

A New Method of Dimensionality Reduction of Hyperspectral Images Implemented in FPGA

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Abstract. *Hyperspectral images present new applications, but they represent new challenges: data high dimension is one of them. This paper deals with a new technique for reducing the dimensionality of the data: Nonlinear Principal Component Analysis (NLPCA). This method applies an self-associative artificial neural network (ANN). The ANN is implemented in a FPGA. The image processing is performed in the hybrid computer (CPU+FPGA).*

Resumo. *Imagens hiper-espectrais apresentam-se como uma nova possibilidade para aplicações, mas elas representam novos desafios: dados com alta dimensionalidade é um desses desafios. Este artigo trata de uma nova técnica para reduzir a dimensionalidade dos dados: Análise de Componentes Principais Não-linear (NLPCA). Este método utiliza uma rede neural artificial (RNA) auto-associativa para realizar a redução da dimensionalidade dos dados. A RNA é implementada em uma FPGA. O processamento de imagem é realizado no computador híbrido (CPU + FPGA).*

1. General Information

The advent of satellite remote sensing with multispectral and hyperspectral images in digital format has brought a new dimension in image classification. However, not all channels provide useful data for an application. Therefore, it is necessary to select appropriate channels for a specific application [Chein-I 2013].

Data reduction can be performed using Principal Component Analysis (PCA) [Gonzalez and Woods 2000], where the Singular Values Decomposition (SVD) of data matrix covariance is calculated [Anton and Rorres 2004]. The singular values may perform the data dimensionality reduction, aiming to be more efficient in hyperspectral image classification.

Traditionally, the PCA performs the dimensionality reduction of the data by a linear approximation, which may lead to an undesired loss of variability in the data [Licciardi et al. 2012]. This limitation can significantly influence the classification of hyperspectral data, mainly, in the classification data of the same class, but having variations in their spectral characteristics [Licciardi et al. 2012]

The above observation has motivated the study of new techniques of nonlinear data reduction. In this study, Non-linear Principal Component Analysis (NLPCA) [Del Frate et al. 2009] is addressed using Artificial Neural Networks (ANN), the Multilayer Perceptron (MLP) with the backpropagation algorithm in the process learning.

The development of hardware components, such as Field Programmable Gate Arrays (FPGA), has allowed many techniques used in pattern recognition to be implemented in hardware, that allows processing embedded in aircraft or satellite.

Thus, the objectives of this study are:

1. evaluation the NLPCA method (compared to the standard strategy based on PCA).
2. implementation of method NLPCA in FPGA (in order to processing boarded an aircraft or satellite).

2. NLPCA Implemented in a FPGA

The architecture of the MLP aims to take full advantage of the computing power and to explorer the parallelism of the FPGA [Gomes et al. 2011]

Two MLP were programmed in VHDL:

- The first MLP performs the data reduction.
- The second MLP recieves the data data reduction to perform the classification.

The design of MLP was implemented for the Cray XD1 reconfigurable hybrid system. The codes of the components described in the previous section were programmed in VHDL using ISE WebPack, provided by Xilinx, which is the manufacturer of FPGA Virtex II Pro FPGA, which make up each of the six nodes of the Cray XD1.

3. Data Set and Methodology

The dataset used in this study was obtained from the Institute of Advanced Studies (IEAv) and covers an area of São José dos Campos-SP. This image was obtained by sensor Hyperspectral Scanner Sensor (HSS) that acquires data in 37 bands of the electromagnetic spectrum [Castro et al. 2005]. The image supplied by IEAv comes together with 4 ground-truth image of 4 regions of interest. This dataset was used in [Silva et al. 2013].

The methodology used in this study is as follows:

- Image acquisition;
- Normalization of the data obtained from images;
- Reducing the dimensionality of the data using the NLPCA method;
- Classification of the data after the reduction of dimensionality by means of a MLP.

Data classification has been done using the spatial information of a pixel region defined by a 3×3 matrix, this strategy is the same applied in [Silva et al. 2013], which obtained significant results with its application.

4. Results

To configure the MLP was used the MPCA a metaheuristic introduced by [Luz 2012], used to optimize the objective functions, and modified by [Anochi et al. 2014], that introduced the objective function given by Equation [Carvalho 2011] to find an optimal architecture or near optimum for a MLP that uses the algorithm of error back-propagation during the training phase.

After finding the optimal architecture or nearly optimal architecture for the MLP that performs data reduction and also for the MLP and that performs classification, the

data set has been presented to the both MLP that producing the result shown in the Figure 1.

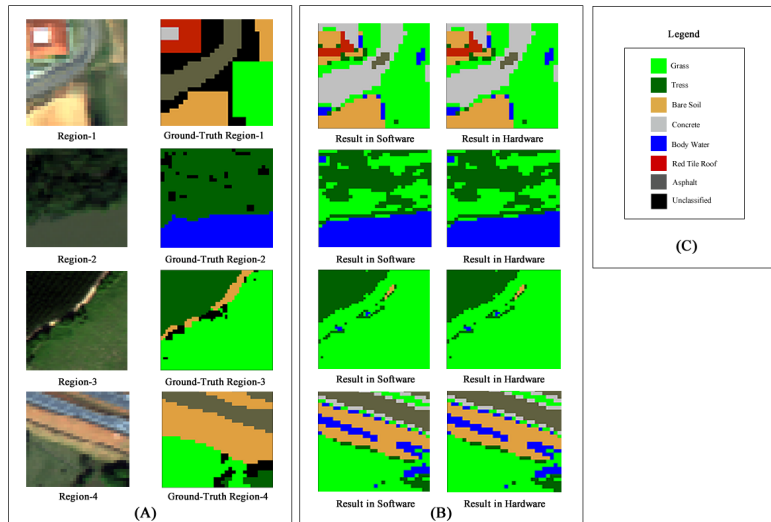


Figure 1. Regions of interest and ground truth of each region in Figure 1 (A), results of data classification in software and hardware are shown in Figure 1 (B) and in Figure 1 (C) the label of class of interest

The Table 1 shows the Kappa index [Cohen 1960], average accuracy [Licciardi et al. 2012] and the overall accuracy [Licciardi et al. 2012] to evaluate the classification in software.

Table 1. Results of Kappa Index, Average Accuracy and Overall Accuracy in Software

	Kappa Index	Average Accuracy	Overall Accuracy
Region 1 in Software	0.4075	39.87	68.95
Region 2 in Software	0.4996	74.70	67.40
Region 3 in Software	0.6763	59.58	85.98
Region 4 in Software	0.6177	71.92	68.95

The Table 2 shows the same metrics of Table 1 but the classification, of same regions, performed in hardware.

Table 2. Results of Kappa Index, Average Accuracy and Overall Accuracy in Hardware

	Kappa Index	Average Accuracy	Overall Accuracy
Region 1 in Hardware	0.4075	39.87	68.95
Region 2 in Hardware	0.4996	74.70	67.40
Region 3 in Hardware	0.6763	59.58	85.98
Region 4 in Hardware	0.6177	71.92	68.95

5. Conclusion

This paper presented a novel method of dimensionality reduction in classification images using artificial neural networks. The methodology was implemented in FPGA. The results indicate that for the dataset used in this study, the NLPCA method can be implemented in hardware, without compromising the results, which facilitates its use in embedded systems.

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