SINGLE VALUES SELECTIONS FOR FILTERING IMAGE

Nilton Correia da Silva[1] & Antônio Nuno de Castro Santa Rosa[2]

1 - Centro Universitário de Anápolis (Unievangélica)
Avenida Universitária km 3,5, Cidade Universitária, Anápolis, GO, Brasil.
nilton@unievangelica.edu.br

2 - IG/UNB – Instituto de Geociências/Universidade de Brasília – Brasil
nuno@unb.br

RESUMO – Este trabalho explora a relação espacial dos valores singulares sobre os pixels da imagem, a fim de propor um processo de filtragem. Diferentes tratamentos de ruído são aplicados a cada pixel, considerando seus efeitos, em um processo não supervisionado de agrupamento - Self Organizing Map. Este procedimento realiza um processo de filtragem distinto para as diferentes características espectrais das imagens. Dois experimentos são apresentados: o primeiro com dados sintéticos e o segundo com dados Landsat-7. O primeiro considera uma cena com freqüências altas e, consequentemente, reduz apenas o espaço nulo dos valores individuais de cada pixel. O Segundo experimento, com dados Landsat-7, mostra um caso com cenas homogêneas. Neste caso, o processo de filtragem define cortes considerando um grupo limitado de classes. A técnica apresentada aqui traz uma maneira eficaz para reconstruir melhores aproximações dos dados originais e, ao mesmo tempo, exclui os intervalos desnecessários de variações de pixel.

PALAVRAS-CHAVE – Transformada SVD, Mapas auto-organizáveis, Filtragem, Processamento de Imagem.

ABSTRACT - This work explores the spatial relation of Single Values over image pixels in order to propose a filtering process. Different denoise degrees are applied to each

pixel considering their effects on an unsupervised clustering process – Self Organizing Map. This results on specific filtering process to different spectral characteristics of the images. Two experiments are presented; the first one with synthetic data and the second with LandSat-7 data. The first one considers a scene with high frequencies and consequently cuts only the null space of the single values of each pixel. The experiment with LandSat-7 data shows a case with homogeneous scenes. In this case, the filtering process implements hard cuts considering a limited group of classes. The technique presented here brings an effective way to reconstruct better approximations of the original data and, at the same time, excludes unnecessary ranges of pixel variations.

KEYWORDS - Single Values Decomposition, Self-Organizing Maps, Filtering, Image Processing.

INTRODUÇÃO

It is difficult to apply a hard threshold to the Single Values which reduces the noise in images and, at the same time, it doesn't make the filtered image losing important features which characterize objects in the real scene. To avoid this problem the authors have studied the contributions of the single values on the reconstructed pixels. The choice of the same single value subset to reconstruct all pixels, results on different effects in different regions of the image. It is due to one single value has different contribution degrees on each pixel. A maximum cut on the reconstructed pixel values is achieved by using a minimum quantity of single values on its reconstruction. In this work we use an unsupervised neural network – Self Organizing Map – to regulate the minimum quantity of single values to each pixel of the reconstructed image.

SVD AND HARD THRESHOLD

The equation 1 brings the inverse process of a Single Values Decomposition (SVD) applied to the image $\overline{\overline{D}}$. This decomposition is known as Single Values Decomposition because the values of the matrix $\overline{\overline{S}}$ are the positive square roots of the eigen values of $\overline{\overline{D}}^{t}.\overline{\overline{D}}$ or $\overline{\overline{D}}.\overline{\overline{D}}^{t}$. So $\overline{\overline{S}}$ is designed by single values of $\overline{\overline{D}}$ (Noble and Daniel, 1986).

The diagonal matrix is sorted by contribution degree of its single values on the reconstruction process.

$$\overline{\overline{D}}^{'} = \overline{\overline{U}} \cdot \overline{\overline{S}} \cdot \overline{\overline{V}}^{t} \tag{1}$$

By the analysis of the diagonal matrix , it is possible to verify the contribution degree of its individual values in different regions of the reconstructed image . If it is defined as an index $0 < k < N$ and changes all value of with indexes greater than k to zero, the reconstructed image will be a softened image (2). The changes in the pixels will depend on how much k is close to one.

$$\overline{\overline{D}}^{'} = \overline{\overline{U}} \cdot \begin{bmatrix} S_{11} & 0 & 0 & 0 & . & 0 \\ 0 & . & . & . & . & 0 \\ 0 & . & S_{kk} & . & . & 0 \\ 0 & . & 0 & 0 & . & 0 \\ . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & . & 0 \end{bmatrix} \cdot \overline{\overline{V}}^{t} \tag{2}$$

This filtering process, by using a hard threshold defined by the constant k, results on a softened image which minimize the noise effects presented in the

high frequencies of the original image (Medeiros et al., 1998; Sant'anna & Mascarenhas, 1994). But applying the same cut criterion to all pixels means to have different effects over different regions of the reconstructed image. In section 4 we propose a filtering process which uses particular constants k to each reconstructed pixel.

SELF ORGANIZING MAP (SOM)

An important feature of neural networks is the ability to learn from their environment, and through learning to improve performance in some sense. They are classified in supervised and unsupervised learning methods. In the supervised method the targets may take the form of a desired input-output mapping that the algorithm is required to approximate. In another way, the purpose of a self-organizing map is to discover significant patterns or features in the input data without a teacher. The algorithm is provided with a set of rules of local nature which enables it to compute an input-output mapping with specific desirable properties. The term "local" means that the change applied to the synaptic weight of a neuron is confined to the immediate neighborhood of that neuron (**Figure 1**) (Ritter & Schulten, 1988; Malsburg, 1990).

The learning process of a self organizing system consists of repeated modifications in the synaptic weights of all system´s connections in response to input (activation) patterns and in accordance with prescribed rules, until a final configuration (Haykin, 1998). Initially, consider one matrix of neuron unit, one weight vector $m_i(t) \in R^n \{t = 1,2,3,...\}$ associated to each unit i and one input pattern $x(t) \in R^n$ being compared with all units. The following two rules explain
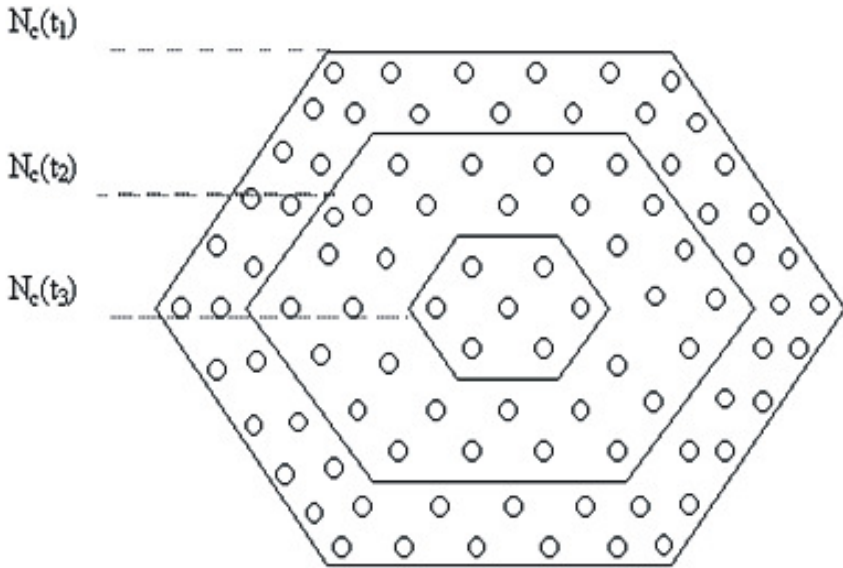
Figure 1. Output layer and the neighborhood function: $N_c(t)\{t_1 < t_2 < t_3\}$

how the map is generated by self organization (Kohonen, 1990):

Rule 1: To find the unit which weight vector is more similar to the input pattern *x(t)*:

$$\|x(t) - m_c(t)\| = \min_i \{\|x(t) - m_i(t)\|\} \qquad (3)$$

The unit *c* is considered the unit which responds to the pattern *x(t)*.

Rule 2: To modify the weight vectors of the unit *c* and its topologic neighbors:

$$\left. \begin{array}{l} m_i(t+1) = m_i(t) + \alpha(t)[x(t) - m_i(t)] \forall i \in N_c \\ m_i(t+1) = m_i(t) \forall i \notin N_c \end{array} \right\} \qquad (4)$$

The topologic neighborhood is a time dependent function (**Figure 1**). $\alpha(t)$ is the learning rate of the winner neuron $(0 < \alpha(t) < 1)$. This rate and the N_c diameter decrease during the learning time (Kohonen, 1990).

In all experiments presented below, an one-dimensional matrix was used with 50 neuron units, $\alpha(0) = 0.8$ and the $N_c(0)$ diameter was maximum – covering all neurons (in this case, the neighborhood topology is linear) (Kohonen, 1990). The input patterns are the pixel amplitude values – codified with 8 bits (values from 0 to 255). At the end of 2000 learning epochs (Kohonen, 1990), the resultant maps are used as clusters sets in the algorithm of the k constants matrix calculation.

K CONSTANTS MATRIX CALCULATION

In order to improve the filtering process that uses a unique threshold to all original pixels (see section 2), we propose to generate specific points of hard threshold to each pixel of the original image.

To avoid the reconstructed image (filtered image) loses the target definitions presented in the original image scene, all filtered pixels must belong to the same original pixel cluster. In this way, the first step is to generate the cluster set from the original image (using SOM, see section 3).

It´s necessary to create a cluster map (with the same image dimensions) which has the respective cluster of each original pixel. This is done by using the equation (3) to each pixel and writing the cluster index in the respective cluster map cell (**Figure 2**). This cluster map will be used to control the quantity of
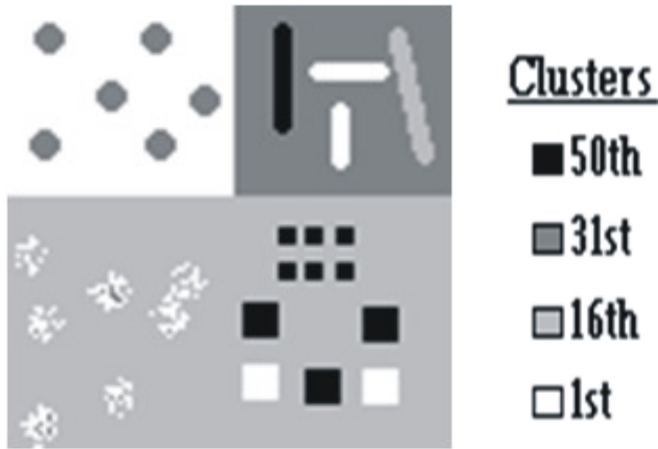
Figure 2. Cluster map of the Synthetic image.

single values that will be used to reconstruct each filtered pixel. One filtered pixel (or a pixel reconstructed with a minimum quantity of eigen values) must be classified by the same cluster of its respective original pixel. Then, the filtering algorithm needs to define a matrix $\overline{\overline{K}}$ of constants (one constant to each pixel of the original image). At the last step, the pixels of the filtered image $\overline{\overline{F}}$ are calculated by equation (5):

$$F(i, j)=\overline{U}_i \cdot \begin{vmatrix} S_{11} & 0 & 0 & 0 & . & 0 \\ 0 & . & . & & . & 0 \\ 0 & . & S_{k(i,j)} & . & . & 0 \\ 0 & . & 0 & 0 & . & 0 \\ . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & . & 0 \end{vmatrix} \cdot \overline{V}_j^{\ t} \qquad (5)$$

EXPERIMENT WITH SYNTHETIC DATA

The filtering process was applied to a synthetic image (100x100 pixels) with 4 different gray degrees (**Figure 3**) in order to illustrate the filtering algorithm.In this case, the 1st, 16th, 31st and 50th SOM clusters classify the four different pixel values of the synthetic image (**Figure 4**).

Figure 2 shows the clusters spatial localization. This cluster map was generated by classifying the original image (**Figure 5**) with the four clusters detected by the SOM learning algorithm (**Figure 4**).

Figure 6 shows a projection of part of the $\overline{\overline{K}}$ matrix calculated in this application. The minimum and maximum quantities of eigen values used to reconstruct the filtered image was 3 and 60 respectively.

Figure 7 shows the whole $\overline{\overline{K}}$ matrix in gray scale (the values vary from 3
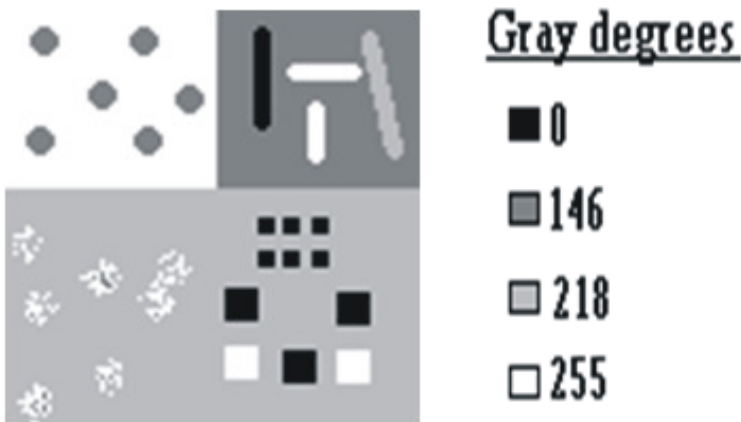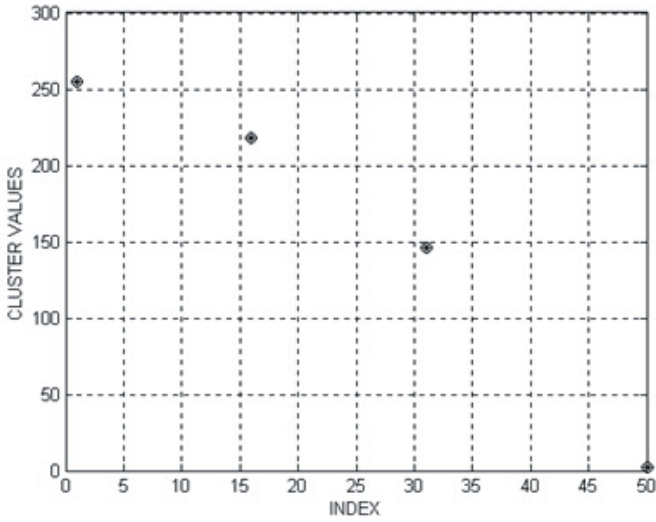

Figure 3. *Synthetic image.*

Figure 4. *Clusters detected in the synthetic image.*

Figure 5. *Original Image (200x200 pixels).*

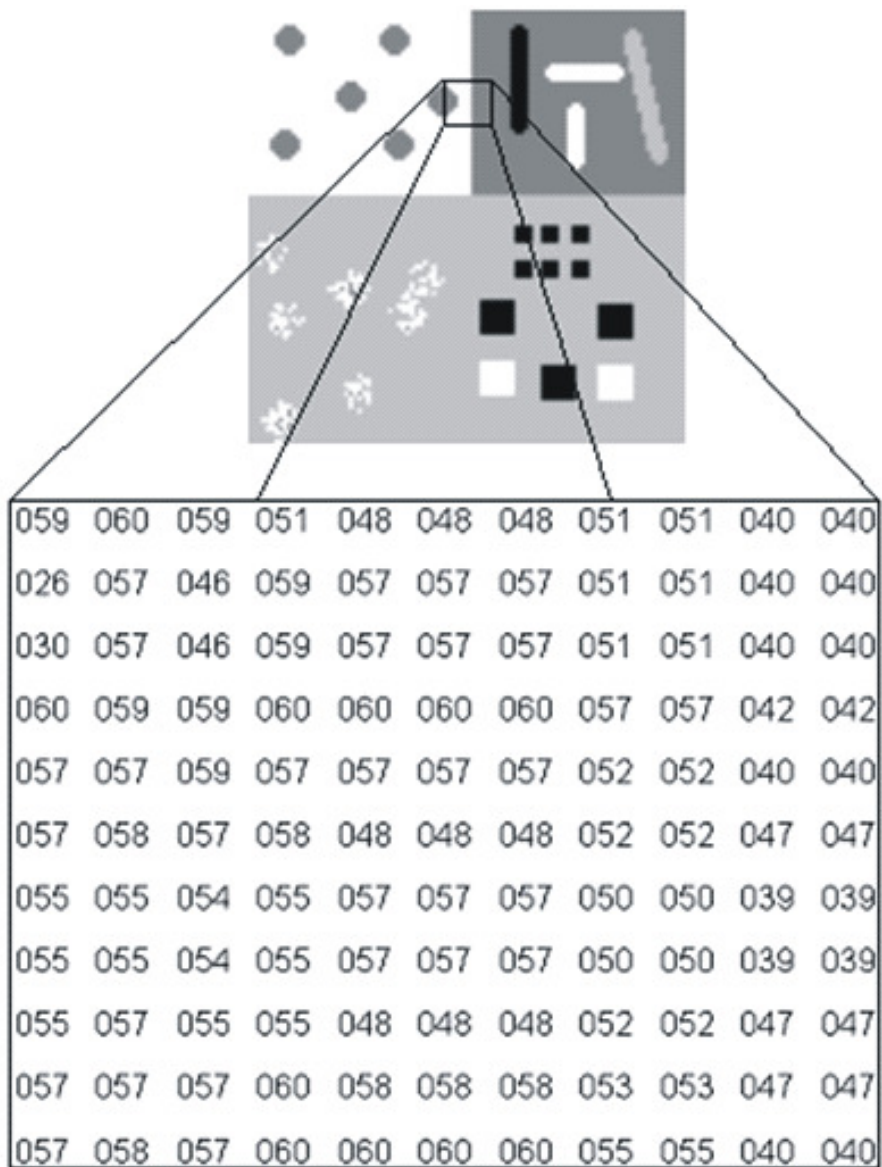| 059 | 060 | 059 | 051 | 048 | 048 | 048 | 051 | 051 | 040 | 040 |
026	057	046	059	057	057	057	051	051	040	040
030	057	046	059	057	057	057	051	051	040	040
060	059	059	060	060	060	060	057	057	042	042
057	057	059	057	057	057	057	052	052	040	040
057	058	057	058	048	048	048	052	052	047	047
055	055	054	055	057	057	057	050	050	039	039
055	055	054	055	057	057	057	050	050	039	039
055	057	055	055	048	048	048	052	052	047	047
057	057	057	060	058	058	058	053	053	047	047
057	058	057	060	060	060	060	055	055	040	040

Figure 6. K *constants used to filter the pixels of the region limited by the black square.*

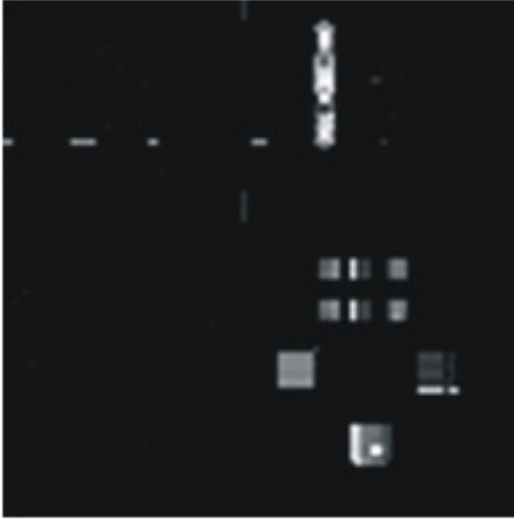*Figure 7. K matrix in gray scale.*

Figure 8. Filtered image.

Figure 9. *Residual matrix.*

to 60). It's easy to see that the high frequency regions are composed by more eigen values linear combinations and homogeneous regions are reconstructed by one or few eigen values combinations. The pixels of the filtered image (**Figure 8**) were calculated by using the equation 5 with the $\overline{\overline{K}}$ matrix of the **Figure 7**.

Figure 9 shows the residual between the original synthetic image ($\overline{\overline{D}}$) and the filtered image ($\overline{\overline{F}}$). The minimum and maximum values of this residual matrix are 0 and 20 respectively. The residuals shown in the **Figure 9** demonstrate the most affected regions by the filtering process.

EXPERIMENT WITH LANDSAT-7 DATA

The filtering process was applied to 8 bits LandSat-7 image, band 4, date: 07/

20/2001, from Alto Paraíso city / Goiás state / Brazil (**Figure 5**). The weights of the SOM net (representing the 50 clusters) generated from the pixel values present in the original image can be seen in **Figure 10**.

Figure 11 shows the clusters spatial localization. This cluster map was generated by classifying the original image (**Figure 9**) with the 50 clusters generated by the SOM learning algorithm (**Figure 10**).

Figure 12 shows a projection of part of the $\overline{\overline{K}}$ matrix calculated in this application. The minimum and maximum quantities of eigen values used to reconstruct the filtered image was 2 and 198 respectively.
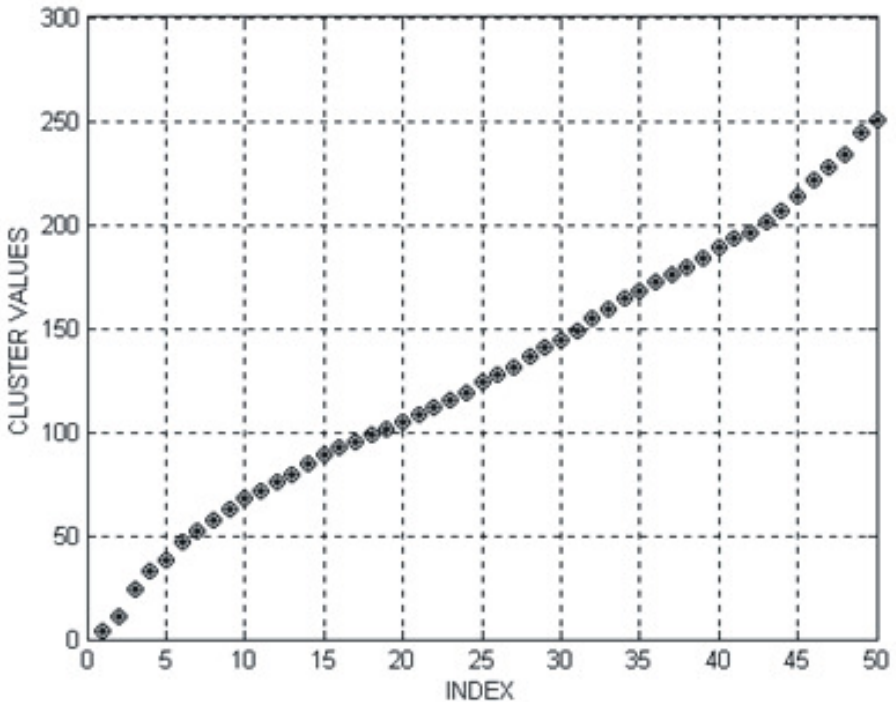

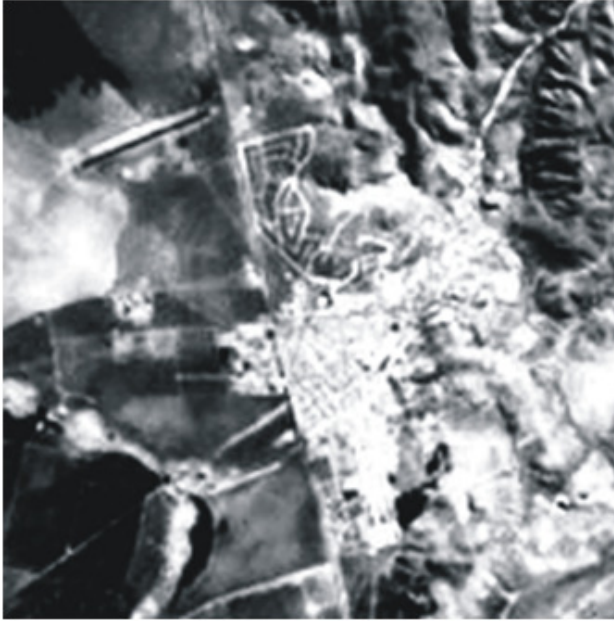*Figure 10. Clusters detected in the original image.*

Figure 11. *Cluster map of the LandSat-7 image.*

Figure 13 shows the whole $\overline{\overline{K}}$ matrix in gray scale. As in the synthetic case, the high frequency regions are composed by more eigen values linear combinations and homogeneous regions are reconstructed by one or few eigen values combinations.

Figure 14 shows the residuals between the original synthetic image ($\overline{\overline{D}}$) and the filtered image ($\overline{\overline{F}}$). The minimum and maximum values of the residual matrix are 0 and 39 respectively.

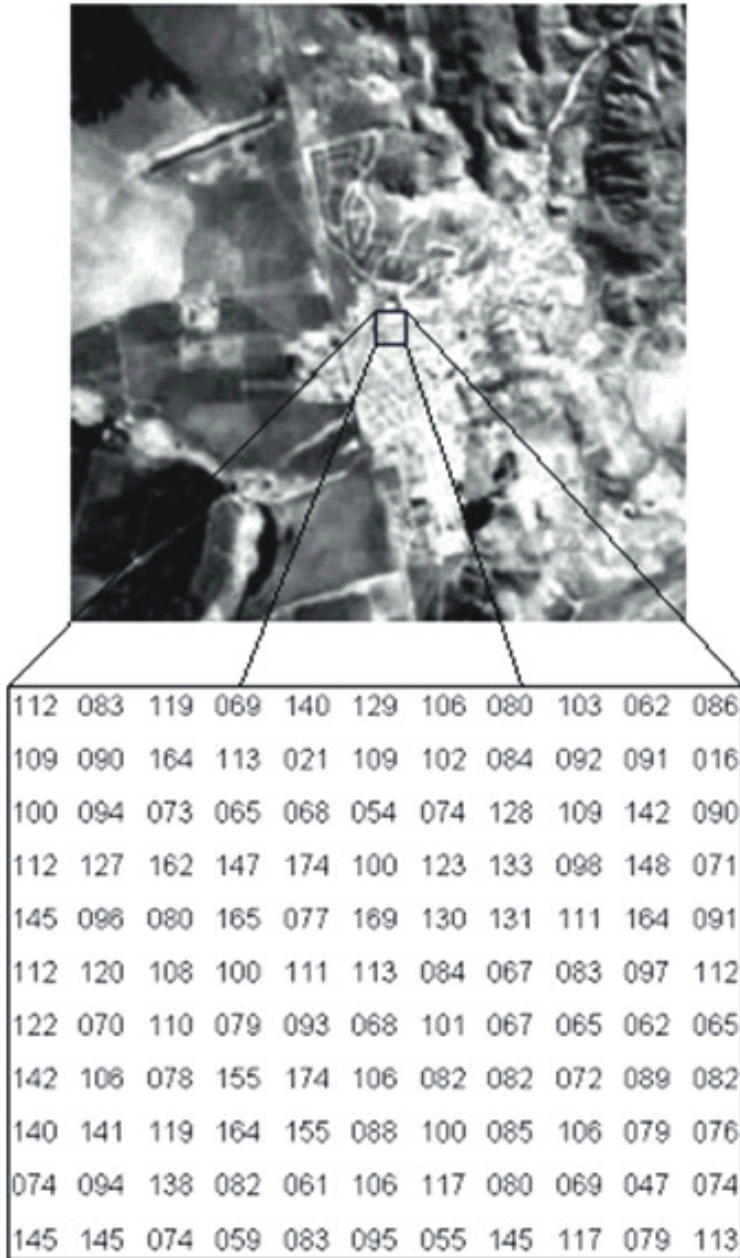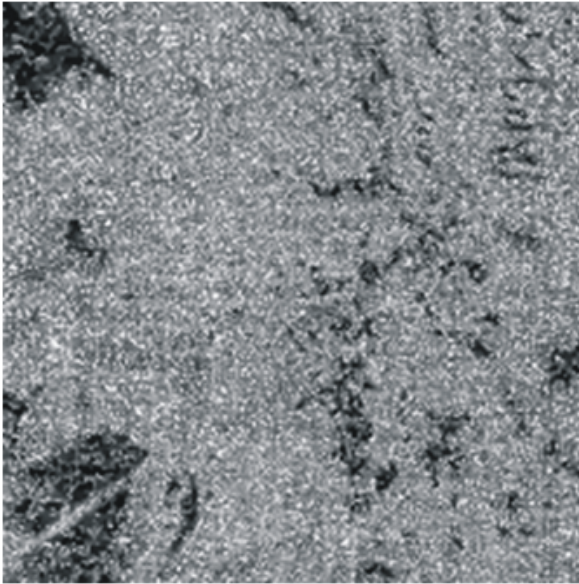| 112 | 083 | 119 | 069 | 140 | 129 | 106 | 080 | 103 | 062 | 086 |
109	090	164	113	021	109	102	084	092	091	016
100	094	073	065	068	054	074	128	109	142	090
112	127	162	147	174	100	123	133	098	148	071
145	096	080	165	077	169	130	131	111	164	091
112	120	108	100	111	113	084	067	083	097	112
122	070	110	079	093	068	101	067	065	062	065
142	106	078	155	174	106	082	082	072	089	082
140	141	119	164	155	088	100	085	106	079	076
074	094	138	082	061	106	117	080	069	047	074
145	145	074	059	083	095	055	145	117	079	113

Figure 12. K constants.
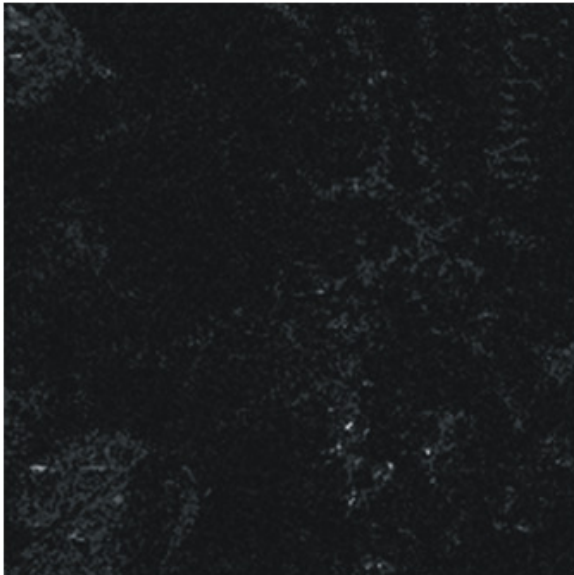
Figure 13. *K matrix in gray scale.*

Figure 14. *Residual matrix.*

The residuals shown in **Figure 14** demonstrate the most affected regions by the filtering process.

COMMENTS AND CONCLUSIONS

The Self Organizing Map was important to define an independent filtering process. Due to its unsupervised classifier feature, there wasn't interference in the process of generate the clusters set and consequently the K matrix.

The final result of the filtering can be tuned by SOM training algorithm parameters. In the case of the synthetic data, the quantity of clusters was super estimated, generating one cluster to each pixel sample. In this case, the thresholds (k values) were very precise and consequently cut just a small part of the original values – basically, this experiment cut the null space of the matrix. This parameterization works in sensible data where details of the image (high frequency) must be preserved.

When homogeneous targets visualization must be improved, the under estimation of the SOM size is recommended. In the case of the LandSat-7 data experiment, 256 pixel samples were grouped in 50 clusters. The figure 15 shows the response to this choice – the residual matrix shows cuts from 0 until 39 in the original pixel values. Different results could be achieved by using other SOM geometries: smaller maps will result in greater cuts.

Changes in the single values matrix could have many effects in the reconstructed image. This technique arises in an effective way to reconstruct better approximations of the original data and, at the same time, excluding unnecessary ranges of pixel variation.

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