Robust Change Detection in Dense Urban Areas via SVM Classifier

LiangLiang He[1]*, Ivan Laptev[2]
[1]NLPR & LIAMA, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, P.R. China
[2]IRISA/INRIA, Campus Beaulieu, 35042 Rennes Cedex, France

Track-Topic : URBAN2009 - (3) Algorithms and techniques for remotely sensed data interpretation in urban areas.

Introduction

The Earth surface is constantly changing; especially in developing countries, urbanization growth is so rapid that current map updating techniques do not allow to track the changes quickly enough. Natural disasters can also cause large scale infrastructure damages and important changes in the landscape; in order to carry out rescue quickly and efficiently, mapping and quantitative assessment of infrastructure damages is required. Change detection in dense urban areas is an essential problem for such operational tasks.

The principle of change detection from remote sensing data is to make comparison between two images taken at different times from the same location. Early methods [2, 7] were pixel based and mainly encode features based on the gray-level information, hence are not robust to illumination or geometric transformations of the scene. Differently, Ünsalan and Boyer [9] use line segments features; however, line features are quite sensitive to shadows and consequently could hardly be applied in dense urban areas under various acquisition conditions.

The core ideas of this paper are : i) to propose an image change detection scheme based on a weakly classification-by-learning of robust features computed at points of interest; ii) to introduce a point matching algorithm that reduces false-positives detection generated from projective effects of high buildings. The approach we propose make the basic assumption that the two images are globally registered (i.e. geo-referenced).

Overview

The overall idea of the approach we propose is to classify as change/no-change a limited number of points of interest (POIs) extracted from the images and to achieve this classification via a statistical classifier (SVM in our case). The motivation behind this is that local features computed at sparse key points provide a more robust description, less sensitive to local noise (i.e., cars, vegetation change, etc) than the sole grey value taken at each pixel, to estimate change between two images. Nevertheless, the shortcoming of local region features classification is to be highly sensitive to projective deformations that can appear between views of high altitude buildings. We tackle this problem via a point-matching procedure. Inspired from optical flow techniques, the POIs are registered without the need to explicitly computing the transformation matrix between the two images. This procedure improves significantly the change detection results computed from images covering dense urban areas.

Binary classification from SVM

At each POI extracted from each of the two images, we compute a differential feature vector that will feed a statistical classifier. We introduce in this subsection the main principles of the approach.

POIs and features extraction We extract POI using Harris corner detector [5] (it could be any other point detector insofar as it satisfies a high degree of reproducibility between images taken from different acquisition conditions). For each of the two images, we then project the points in the other image respectively, that is, take the union of the two sets of points. We compute HOG descriptors [4] for image patches around each POI and build a differential HOG descriptor (dHOG) by subtracting corresponding HOGs in two images. The dHOG is invariant to linear illumination change which makes it to a robust descriptor.

Classification dHOG features are classified as change/no-change using a robust statistical classifier. We chose to use SVM with RBF kernel [3].

Each patch is classified as change or no-change. As shown in [8], the classification error will decrease with the increase of patch size. To make a trade-off between patch size and precision, we chose a patch size of 64^2 pixels. Because the size of patches is relatively small and the patches themselves can overlap, the classification result can be used for fine segmentation.

Removal of false change detection via point correspondence

Projecting Harris points from one image to the other to compute the dHOG features is a strategy that can be used to handle cases in rural or sub-urban areas, but which intrinsically

*Corresponding author. Tel: +86-10-82614490. Fax: +86-10-62647458. Email:llhe@nlpr.ia.ac.cn.

fails for dense urban areas where the presence of high buildings predominates. Indeed, the projection of real world 3D buildings into the 2D image plane generates (projective) distortion which amplitude and direction depend on the acquisition geometry. This compels us to search for point correspondence between the two images. For image pairs without structural changes, trying to estimate a global transformation which would map one image onto the other can only fail because we are not in conditions where global homographic or affine transformation hypothesis are satisfied. Rather, similarly to [6], we propose a point-to-point matching derived from optical flow techniques.

It consists in minimising a global energy, which data term is defined by the dHOG features while the regularisation terms are conditioned by a (known) projection direction (note that this assume that we are in nearly epipolar geometry, which is true for images that do not cover a too large region on the ground). Hence we propose the following cost function :

$$\begin{aligned} E(P,P') = &\sum_{p_i} \|dHOG(p_i,p'_i)\| \\ &+ \alpha \sum_{p_i} \|\overrightarrow{p_ip'_i} - \|\overrightarrow{p_ip'_i}\| \cdot \vec{\mu}\|^2 \\ + \sum_{p_i} \sum_{p_j \in N(p_i)} &\|min(\beta \|\overrightarrow{p_ip'_i} - \overrightarrow{p_jp'_j}\|, D_{max})\| \quad (1) \end{aligned}$$

$P = \{p_i\}$ and $P' = \{p'_i\}$, $i \in \{1,..,K\}$ are POIs extracted from each of the two images respectively, $\vec{\mu}$ is a unit vector of the normalised projection direction, $N(p_i)$ is the neighborhood of p_i, and D_{max} is a threshold to prevent over-penalty at the border of buildings, α is a weight factor fixed manually on the training set. We use ICM algorithm [1] to minimise E with respect to (p, p'). Experiments show that convergence is reached in a few iterations. An example of matching is illustrated in Figure 1.

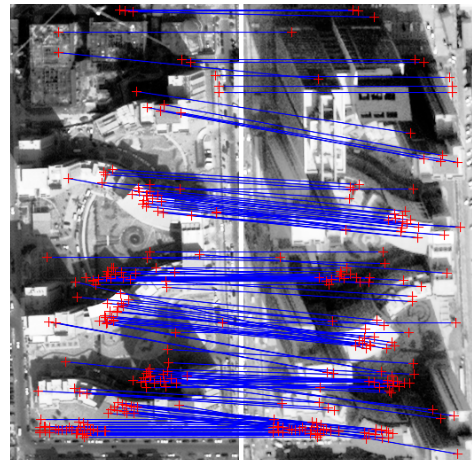

Figure 1: Point matching result from a pair of Quickbird images (resolution 0.6m/pixel) acquired during 2003/2007. Partial structural changes (top) and projective deformations are visible.

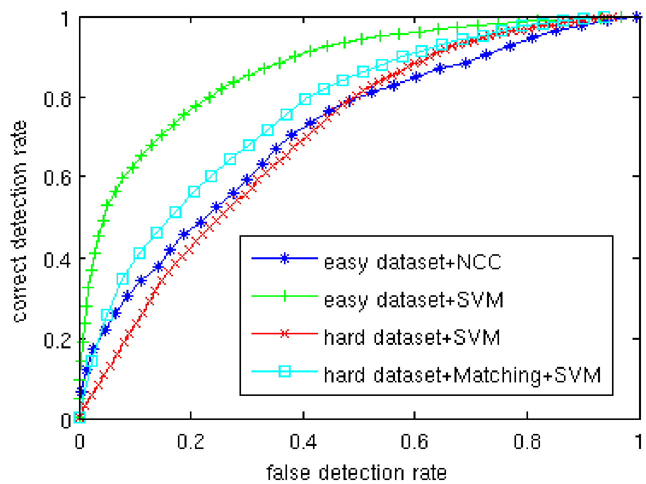

Figure 2: Receiver operating characteristic(ROC) curve.

Results and conclusion

An 'easy dataset' (i.e. which does not contain high altitude buildings) which includes 16 positive pairs of images (i.e. pairs of change) and 20 negative pairs are taken from georegistered Quickbird images [1]. We perform SVM classification 36 times with a leave-one-out procedure for evaluation. Normalized Cross Correlation (NCC) is used as the baseline method for comparison. To evaluate the performance of our matching process, we add 'difficult' images (i.e. which contain high altitude buildings with view angle variation) to create a 'hard dataset'. We make experiments with and without the matching step using the same SVM classifier.

The ROC curves are illustrated in Figure 2. For the easy dataset, dHOG features with SVM classifier perform much better than the basic NCC. When there are view angle variations, the classification performance drops dramatically if there is no proper preprocessing. Our matching procedure improves significantly the results.

[1] Data have been labelled by the Beijing Institute of Survey and Mapping.

References

[1] J. Besag. On the Statistical Analysis of Dirty Pictures. *Journal of the Royal Statistical Society*, 48(3):259–302, 1986.

[2] M. Carlotto. Detection and analysis of change in remotely sensed imagery withapplication to wide area surveillance. *IEEE Transactions on Image Processing*, 6(1):189–202, 1997.

[3] N. Cristianini and J. Shawe-Taylor. *An introduction to support Vector Machines*. Cambridge University Press New York, NY, USA, 1999.

[4] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005.*, volume 1, 2005.

[5] C. Harris and M. Stephens. A combined corner and edge detector. In *Alvey Vision Conference*, volume 15, page 50, 1988.

[6] C. Liu, J. Yuen, A. Torralba, J. Sivic, and F. W. T. SIFT Flow: Dense Correspondence across Different Scenes. In *European Conference on Computer Vision (ECCV) 2008*, volume 1, 2008.

[7] A. Singh. Review Article Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, 10(6):989–1003, 1989.

[8] H. Wang and E. Ellis. Image Misregistration Error in Change Measurements. *Photogrammetric Engineering and Remote Sensing*, 71(9):1037, 2005.

[9] C. Ünsalan and K. L. Boyer. A theoretical and experimental investigation of graph theoretical measures for land development in satellite imagery. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27:575–589, 2005.