STACKED AUTOENCODERS FOR MULTICLASS CHANGE DETECTION IN HYPERSPECTRAL IMAGES

Experimental results and addictional information related to the paper “STACKED AUTOENCODERS FOR MULTICLASS CHANGE DETECTION IN HYPERSPECTRAL IMAGES”, under revision in the International Geoscience and Remote Sensing Symposium, IGARSS 2018.

Abstract

Change detection (CD) in multitemporal datasets is a key task in remote sensing. In this paper, a scheme to perform multiclass CD for remote sensing hyperspectral datasets extracting features by means of Stacked Autoencoders (SAEs) is introduced. The scheme combines multiclass and binary CD to obtain an accurate multiclass change map. The multiclass CD begins with the fusion of the multitemporal data followed by feature extraction by SAE. The binary CD is based on the spectral nformation by calculating pixel-wise distances and thresholding, and it also incorporates spatial information through watershed segmentation. The data coming from the multiclass CD is filtered by using the binary CD map and later classified by a Support Vector Machine or an Extreme Learning Machine algorithm. The scheme was evaluated over a multitemporal hyperspectral dataset obtained from the Hyperion sensor. Experimental results show the effectiveness of the proposed scheme using SAE for extracting the relevant features of the fused information when compared to other published feature extraction methods

Input datasets

All the images are avaiable in Matlab (.mat) format, among others. For further information see the readme in the files.

* Hermiston

Experimental setup

* Codes were run in Ubuntu 14.04.

* Caffe framework 1.0.0-rc3 to perform the feature extraction by means of SAE.

- The SAE is configured to obtain 12 features.
- Two consecutive layers reduce the dimensionality of the data from 242 to 100 and from 100 to 12 features,respectively.
- The SAE is trained with 20% of the available pixels randomly chosen.
- A batch of 64 pixels per iteration is used.
- The iteration limit is fixed to 300000 iterations.
- The back-propagation process uses a Stochastic Gradient Descent (SGD) and the ’inv’ learning rate policy [inv = base lr ∗ (1 + γ ∗ i)^(−power)] being i the iteration number and with a base

learning rate (base lr) of 0.01, and values for the parameters γ and power of 0.0001 and 0.75 respectively.

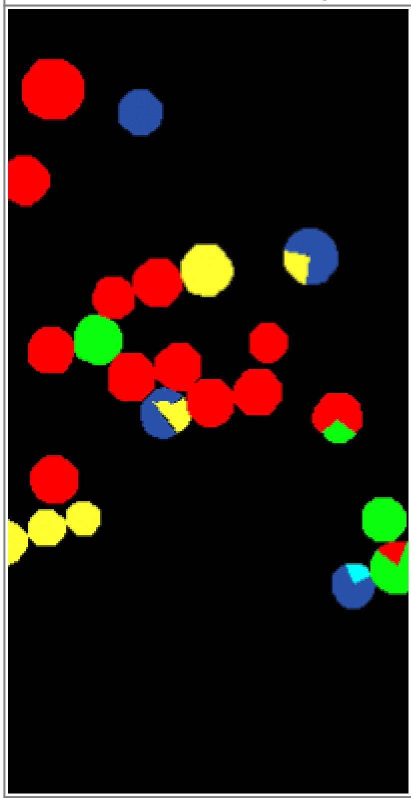
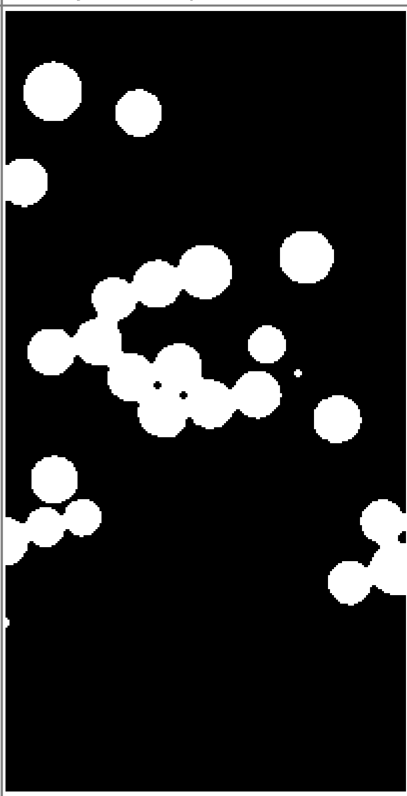
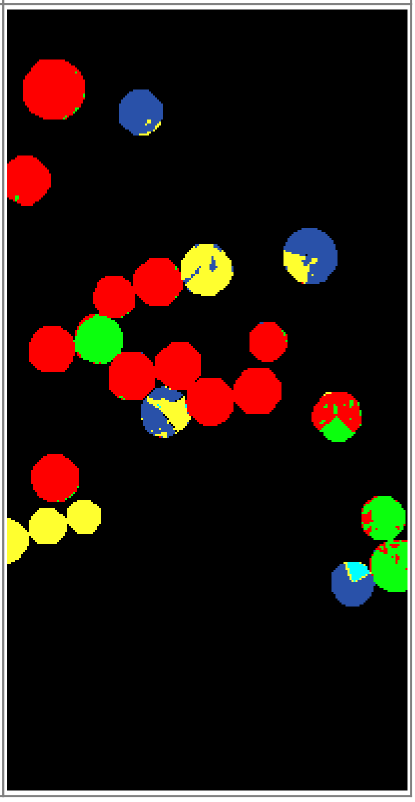
* NWFE and PCA used for comparision purposes retaining 12 features.

* ELM and SVM trained with 5% of the reference data available for each class.

- Training samples randomly chosen in each run.
- 10 independent runs for each classifier.
- SVM classification carried out using the LIB-SVM library and the Gaussian radial basis function (RBF).
- ELM configured with a sigmoidal activation function.

Outputs

Image files

Reference data of changes	Binary CD map	Multiclass CD map
		

Accuracy results

Binary CD accuracies

Corect	Missed Alarms	False Alarms	Total Error
77020 (98.74%)	509	471	980 (1.25%)

Multiclass CD accuracies

Classifier	Parameters	FE	OA (%)	AA (%)	Kappa

ELM	N=120	PCA	91.73	76.06	86.83
ELM	N=120	NWFE	91.76	76.75	86.83
ELM	N=60	SAE	95.19	90.45	92.31
SVM	C: 64.0 γ: 32.0	PCA	91.46	71.16	86.46
SVM	C: 32.0 γ: 16.0	NWFE	91.29	90.61	86.05
SVM	C: 32.0 γ: 0.0625	SAE	95.52	92.56	92.90

C: penalty term in the training of the SVM. γ: radius of the gaussian function of the SVM. N: Number of neurons in the hidden layer of the ELM. FE: Feature Extraction method.

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