Additional Results for Efficient ELM-based Techniques for the Classification of Hyperspectral Remote Sensing Images on Commodity GPUs.

Javier López-Fandiño, Pablo Quesada-Barriuso, Dora B. Heras, and Francisco Argüello

***Abstract*—Extreme Learning Machine (ELM) is an efficient learning algorithm that has been recently applied to hyperspectral image classification. In this paper, the first implementation of the ELM algorithm fully developed for Graphical Processing Unit (GPU) is presented. ELM can be expressed in terms of matrix operations so as to take advantage of the Single Instruction Multiple Data (SIMD) computing paradigm of the GPU architecture. Additionally, several techniques like the use of ensembles, a spatial regularization algorithm, and a spectral-spatial classification scheme are applied and projected to GPU in order to improve the accuracy results of the ELM classifier. In the last case, the spatial processing is based on the segmentation of the hyperspectral image through a watershed transform. The experiments are performed on remote sensing data for land cover applications achieving competitive accuracy results compared to analogous SVM strategies with significantly lower execution times. The best accuracy results are obtained with the spectral-spatial scheme based on applying watershed and a spatially regularized ELM.**

***Index Terms*—Hyperspectral images, remote sensing, spectral-spatial classification, watershed, Extreme Learning Machine, SVM, GPU, CUDA.**

I. Additional Remote Sensing Classification Results

In this document, we present additional experimental results obtained by the ELM classifier in GPU including another ensemble configuration and more detailed results for the three datasets studied. The experimental conditions remain exactly as presented in the published paper. The additional results are highlighted in grey in the tables.

A. ELM-based Classification Results

We compare three different GPU optimized configurations using ELM. The last one (V-ELM-2) is an addition to the results published in the paper:

1) A single ELM trained with 200 samples for each class (ELM).
2) A V-ELM comprising 8 ELMs trained with 200 samples for each class for each one of the ELMs, so that each ELM is the same as in the first configuration (V-ELM-1).
3) **A V-ELM comprising 8 ELMs trained with a total of 200 samples for each class equally spread (with bootstrap) among the ELMs. This way the number of training points used by the 8 ELMs is the same as those used by the single ELM of the previous configuration (V-ELM-2).**

The authors are with the Centro de Investigación en Tecnoloxías da Información (CITIUS), University of Santiago de Compostela, Spain. (E-mail: {javier.lopez.fandino, pablo.quesada, dora.blanco, francisco.arguello}@usc.es)

TABLE I
Classification accuracy as percentages (and standard deviations between brackets) The ELMs contained 500, 950, and 350 nodes in the hidden layer respectively.

	Pavia Univ.			Indian Pines			Salinas		
	OA	AA	kappa	OA	AA	kappa	OA	AA	kappa
SVM [2]	81.01	88.25	75.86	78.76	69.66	75.75	81.25	–	–
ELM	86.75	89.55	82.61	**80.72**	**85.48**	**77.70**	**91.55**	95.97	**90.55**
	(0.71)	(0.26)	(0.87)	**(0.58)**	**(1.31)**	**(0.64)**	**(0.27)**	(0.13)	**(0.29)**
V-ELM-1	**90.32**	**91.81**	**85.77**	79.84	90.62	72.40	90.74	**96.22**	89.18
	(0.31)	**(0.20)**	**(0.43)**	(0.83)	(2.82)	(1.08)	(0.11)	**(0.15)**	(0.13)
V-ELM-2	78.17	77.16	71.42	66.80	76.63	62.23	89.21	94.49	87.91
	(1.21)	(1.02)	(1.45)	(1.28)	(1.97)	(1.38)	(0.56)	(0.24)	(0.63)

The number of training samples for the ELM are 200 per class, or half the number of samples in the class if there are not enough samples. These samples are randomly chosen and all the remaining samples are used for test. The number of hidden layer neurons employed are 500 for Pavia Univ., 950 for Indian Pines, and 350 for Salinas in all the cases [1].

Table I shows accuracy results for the images in terms of OA, AA, and kappa. The best results are highlighted in bold in the Table. The first thing to highlight is that both configurations obtain acceptable accuracy results, being slightly better than the SVM for the three datasets.

For the Pavia Univ. image, the V-ELM-1 configuration clearly improves on the ELM configuration in terms of accuracy results while for the Indian Pines and Salinas images both configurations obtain similar results, being the ELM configuration only slightly better. Finally, it is worth noting than the standard deviation values remain low in all the cases. **Regarding the V-ELM-2 configuration, as expected, it offers in all cases a lower accuracy than a single ELM. This is due to the fact that this configuration leaves very few samples to train each class in each ELM and overfitting is produced resulting in poor generalization capabilities. This is supported by the fact that every ELM in this configuration obtains 100% accuracy in the training phase but much lower accuracy in the later test phase.**

The performance results in terms of execution times and speedups calculated over the OpenMP multicore implementations are detailed in Table II. It has been observed in the experiments that the V-ELM-1 configuration provides more stable accuracy results than a single ELM at the cost of

TABLE II
PERFORMANCE RESULTS.

Pavia Univ.	SVM	ELM	V-ELM-1	V-ELM-2
OpenMP CPU	20.5876s	2.3304s	18.9022s	17.2394s
CUDA GPU	2.5834s	**0.3063s**	2.4501s	1.9960s
Speedup	8.0×	7.6×	7.7×	8.6×
Indian Pines	SVM	ELM	V-ELM-1	V-ELM-2
OpenMP CPU	3.0084s	1.1653s	9.6903s	4.5749s
CUDA GPU	0.7652s	**0.3096s**	2.6058s	0.8032s
Speedup	3.9×	3.8×	3.7×	5.7×
Salinas	SVM	ELM	V-ELM-1	V-ELM-2
OpenMP CPU	5.6018s	1.1023s	8.7055s	7.9127s
CUDA GPU	0.8708s	**0.3439s**	3.0114s	2.0271s
Speedup	6.4×	3.2×	2.9×	3.9×

TABLE III
SPEEDUPS AGAINST SVM.

	Pavia Univ.		Indian Pines		Salinas	
	CPU	GPU	CPU	GPU	CPU	GPU
ELM	**8.8×**	**8.4×**	**2.6×**	**2.5×**	**5.1×**	**2.5×**
V-ELM-1	1.1×	1.1×	0.3×	0.3×	0.6×	0.3×
V-ELM-2	1.2×	1.3×	0.7×	1.0×	0.7×	0.4×

slightly higher execution times. **Results also indicate that the execution times of the V-ELM-2 configuration are almost as big as the ones of the V-ELM-1 configuration. This is due to the fact that V-ELM-2 only saves time against V-ELM-1 in the training phase, that is shorter than the test phase.**

The speedups of the ELM as compared to the SVM in both the CPU and GPU architectures are shown in table III. For the three images, the single ELM configuration is faster than SVM, achieving, for the Pavia Univ. image, a speedup of 8.8× in CPU and 8.4× in GPU. The V-ELM-1 configuration is more adequate when the dataset size is large because otherwise (as in the case of Indian Pines) there are not enough samples to take advantage of the voting to improve accuracy results.

Summarizing, on the one hand, for the remote sensing datasets considered the raw ELM algorithm described in this paper is significantly faster than SVM and, on the other hand, the V-ELM-1 algorithm always approaches or improves the raw ELM accuracy although it requires a higher number of training samples. This last one is a good configuration if we want to prioritize execution times.

B. Spectral-Spatial Classification Results

In this section, the experimental results obtained by the application of the spectral-spatial classification scheme are shown. The impact of spatial regularization over an ELM classification map is also studied.

Figures 1, 2 and 3 show the results of the spectral-spatial scheme using a spatially regularized ELM (ELM+reg+wat con(8)) for the three studied datasets.

The classification accuracy of the proposed method is compared to results published in the literature, as the pixel-wise spectral classification by a SVM, spatial regularization (SVM+reg) [3], and the similar spectral-spatial schemes based on segmentation (SVM+wat) [2] and (SVM+EM) [3]. In addition, the combination of segmentation and spatial regularization (SVM+EM+reg) [3] is also included in the results. SVM+wat denotes that the segmentation map of the spectral-spatial scheme is created by watershed, and SVM+EM the same but using expectation maximization (EM) [4] for segmentation by partitional clustering. In all the schemes, the spectral-spatial information is combined by the majority vote algorithm within each segmented region. The spatial regularization of SVM+reg and SVM+EM+reg is done using Chamfer connectivities of eight and sixteen neighbours [3]. Results for another work based on ensembles of ELM and a similar spectral-spatial scheme (V-ELM) are also included [5].

Table IV shows the accuracy obtained using the developed classification scheme (best results for each dataset in bold). Results from the literature obtained using a SVM pixel-wise classifier are also included for comparison purposes.

As it can be observed in table IV, the ELM-based strategy obtains better results for the three datasets. Therefore, it can be stated that in accuracy terms ELM is suitable to replace SVM in this spectral-spatial scheme. The connectivity of 8 neighbours, as expected, improves the results of the 4 neighbours one. Table IV also shows that the spatially regularized configurations always give better results. It is worth noting that the spectral-spatial scheme using a spatially regularized ELM (ELM+reg+wat con(8)) requires less computation time that the one based in ensembles of ELM (V-ELM-1+reg+wat con(8))) but achieves better results.

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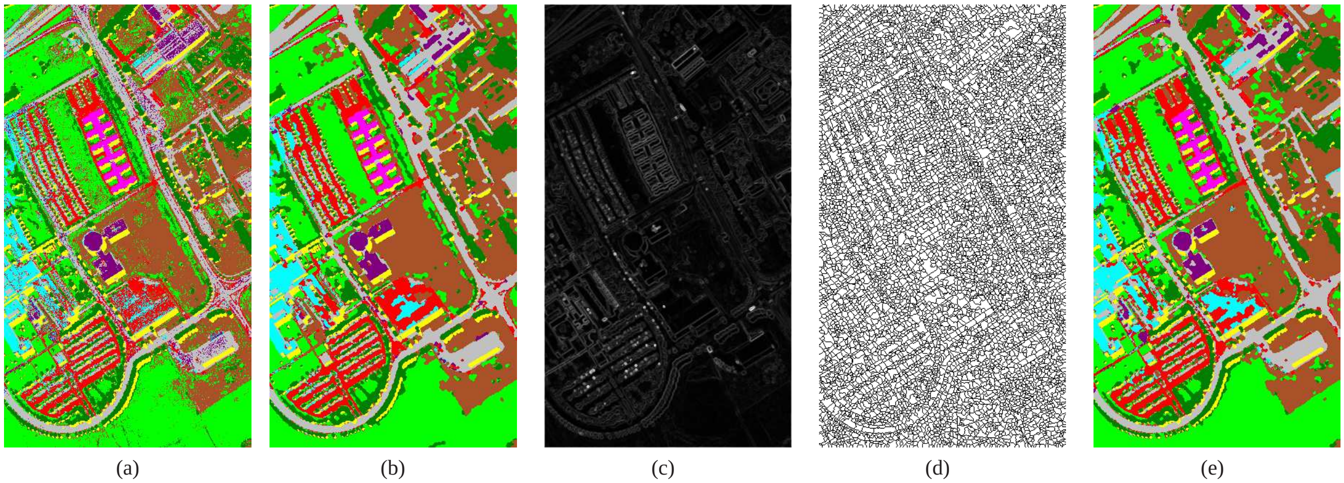

Fig. 1. Spectral-spatial phases for the Pavia Univ. image. (a) ELM, (b) Spatial Regularization, (c) RCMG, (d) Watershed, (e) MV.

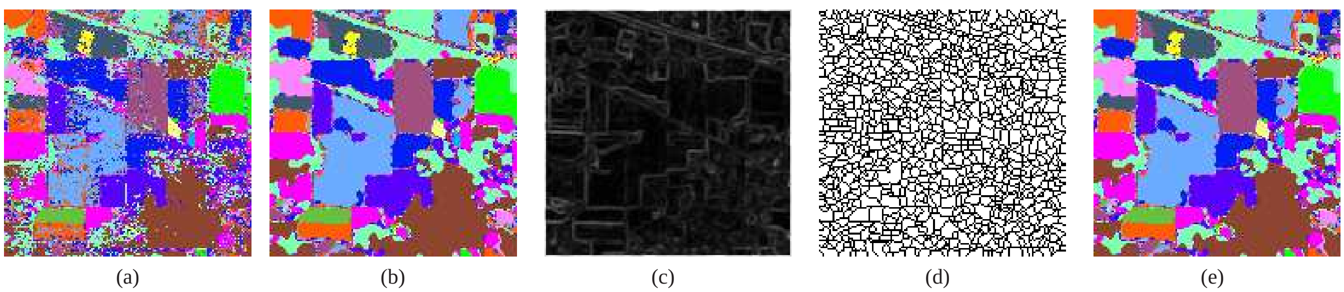

Fig. 2. Spectral-spatial phases for the Indian Pines image. (a) ELM, (b) Spatial Regularization, (c) RCMG, (d) Watershed, (e) MV.

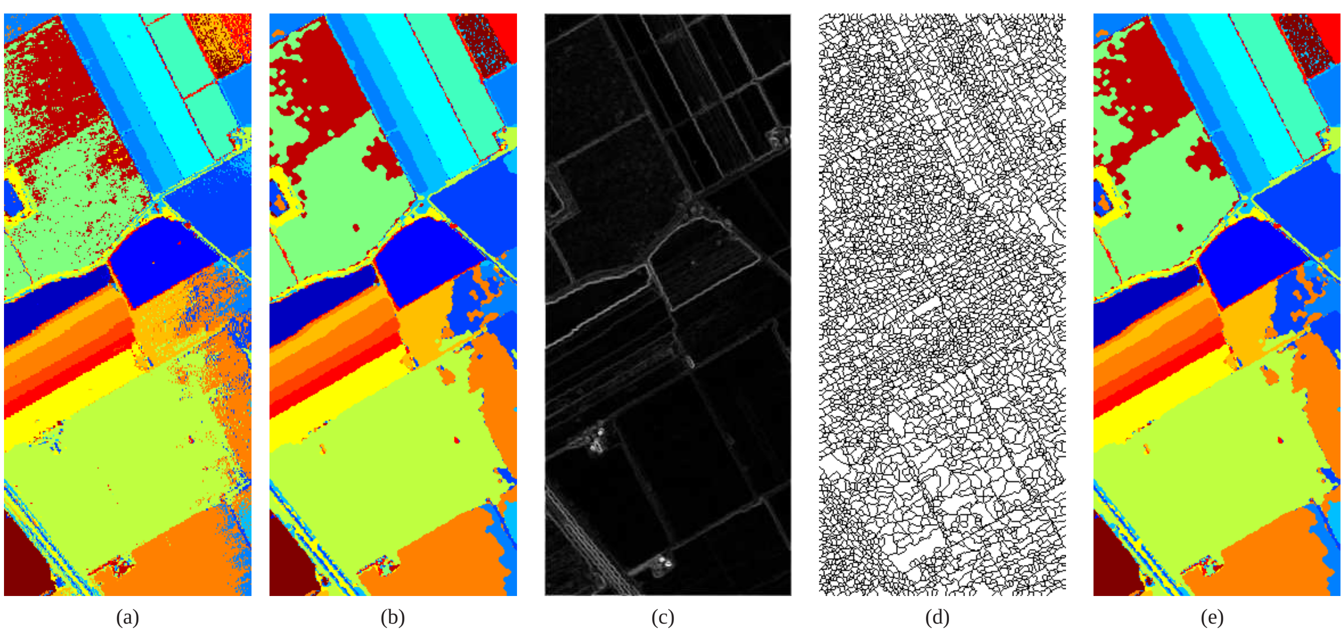

Fig. 3. Spectral-spatial phases for the Salinas image. (a) ELM, (b) Spatial Regularization, (c) RCMG, (d) Watershed, (e) MV.

TABLE IV

CLASSIFICATION ACCURACY AS PERCENTAGES (AND STANDARD DEVIATIONS BETWEEN BRACKETS). 'REG' INDICATES THAT THE PIXEL-WISE CLASSIFIER WAS SPATIALLY REGULARIZED. 'WAT' INDICATES SPATIAL PROCESSING BY WATERSHED. 'CON(X)' INDICATES CONNECTIVITY OF 'X' NEIGHBOURS.

	Pavia Univ.			Indian Pines			Salinas		
	OA	AA	kappa	OA	AA	kappa	OA	AA	kappa
SVM [2]	81.01	88.25	75.86	78.76	69.66	75.75	81.25	–	–
SVM+reg [3]	84.27	90.89	79.90	88.58	77.27	86.93	–	–	–
SVM+wat con(8) [2]	85.42	91.31	81.30	92.48	77.26	91.39	–	–	–
SVM+EM [3]	93.59	94.39	91.48	87.25	70.34	85.43	–	–	–
SVM+EM+reg [3]	94.68	95.21	92.02	88.83	71.90	87.24	–	–	–
V-ELM [5]	89.18	–	–	70.08	–	–	**93.88**	–	–
ELM	86.75(0.71)	89.55(0.26)	82.61(0.87)	80.72(0.58)	85.48(1.31)	77.70(0.64)	91.55(0.27)	95.97(0.13)	90.55(0.29)
ELM+reg	95.13(0.65)	95.51(0.40)	93.50(0.86)	91.04(0.82)	92.32(1.25)	89.54(0.94)	93.56(0.28)	**97.02(0.15)**	92.78(0.32)
ELM+wat con(4)	93.84(0.83)	94.05(0.47)	91.79(1.08)	88.73(0.67)	90.76(1.55)	86.90(0.76)	92.91(0.25)	96.15(0.18)	92.06(0.27)
ELM+wat con(8)	95.09(0.71)	95.14(0.47)	93.44(0.93)	91.41(0.97)	93.91(1.32)	89.98(1.12)	93.31(0.33)	96.52(0.17)	92.51(0.37)
ELM+reg+wat con(4)	95.37(0.67)	95.00(0.47)	93.81(0.88)	90.90(0.96)	91.47(1.63)	89.38(1.10)	93.46(0.31)	96.48(0.18)	92.67(0.35)
ELM+reg+wat con(8)	95.65(0.77)	95.52(0.52)	94.18(1.02)	**92.67(1.08)**	94.29(1.22)	**91.43(1.24)**	93.70(0.35)	96.78(0.16)	**92.95(0.39)**
V-ELM-1+reg+wat con(8)	**96.66(0.28)**	**95.92(0.29)**	**95.00(0.42)**	90.41(1.06)	**95.35(1.83)**	86.21(1.43)	92.43(0.31)	96.75(0.16)	91.15(0.36)
V-ELM-2+reg+wat con(8)	93.98(1.09)	92.68(1.06)	91.91(1.43)	85.71(1.66)	91.66(2.07)	83.63(1.86)	92.90(0.49)	96.31(0.26)	92.04(0.55)