, we select the subsequent display $\mathcal{D}_{t+1}$ depending on how good was the previous display $\mathcal{D}_t$. In practice, we either *keep* the previous action (exploration or exploitation) or we *switch* from exploration to exploitation or vice-versa, depending on a score $\mathcal{S}_t = \sum_{\mathbf{x} \in \mathcal{D}_t} \mathbb{1}_{\{\text{sign}[f_{t-1}(\mathbf{x})] \neq \mathcal{C}(\mathbf{x})\}}$. This score measures how informative is the display $\mathcal{D}_t$ obtained using the previous action; a good action should produce a display that allows the user to correct as many change detection results as possible thereby discovering new modes and better refining the subsequent decision criterion. In practice, we switch from one action to the other iff $\mathcal{S}_t \leq \frac{1}{3}|\mathcal{D}_t|$.

4. EXPERIMENTS

Test Set. In order to evaluate the performance of our interactive change detection method, we run experiments on two (reference and test) Quick-Bird 2 satellite images of $7,165 \times 6,776$ pixels with a spatial resolution of 2.4m; these two images are registered and correspond to the same area with many relevant changes (new buildings, etc.) and no-changes (including irrelevant ones; illumination, noise, etc.), see Fig. 1, right. Both reference and test images are processed in order to extract $53,550$ non overlapping patches, each one includes 30×30 pixels in RGB. The underlying ground truth contains $52,558$ negative patches (no changes) and only 992 positive patches (relevant changes), so $< 2\%$ of these patches correspond to relevant changes.

Features. Each patch (in reference and test images) is encoded with 100 coefficients corresponding to its projection on the 100 principal axes of principal component analysis (PCA). These principal axes of PCA were estimated using all patches of the reference image and capture more than 90% of the statistical variance of the data. Afterwards each patch pair $\mathbf{x}_i = (\mathbf{p}_i, \mathbf{q}_i)$ in $\mathcal{I}$ is described

[3] http://www.csie.ntu.edu.tw/∼cjlin/libsvm/

as $\psi(\mathbf{q}_i)-\psi(\mathbf{p}_i)$ with $\psi(\mathbf{p}_i)$ beeing the projection of $\mathbf{p}_i$ using PCA.

Evaluation measures. Performances are reported using equal error rate (EER) on unlabeled data of $\mathcal{I}$. EER is the balanced generalization error that equally weights errors in change and no-change classes. A smaller EER implies better performance.

Display strategies. We run the RF algorithm described in Section 2, with different display strategies, in order to evaluate their impact on performances; Table. 1, shows the underlying equal error rates. First, we observe that combined exploration-exploitation (i.e., strategies 3, 4 and 5) outperform exploration/exploitation when taken separately (i.e., strategies 1 and 2). Moreover, adaptive selection of exploration/exploitation (i.e., strategy 5) outperforms combined exploration-exploitation when taken successively (i.e., strategies 3 and 4). All these results were obtained by averaging EERs of 50 relevance feedback runs, each one corresponds to a random setting of the first element in $\mathcal{D}_0$ (see comment in Algorithm 1). These EERs reach their smallest values at the end of the iterative process, i.e., when many modes of the decision criteria are explored and exploited (see again Table. 1), and this happens after 10 iterations with only $(16 \times 10)/53,550 \times 100 \sim 0.3\%$ of patch pairs being visited and labeled by the oracle.

	Strategy-1 (Baseline-1)	Strategy-2 (Baseline-2)	Strategy-3	Strategy-4	Strategy-5
t	(EER+sd)	(EER+sd)	(EER+sd)	(EER+sd)	(EER+sd)
0	48.7 ± 7.6	48.7 ± 7.6	48.7 ± 7.6	48.7 ± 7.6	48.7 ± 7.6
1	$\mathbf{20.1 \pm 4.5}$	43.1 ± 5.0	$\mathbf{20.1 \pm 4.5}$	43.1 ± 5.0	$\mathbf{20.1 \pm 4.5}$
2	17.1 ± 4.0	34.2 ± 6.1	11.5 ± 2.3	34.2 ± 6.1	$\mathbf{12.0 \pm 2.6}$
3	15.6 ± 2.6	21.5 ± 10.5	7.7 ± 1.8	21.5 ± 10.5	$\mathbf{8.0 \pm 1.9}$
4	15.1 ± 2.5	17.2 ± 11.8	7.4 ± 1.9	17.2 ± 11.8	$\mathbf{7.3 \pm 1.8}$
5	14.5 ± 2.4	12.6 ± 9.4	7.1 ± 1.6	12.6 ± 9.4	$\mathbf{6.6 \pm 1.6}$
6	14.0 ± 2.6	10.4 ± 7.7	6.4 ± 1.6	10.4 ± 7.7	$\mathbf{6.1 \pm 1.4}$
7	13.9 ± 2.4	9.3 ± 6.4	6.0 ± 1.6	9.3 ± 6.4	$\mathbf{5.9 \pm 1.4}$
8	13.8 ± 2.5	8.5 ± 5.6	$\mathbf{5.5 \pm 1.7}$	8.5 ± 5.6	$\mathbf{5.7 \pm 1.3}$
9	13.5 ± 2.2	7.6 ± 4.7	$\mathbf{5.2 \pm 1.7}$	7.4 ± 1.0	$\mathbf{5.6 \pm 1.3}$

Table 1. This table shows evolution of EERs (in %) and standard deviations, w.r.t iteration number t. As t increases accuracy (1-EER) gets better and reaches 94.8%.

Comparison. We compare the performance of our change detection criteria f_t, $t = 0, \dots, T-1$, against two criteria, which are independent of t
(i) Image difference: a patch pair $\mathbf{x}_i = (\mathbf{p}_i, \mathbf{q}_i) \in \mathcal{I}$ is declared as a change iff $\|\psi(\mathbf{p}_i) - \psi(\mathbf{q}_i)\|_2 \leq \epsilon$.
(ii) Large scale SVM: we train an SVM decision function (denoted f) and we use it to detect changes in $\mathcal{I}$. The training set of f (denoted $\mathcal{T}' = \{(\mathbf{x}'_i, \mathbf{y}'_i)\}_i$) includes 291 positive examples and $2,624$ negative examples extracted from two other Quick-Bird 2 satellite images (including $1,677 \times 1,619$ pixels), of the same area, taken at two different instants. Note that the training set $\mathcal{T}'$ is much larger than the one used to train the final classifier f_{T-1}.

Fig. 2, top-right shows EERs of these two baselines (i)+(ii) as well as our proposed method. The out-performance of the proposed method, comes essentially from the adaptation of decision functions $\{f_t\}_t$ to the user's intention as well as to reference and test images in $\mathcal{I}$. Figs. 2-bottom, show the underlying detection and false alarm rates. Whereas the three methods converge to comparable detection rates, the proposed method dramatically reduces false alarms, at the end of the iterative process. These figures show that the proposed RF algorithm is able to find relevant changes and discard many irrelevant ones. At each iteration t, learning and display strategies run promptly (in less than 1s), provided that PCA features are extracted off-line; so the user gets updated change detection results in real-time.

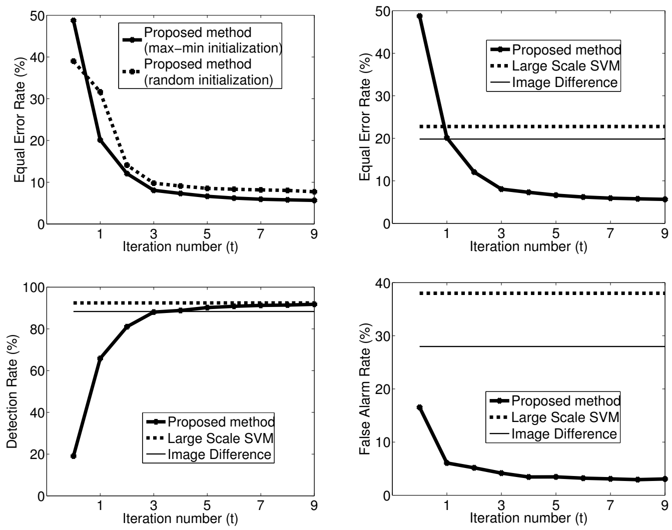

Fig. 2. (Top-left) this figure shows a comparison of two "display zero" selection procedures: max-min and random selection. (Other figures) show a comparison of our RF method w.r.t the two baselines discussed in Section 4: image difference and large scale SVM. All these results are obtained by averaging EERs, detection and false alarm rates of 50 RF runs. For all these experiments strategy-5 is used as a display model.

5. CONCLUSION

We introduced in this paper a novel satellite image change detection algorithm based on relevance feedback. The strength of this method resides in its ability to adapt change detection criteria to input images as well as user's intention.
The proposed method is interactive and it is based on a Q&A model that effectively and efficiently *learns* from user's responses and also *asks* the most informative questions to the user. This improves detection rates while reducing dramatically false alarms due to irrelevant changes.

Even though the proposed method is dedicated to detect changes between pairs of satellite images, it can easily be extended to sequences of multi-temporal images. Indeed, one can exploit the redundancy in these sequences, in order to further enhance performance.

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