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Supervised Change Detection on Simulated Data employing Support Vector Machines

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Introduction

- *Automatic change detection of manmade objects*
  - *Necessary for map or GIS update*
  - *Gain time, effort, money*
- *Lots of research in the field*
- *Success in certain very well-defined cases, by imposing certain constraints*
- *Far from a turn-key solution*

Traits of change detection methods (1/2)

- Scale of the changes to be detected
  Urban area expansion, single building scale
- Type of the basic comparison unit (compared feature)
  Grey tones, features, objects
- Number of steps in which the process is completed
  Object extraction and comparison vs direct comparison
- Path to change detection and a priori knowledge
  Bottom-up, top down approaches

Traits of change detection methods (2/2)

- Deterministic (decisive answer as to what change is) or stochastic approach (a measure of how possible change is)
- Level of automation
  Fully autonomous
  Automatic
  Semi automatic (training phase + prediction of changes)
- Type of data used
  Raster, vector from different sources and sensors

Proposed methodology for Change detection of manmade objects

Supervised classification paradigm

- *Data for the same region in different time periods (orthoimages, DSMs)*
- *Evaluation of a number of predefined cues for the region*
- *Use of some manually collected positive and negative samples to train a classifier - Support Vector Machines algorithm:*
  - *convergence to a global maximum*
  - *requirement of a small number of training samples*
  - *availability of good open source implementations*
- *The classifier asserts change in the remaining data*
- *Tests of the proposed strategy with simulated data (validity and performance aspects of the strategy)*

Proposed method for buildings change detection

- *Single building scale*
- *Orthoimages and DSMs from two measurement epochs*
- *Direct comparison (one stage approach)*
- *Bottom up technique, from pixels to changes*
- *Semi-automatic, supervised classification*
- *Deterministic method*
- *Classifier: Radial Basis Function Support Vector Machines*

Workflow of the method

1. *Acquisition of images from different periods + DSMs*
2. *Orientation of the images*
3. *Production of orthoimages for each period*
4. *Layering of the orthoimages & DSMs and calculation of the appropriate feature vectors*
5. *Training phase: manual labeling of positive and negative samples of changes*
6. *Classification of data as changed or not, using the trained SVM*
7. *Manual assessment of the resulted changes*

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Support Vector Machines – Linear classifier

SVM applications: from text recognition to image analysis

Goal of SVM: to classify a given object to one of two available classes based on its characteristics

- *Binary classification*
- *Each object is viewed as N-dimensional vector*
- *Calculation of appropriate (N-1 d) hyperplane which best separates the two object classes: the distance to the nearest feature vector on each side is maximized*
- *Best separation of the training samples*
- *Use the classifier for new samples: classified depending on which side of the hyperplane they lay*

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Linear SVM

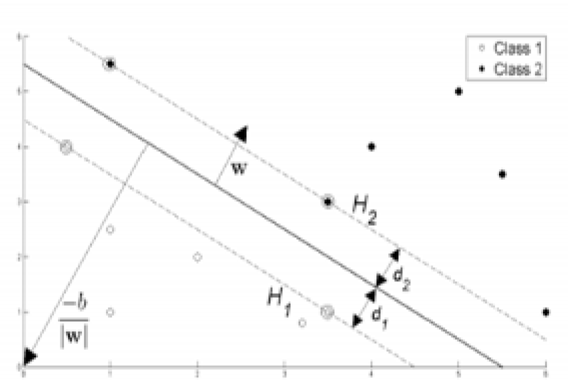

Illustration of 2D Linear SVM from Burges (1998)

Kernel functions

- *Non-linear hyperplanes*
- *Better separation*
- *Better accuracy*
- *Common kernels*
  - *Polynomial*
  - *Radial basis function (RBF)*

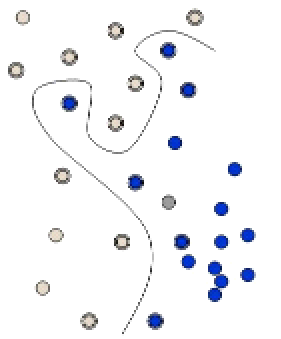

Illustration of non-linear hyperplane (DTREG, 2009)

SVM are a subclass of the kernel methods

Testing on simulated data

- Check the validity, effectiveness and robustness of the strategy
- Information to improve the Selection of features, Feature space dimensionality, Fine tune feature selection
- Testing configuration of SVM parameters

Automated generation of data and classification

- Computer program in Python programming language

Input for data generation

- Buildings' average area, height and shape (buildings' roof is considered flat)
- Area of testing size and density in buildings
- Distribution of buildings in the scene (grid or random type)
- DTM with a uniform slope
- Percentage of changes
- Radiometric ($N(m,\sigma)$) and geometric noise (uniform translation, rotation, scaling) to the images
- Height noise ($N(m',\sigma')$) of DSMs

Output of data generation

- *Data for two measurement epochs*
- *Greyscale simulations of orthoimages*
- *Simulations of DSMs*
- *Difference products from the above images and DSMs*

Data characteristics of the simulation tests

- *Area of interest: 1100 x 1000 pixel images*
- *100 buildings: 75 old buildings (1st period) + 25 new buildings*
- *Size of building: 200 pixels mean area*
- *Shape of building: Orthogonal with arbitrary rotation and aspect ration of sides*
- *Building height: 4m in average*
- *Slope of original DTM: 10%*
- *Size of cells to extract features: 10 x 10 pixels*
- *Classification method: SVM*

Testing scenarios:

- *Different buildings distributions (grid and random)*
- *Data: Images or Images & DSMs*
- *Different types of noise with varying magnitude*

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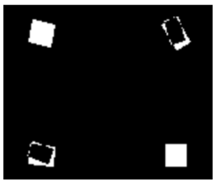
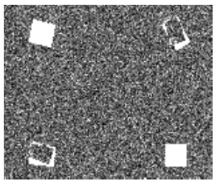
Example of grid building distribution

1^{st} period

2^{nd} period + Geometric noise

Image Difference





Difference + Radiometric noise

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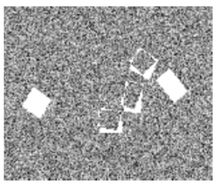
Example of random building distribution

1^{st} period

2^{nd} period + Geometric noise

Difference



Difference + Radiometric noise

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Testing procedure

- *In each scenario one train set and one test set are created*
- *Generate differences and apply noise*
- *Split area of interest in grid cells half the size of buildings*
- *Calculate feature vectors (mean & standard deviation)*
- *Automatically label changes for both datasets*
- *The SVM is trained on the train set and then classifies the test set*
- *The SVM also classifies the train set, to assess the validity of training*

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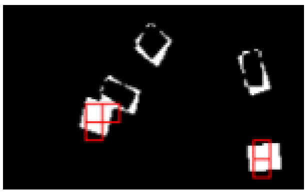
Assessing results

- *Measurement of accuracy at object level:*

  How many buildings were correctly detected as changed
- *Measurement of accuracy at grid cell level:*

  True positive, true negative, false positive and false negative results

Sample difference image and grid cells



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1. Classifying images with radiometric and geometric noise

In each scenario the geometric noise is fixed to:

- *1 pixel displacement in x axis & 2 pixels in y axis*
- *18 degrees rotation*
- *+10% scale in x axis & + 20% in y axis*

Radiometric noise varies (greyscale 0-255):

- *mean noise 100 – 200*
- *std noise 30 – 50*

Results

- *Objects accuracy: >96%*
- *True positives: >90%* *True negatives: 100%*
- *False positives: 0%* *False negatives: <1‰*

- *Geometric and radiometric noise have no significant impact to the results*

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2. Classifying images and DSMs

- *Geometric noise as previously*
- *Radiometric noise in 2 steps (add noise to the difference image):*
  mean noise 1 = 180 – 200 *std noise 1 = 10*
  mean noise 2 = 100 *std noise 1 = 60*
- *DSM noise: N(0,1m)*

Results

- *Objects accuracy: >80%*
- *True positives: >67%* *False positives: <5%*

- *The two step radiometric noise significantly reduces the accuracy of the process*
- *DSM improves the results (successfully detected new buildings: > 90%)*
- *The final accuracy is proportional to the DSM quality*

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3. Classifying images and DSMs with different quality training and testing data

- Low noise training data
- High noise testing data

Results

- DSM improves the results
- The final accuracy is proportional to the DSM quality:
  high quality DSM can greatly enhance the overall performance of the algorithm
- To achieve uniform levels of acceptable accuracy it is very crucial to train and test the SVM in almost the same conditions

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Conclusions (1/2)

To improve the procedures for automated and reliable detection of new buildings, for several applications such as

map updating, monitoring of informal development etc,

a procedure using Support Vector Machines was developed and tested.

The results using the ***Radical Basis Function SVM classifier*** *are especially encouraging.*

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Conclusions (2/2)

- *Applying simple noise conditions, even with high radiometric noise, the results are excellent*
  All new buildings were detected and few false replies (positive or negative) were mentioned
  The proposed procedure works perfectly under ideal conditions
- *When the noise becomes complicated the success indicators are reduced (detection of new buildings 80% and 5% false negative responses)*
  The use of DSMs seems to be necessary
  The proposed procedure gives the best results with DSMs of high quality and accuracy
- *When training and testing data differ in quality, the difficulties in detection of changes grow*
  The use of images alone is no longer adequate (<70% detection accuracy)
  The use of DSMs is necessary; the increased quality of DSM leads to better results