Segmentation of TEM Images Using Oscillatory Neural Networks

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Abstract. Oscillatory neural networks are a relatively recent approach for the problem of image segmentation. Inside of this context, the oscillator neuron of Terman-Wang is presented, which one is used as base element of an oscillatory network called LEGION (Locally Excitatory Globally Inhibitory Oscillator Network). The continuous version of the LEGION network, based on a set of differential equations, presents high computational complexity and has limited capacity of segmentation, what restricts its practical application, being adequate for implementation in parallel hardware topologies. To reduce the computational complexity in serial computers, an algorithm proposed by Terman and Wang is presented, which implies significant gain of speed in comparison to the continuous version and, in contrast, capacity to discriminate a unlimited number of segments. An interactive version of this algorithm was proposed and the results obtained in segmentation of transmission electron microscopy (TEM) images were evaluated, with the objective of measuring helium bubbles in silicon samples. As final result we found that the LEGION network presents itself as a singular alternative to solve problems of image segmentation, which provides simultaneously both spatial and temporal discrimination of segments.

1 Introduction

Innumerable applications imply the extraction of features from an image in order that the same can be understood by a system of artificial vision. The pre-processing implies the restoration, the improvement or simply the adequate representation of the image data, improving some features, as the contours of objects, for example, or the transformation of the image for some other domain more appropriated to the application. The conveniently pre-processed image is then segmented through the use of some appropriated technique, with the objective to isolate regions with similar features (segments). The posterior application of a classifier relates a label with each one of the regions or segments identified according to a previous base of knowledge. With the results of the classification procedure, a description or an interpretation of the image, appropriated to the context of the application, can finally be elaborated.

The procedures used in image segmentation can be classified in 4 great categories [7]: a) the classic methods based on amplitude thresholding, detection of edges or growing/contraction of regions; b) statistical methods, such as the classifier of maximum likelihood; c) methods based on fuzzy logic, as the algorithm fuzzy c-means and d) methods based on artificial neural networks with varied topologies.

Several techniques of image segmentation based on artificial neural networks have been developed, particularly using MLP networks (MultiLayer Perceptron) associated to the Backpropagation algorithm [5,8], Hopfield networks [5] or Kohonen maps (SOFM - Self-Organizing Feature Map) [5], with typical examples found respectively in [3,4,9]. Such algorithms have presented good results even in the presence of noise or distortions in the image to be segmented, bringing with itself the inherent advantages of the neural networks related to the robustness in relation to the occurrence of faults and to the parallelism that can be expressed as velocity of operation when used the adequate hardware. As disadvantages, some of these methods present the training necessity, what can be problematic due to the long necessary time, the number of available samples previously segmented and also very high complexity, in some cases, for implementation using non parallel machines.

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Recently, alternative topologies of artificial neural networks, called oscillatory neural networks or simply oscillatory networks, have been applied in procedures of image segmentation with favorable results. In this area, is particularly interesting the work developed by DeLiang Wang and David Terman [14], who have lead most of the practical research with this type of network. For example, in [6] it is found a procedure involving MLP networks associated to the oscillatory networks, used for extraction of hydrographic regions in images of remote sensing. In [10], can be found a study about the use of networks of oscillator neurons applied to the segmentation of medical computerized tomographic images (CT) and magnetic resonance (MRI). A different application can be found in [17], where an oscillatory network is used to separate the speech of a speaker from interfering signals.

The study of such topologies of neural networks, which have direct biological inspiration on the mechanism of segmentation executed by the human brain, and applications of the same ones, is presented as a fertile field, as well as the development of architectures of hardware for practical implementation of the networks, exploring the parallel nature of them.

In this work, a topology of oscillatory neural network called LEGION is presented (Locally Excitatory Globally Inhibitory Oscillator Network), in both its continuous and discrete versions, based on the called Terman-Wang oscillator neuron. Also are presented some results relative to the use of a modified LEGION network for segmentation of images of silicon samples obtained by transmission electron microscopy (TEM).

2 The Terman-Wang Oscillator Neuron

The Terman-Wang oscillator is a relatively recent proposal, which, due to mathematical and computational reasons, has been used for composition of oscillatory artificial neural networks with application in segmentation of signals. The behavior of the Terman-Wang oscillator can be described through the pair of non-linear differential equations (1) and (2) [16]. The state variables $x(t)$ and $y(t)$ represent the system. Under the biological point of view, $x(t)$ can be understood as the potential of the nervous cell membrane, or the physical variable that represents the output in the neuron. α, β and ε are parameters of the model and I is an external input.

$$\frac{dx(t)}{dt} = 3x(t) - x^3(t) + 2 - y(t) + I \tag{1}$$

$$\frac{dy(t)}{dt} = \varepsilon\big(\alpha\big(1 + \tanh\big(x(t)/\beta\big)\big) - y(t)\big) \tag{2}$$

Fig. 1 presents the phase trajectory of the Terman-Wang oscillator with parameters $I=1$, $\beta=0,2$ and $\alpha=3$. The functions $y_1(t)$ and $y_2(t)$ are obtained by making both the derivatives represented by (1) e (2) equal to zero. These functions are called *nullclines* of the system. The points, B and C correspond to examples of initial conditions for the presented differential equations. When the points B or C are used as initial conditions, the system acquires oscillatory response whose trajectory of phase is represented by the bold line, with the indicated direction. The initial condition represented by $x(0)=0$ and $y(0)=3$ implies an equilibrium situation for which oscillation does not occur, and must be avoided. Normally, a random noise of small amplitude can be added to the input in order to avoid such equilibrium state.

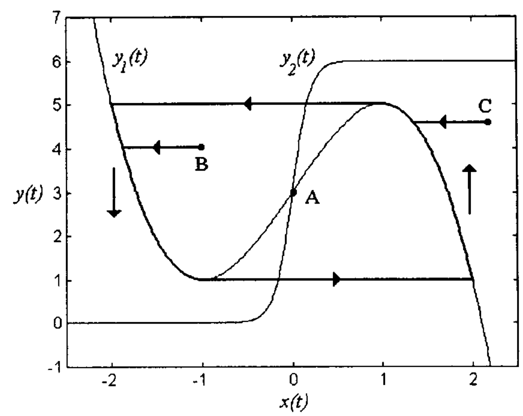

Figure 1 Phase trajectory of the Terman-Wang oscillator for $I=1$, $\beta=0,2$, $\alpha=3$.

Fig. 2 represents the output of the Terman-Wang oscillator in function of the time, characterizing the behavior of a relaxation oscillator. The intervals of time where the value of the output ($x(t)$) is high or positive are called active phases, while the intervals of time where the value of the output is low or negative are called silent phases [16].

In the case of $I\leq 0$, one says that the oscillator is excitable or it is not stimulated and there is no oscillation in the system [16]. For values of I that result in oscillatory behavior, a correlation can be observed between the value of the input and the value of the ratio of the times of permanence in the active and silent phases. In order to such oscillation occurs, the value of the external input received by the oscillator must be restricted to the band $0<I<(2\alpha-4)$, situation which the oscillator is said stimulated [16].

The Terman-Wang oscillator mathematically has a similar behavior to other models, being simpler than the Morris-Lecar oscillator and presenting bigger flexibility that the oscillators of van der Pol and of FitzHugh-Nagumo [16]. Such properties make the Terman-Wang oscillator a better alternative to implement networks of oscillators with several practical applications, including image segmentation.

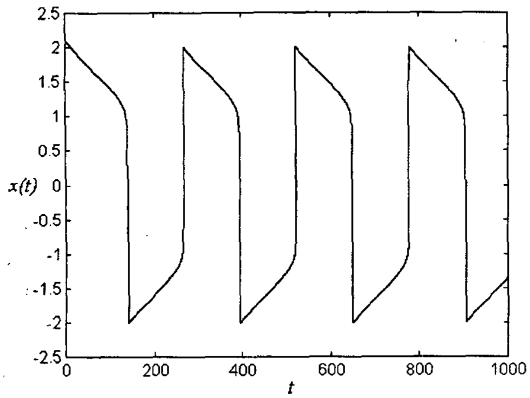

Figure 2 Output of the Terman-Wang oscillator in function of the time for $I=1$, $\beta=0{,}2$, $\alpha=3$, $\varepsilon=0{,}01$, $x(0)=0$ and $y(0)=0$.

3 Continuous LEGION Network

In the end of 80's decade, oscillations of approximately 40 Hz had been discovered in the visual cortex and in other areas of the human brain. It was verified that such neural oscillations present strong correlation with the coherence of the visual stimulus, occurring synchronism of phase between physically near neurons that receive similar external stimuli, what can characterize a homogeneous region of the perceived image. On the other hand, physically near neurons that receive different external stimuli or physically distant neurons that receive similar external stimuli do not present the cited synchronism of phase [16].

Since the discovery of the coherent neural oscillations, diverse types of networks composed by oscillator neurons have been studied with the objective to create artificial models for the phenomenon. Extending the study of Somers and Kopell [12], Terman and Wang had proved that in a network of relaxation oscillators with local coupling and arbitrary dimensions, an attraction domain exists for which whole the network tends to the synchronism with an exponential rate [13]. Using such property of local synchronism between coupled oscillators and adding a mechanism of global inhibition to get desynchronism among several groups of oscillators, Terman and Wang obtained a network they called LEGION. Moreover, a gaussian signal of small variance is added to the input of each oscillator to prevent that the initial conditions of the network imply not desired states of stability and also to prevent the possible synchronism between distant oscillators with similar inputs [16]. The lateral excitation of an oscillator of the LEGION network (S_i), also added to the input, is defined as the coupling received from the others oscillators of the network and from the global inhibitor, being represented by the equation (3). Only the oscillators that belong to a near neighborhood possess coupling, as it can be observed in the example of topology presented in fig. 3. The global inhibitor ($z(t)$), on the other hand, is connected to all the oscillators of the network. W_{ik} are weights related to the connections between oscillators k and i, W_z is the weight of the global inhibitor, θ_x and θ_z are thresholds, $N_i(R)$ is the neighborhood of radius R of the oscillator i, $H(x-\theta)$ is the function of Heaviside, k is a parameter that controls the inclination of the function defined by (5) and ϕ adjusts the rate of variation of the global inhibitor output.

$$S_i(t) = \sum_{k\in N_i(1)} W_{ik} S_\infty(x_k(t),\theta_x) - W_z S_\infty(z(t),\theta_z) \quad (3)$$

$$\frac{dz(t)}{dt} = \phi(H(x_i(t)-\theta_z) - z(t)) \quad (4)$$

$$S_\infty(x,\theta) = \frac{1}{1+e^{-\kappa(x-\theta)}} \quad (5)$$

A mechanism used for normalization of the weights is proposed in [15]. The normalization of the weights is not a necessary condition for the correct functioning of the LEGION network, but it improves the quality of the synchronism between neighbor oscillators that are submitted to similar external stimuli. The W_{ik} weights can be determined in the beginning of the process representing the similarity between the external inputs of neighboring oscillators [15].

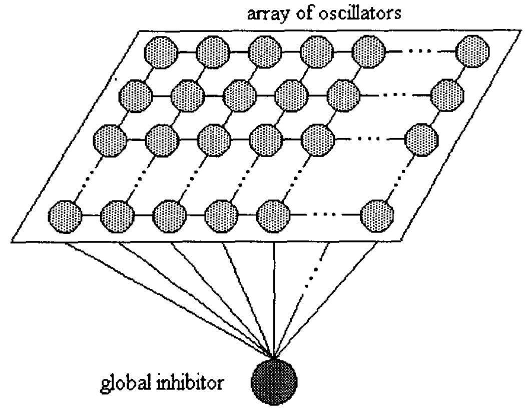

Figure 3 Example of a topology of a 2-dimentional LEGION network.

The fig. 4 presents the behavior of a LEGION network with 4 neurons hardwired in a 1-dimentional ring architecture, where it can be observed the synchronism between neighbor oscillators with similar external inputs and desynchronism between oscillators with distinct external inputs. The temporal discrimination of groups of physically near neurons with similar inputs can be observed in the output of the network.

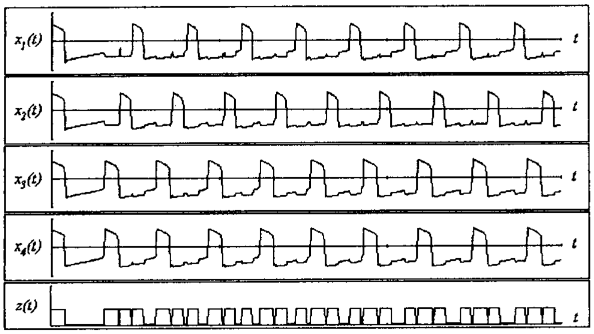

Figure 4 Outputs of the oscillators and of the global inhibitor of a LEGION network with external inputs $I_1=0,3$, $I_2=0,4$, $I_3=0,5$ and $I_4=0,5$.

For a set of parameters, a continuous LEGION network can discriminate a limited number of segments, which depends on the ratio between the permanence times in the active and silent phases. This limit is called capacity of segmentation of the network and places in the band of 5 to 10 segments [16]. This property, although presenting itself as a restriction to practical applications of the network in segmentation, has biological correlation because it is also observed in human beings, which present a quantitative limitation for discrimination of several objects at the same time [15].

In [15] is also presented a modification in the excitation of the Terman-Wang oscillator, considering the basic idea that a set of oscillators with similar inputs must possess at least one oscillator, called leader oscillator, which must receive great lateral excitation from its neighborhood. On the other hand, isolated oscillators that belong to noisy regions, cannot be characterized as leaders. So, an oscillator with great lateral potential can lead the activation of a group of oscillators that correspond to a homogeneous region of the external input.

The results found in the bibliography demonstrate that the continuous LEGION network presents itself as a potentially efficient tool for image segmentation. As positive aspect, can be pointed the property of simultaneous spatial and temporal segmentation presented by the network. As negative aspect, can be pointed the high computational complexity, due to the great number of differential equations to be solved. On the other hand, the use of the model based on differential equations is presented as an alternative for realization of a full parallel network using analog circuits, associating the high speed presented for such circuits and the inherent high level of parallelism of the LEGION network.

4 Discrete LEGION Network

With the objective to reduce the computational effort in the use of serial computers, Terman and Wang had developed an algorithmic discrete version of the LEGION network, with basically the same properties of the continuous version [15]. The limitation related to the number of segments to be distinguish presented by the continuous network is not verified in this proposal, adding a positive feature to the same one. In the developed algorithm, the state variable *x(t)* is the only one considered, since the same represents the output of the oscillator. A neighborhood relation was used considering the 8 neighbor pixels for determination of the lateral excitation of each oscillator in a 2-dimentional network used for applications of image segmentation, what can be easily modified. The algorithm can be divided in three great stages, which are presented to follow:

1) Phase of initialization

- Make the global inhibitor z(t) equal to zero:

$$z(0) = 0$$

- Calculate the weights of the connections between neighbor oscillators (W_{ik}) considering the input image, where I_M the maximum intensity found among the pixels of the same one:

$$W_{ik} = \frac{I_M}{1+|I_i - I_k|} \quad , k \in N(1) \qquad (6)$$

- Find the leaders p_i using the function of Heaviside with a threshold θ_p:

$$p_i = H\left(\sum_{k\in N(i)} W_{ik} - \theta_p\right) \qquad (7)$$

- Set the outputs of all the oscillators in random positions in the silent phase:

$$-2 < x_i(0) < -1$$

2) Determination of the first oscillator to pass to the active phase

- Considering that all the oscillators (x_k) are in the silent phase, choose the leader oscillator (p_j=1) which will be the oscillator with its state next to the point of transition for the active phase (state x=-1) and carry it to the active phase (state $x=1$), increment the global inhibitor ($z(t)=1$) and recalculate the states of the others oscillators in the silent phase:

$$[\, x_j(t+1) = 1 \text{ and } z(t+1) = 1 \,]$$

$$\text{for } [\, x_j(t) \geq x_k(t) \quad , \forall k \,] \tag{8}$$

$$\text{and } x_k(t+1) = x_k(t) - 1 - x_j(t) \quad , k \neq j \tag{9}$$

3) Dynamics of the network

- Keep the oscillators that are in the active phase if the global inhibitor was incremented. Return the oscillators that are in the active phase to the beginning of the silent phase (defined as the state *x=-2*) if the global was decreased or kept constant. For each oscillator that returns to the silent phase decrement the global inhibitor. When no more oscillator neurons exist in the active phase (*z(t)=0*), return to the stage 2.

$$[\, x_i(t+1) = x_i(t) \,]$$

$$\text{if } [\, z(t) > z(t-1) \text{ and } x_i(t) = 1 \,] \tag{10}$$

$$\text{and } [\, x_i(t+1) = -2 \text{ and } z(t) = z(t-1) - 1 \,]$$

$$\text{if } [\, z(t) \leq z(t-1) \text{ and } x_i(t) = 1 \,] \tag{11}$$

- Find the lateral excitation of the oscillators that are in the silent phase according to the criterion established for (12) or other alternatives presented in [1]. Those oscillator neurons that possess enough potential will pass to the active phase and the global inhibitor will be incremented.

$$S_i(t) = \sum_{k \in N(i)} W_{ik} H\big(x_k(t) + 1\big) - W_z H\big(z(t) - 0{,}5\big) \tag{12}$$

$$[\, x_i(t+1) = 1 \text{ and } z(t) = z(t-1) + 1 \,]$$

$$\text{if } [\, S_i(t) > 0 \text{ and } x_i(t) < 1 \,] \tag{13}$$

$$\text{and } [\, x_i(t+1) = x_i(t) \text{ and } z(t) = z(t-1) \,]$$

$$\text{if } [\, S_i(t) \leq 0 \text{ and } x_i(t) < 1 \,] \tag{14}$$

- Execute the dynamics of the network until reach the condition of no oscillators in the active phase and then go to the stage 2.

The algorithm presented for the LEGION network considers that the leaders and the weights of the connections must be determined in the initialization phase, not needing posterior update. It must be observed that the number of leaders does not correspond to the number of discriminated segments, since each segment can generate several leaders.

The results presented in the bibliography demonstrate that the LEGION network, in its algorithmic version are efficient for segmentation of signals of diverse natures and, in particular, for segmentation of images. The significant increase in the speed makes the discrete version of LEGION network more suitable for implementations that use serial computers.

5 Sensitivity to Noise of the LEGION Network

Preliminary evaluations had demonstrated that the result of the segmentation using LEGION network in its two versions is sensible to the noise present in the image signal, due basically to the use of the intensity similarity criterion between adjacent pixels.

In [1,2] is proposed an algorithm for smoothing called FPS (Feature-Preserving Smoothing), which reduces the noise while preserving relevant details found in the original image. The related algorithm can be used with the algorithms presented for the LEGION network, promoting a gradual update of the weights, whose effect is equivalent to the one of a filtering that attenuates the noise and simultaneously preserves details of the original image [2]. The FPS algorithm can also be directly used in a previous stage of the LEGION network, acting on the pixels of the image as a non-linear filter. The equation (15) presents the cited procedure of smoothing for application over images [2]. I_{ij}^t is the intensity of pixel *ij* at iteration *t*, D_{ij}^t is a measure of the local discontinuities around the pixel, σ_{ij}^t is the normalized variance of the intensities of the pixels calculated in a neighborhood of radius *R* of the pixel *ij*, θ_σ is a threshold for the influence of the variance and k_1 and k_2 are weight parameters.

$$I_{ij}^{t+1} = I_{ij}^t + \frac{\sum_{(m,n)\in N_{ij}(1)} (I_{mn}^t - I_{ij}^t)\, e^{-(k_1\Phi(\sigma_{mn}^2,\theta_\sigma) + k_2 D_{mn}^t)}}{\sum_{(m,n)\in N_{ij}(1)} e^{-(k_1\Phi(\sigma_{mn}^2,\theta_\sigma) + k_2 D_{mn}^t)}}\, e^{-k_1\Phi(\sigma_{ij}^2,\theta_\sigma)} \tag{15}$$

$$D_{ij}^t = \frac{1}{4}\left(\begin{array}{l} \left|I_{i-1,j}^t - I_{i+1,j}^t\right| + \left|I_{i,j-1}^t - I_{i,j+1}^t\right| + \\ + \left|I_{i-1,j-1}^t - I_{i+1,j+1}^t\right| + \left|I_{i-1,j+1}^t - I_{i+1,j-1}^t\right| \end{array} \right) \tag{16}$$

$$\Phi(\sigma_{ij}^2, \theta_\sigma) = \begin{cases} \sigma_{ij}^2 & , \sigma_{ij}^2 \geq \theta_\sigma \\ 0 & , \sigma_{ij}^2 < \theta_\sigma \end{cases} \tag{17}$$

6 Segmentation of TEM Images

The fig. 5 presents an image with dimensions of 1482x2060 pixels and resolution of 8 bits in gray level scale, which was obtained through transmission electron microscopy (TEM), representing a silicon sample in which had been implanted ions of helium with the objective to reduce defects in the crystalline structure of the semiconductor. Due to its physical properties, the helium tends to accumulate itself in small bubbles concentrated in one determined depth of the silicon sample. For evaluation of the process, whose result depend on factors as the temperature of implantation, it is necessary to determine the amount of helium bubbles in one determined region, as well as the volume of the present gas, which can be estimated through the diameter or the area of the bubbles [11]. This procedure must be carried through for several images, being a complex task for manual execution by a human being.

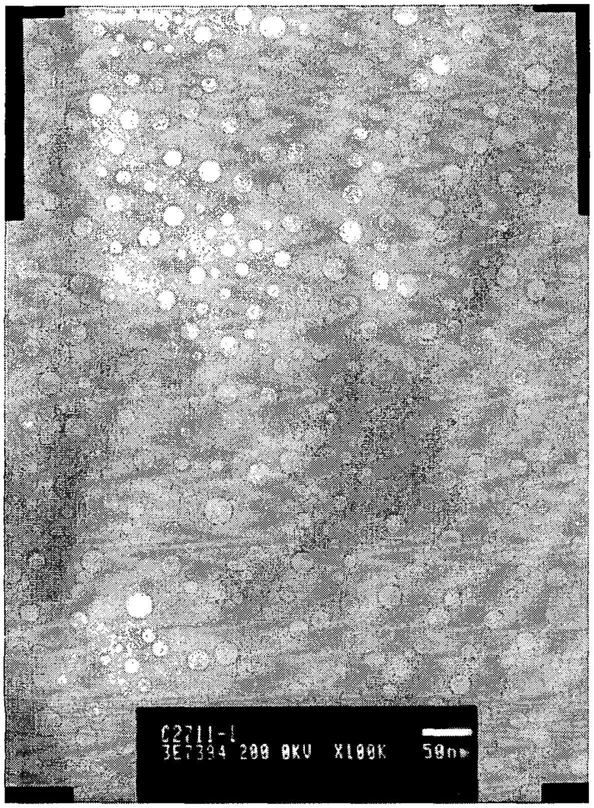

Figure 5 Image of TEM representing a silicon sample with helium bubbles.

To segment the helium bubbles and simultaneously separate the same ones in time, facilitating the implementation of an automatic process of counting and measuring its areas or diameters, it was opted to use a discrete LEGION network with the same dimensions of the image (1482x2060 oscillator neurons). The fig. 6 presents an region extracted from the image of the fig. 5, which is used to verify the qualitative results of the proposed segmentation procedure.

Fig. 7 presents the result of filtering the image of fig. 6 using the FPS algorithm, being able to be observed the preservation of the contours of the helium bubbles. The used parameters had been $R=3$, $\theta_\sigma=90$, $k_1=20$, $k_2=5$ and 10 iterations.

Fig. 8 presents the segments related to the 9 bubbles segmented for the LEGION network using the image of the fig. 7 as input. The parameters used in the network had been $\theta_p=4$ and $W_z=0{,}4$. The black color represents the oscillators in the silent region (inactive), while that the white regions represent the oscillators with output in the active phase. An additional segment, presented in fig. 9, presents the silicon background and also is supplied by the network, which, due to its very big area, can easily be detected and discarded in the automatic procedure of measure. Pixels pertaining to not homogeneous regions are not incorporated to the extracted segments got from the LEGION network. Fig. 10 presents pixels that had not been segmented by the network (represented in black color) relative to the image of fig. 7.

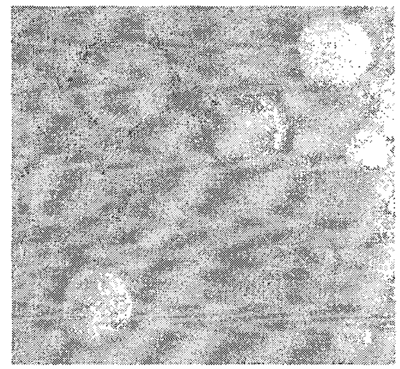

Figure 6 Region extracted from the image of fig. 5.

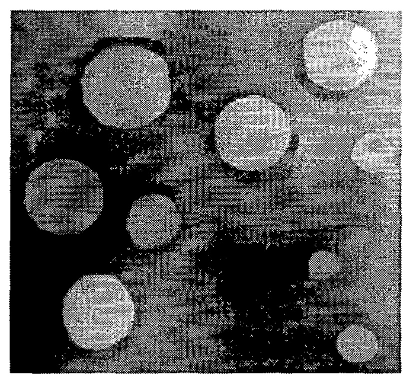

Figure 7 Image of fig. 6 filtered with the FPS algorithm.

The relative areas of each one of the bubbles can quickly be obtained from the segments presented in fig. 7, as the ratio between the number of oscillators with output in the active phase and the total number of oscillators of the network, which corresponds to the number of pixels of the image. Being known the relation in pixel/nm of the image obtained of a TEM (showed near de right bottom corner in fig. 5), the volume of helium in the region represented by the image can then be estimated. It must be observed that the visual determination of the area of each bubble (or of the average diameter) can be inexact in the cases in which the bubbles are not perfectly circular. Such limitation is not observed in the considered method, since the relative area of each segment can be determined with exactness, independently of the form of the same. On the other hand, incomplete bubbles, located at the extremities of the images, bubbles with very degraded contours and bubbles superimposed lead to wrong measures. To avoid such limitation, an interactive procedure was adopted, where points on the regions to be segmented are marked (bubbles). Such points are used to determine the leader oscillators of the LEGION network. In this way, the homogeneous regions around the indicated leaders will be the only regions segmented by the network. The bubbles not marked, in number relatively reduced, can be measured later through a manual procedure.

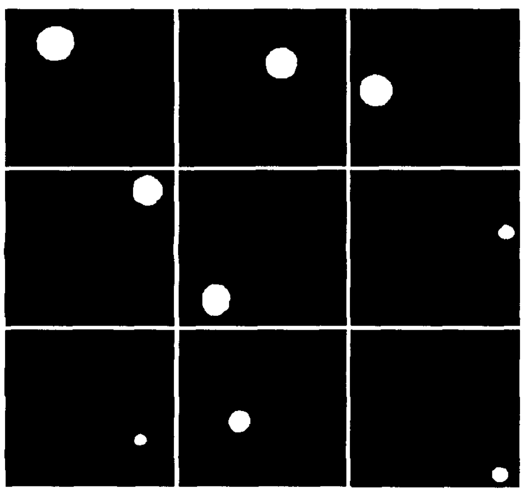

Figure 8 Result of the segmentation of the image of fig. 7 with a LEGION network.

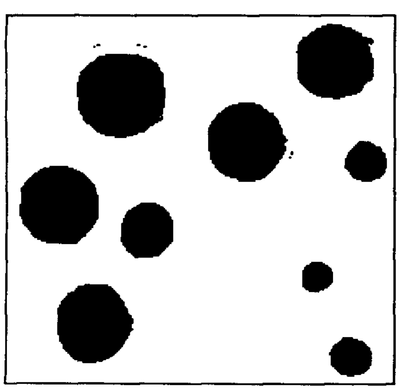

Figure 9 Segment related to the homogeneous silicon background.

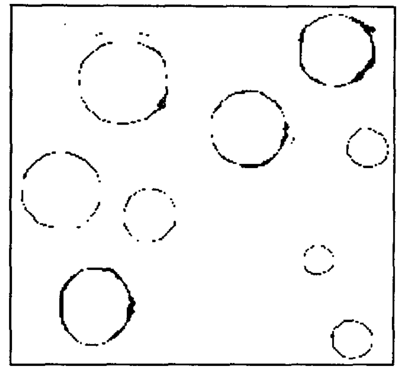

Figure 10 Pixels not segmented by the network (represented in black color).

7 Conclusion

The use of oscillator networks to simulate the capacity of temporal segmentation that is given credit to possess the human brain is presented as a recent alternative and with satisfactory results. The researchers DeLiang L. Wang and David Terman have developed works where a called LEGION network (Locally Excitatory Globally Inhibitory Oscillator Network) is proposed, which is constructed based on relaxation oscillators locally connected and with a mechanism of global inhibition. This mechanism of connections allows that neighboring oscillators submitted to similar external inputs oscillate in synchronism of phase and desynchronism with other groups of oscillators of the network. Of this form, each group of oscillators corresponding to coherent regions of the input signal of the network is activated in a different time interval, propitiating both spatial and temporal segmentation of the input signal simultaneously.

The Terman-Wang oscillator, used as the basic element of processing of the LEGION network, is based on a pair of differential equations, what implies high computational complexity for application of the network in non-parallel machines. An algorithm for implementation of the LEGION network in serial computers was proposed by Terman and Wang, having presented a significant gain of speed in relation to the continuous version of the network and still supplanting the limitation of the continuous version related to the capacity of segmentation for simultaneous discrimination.

One of the key points for the correct operation of the LEGION network, as much in its continuous version how much in its discrete version it is the determination of the weights of the connections between neighboring oscillators. According to proposal of Terman and Wang, the related weights can be determined in the beginning of the process, in a single step, based on some attributes of the signal applied to the input of the network, what implies relatively low computational complexity to develop such task. Another relevant aspect says respect to the determination of the parameters of the network, θ_p and W_z, which must interactively be determined for the correct operation of the network. The quality of the segmentation supplied by the network is also strongly related with the quality of the image to be segmented, leading to the necessity of application of a previous procedure of smoothing, such as the FPS filtering presented, which has the property of drastically attenuate the noise in the image, preserving relevant characteristic, as the borders between distinct regions.

The work developed by Terman and Wang includes applications of LEGION network for segmentation of signals of diverse natures, including medical images, images of remote sensing and signals of speech, having been found favorable results. In this work, the application of the LEGION network in the segmentation of TEM images to estimate the volume of helium in silicon samples, qualitatively shows that this network presents itself as a singular tool for applications that requires simultaneously both spatial and temporal image segmentation. The procedure of interactive indication of leaders, proposed in this work, forces the LEGION network to segment only the respective regions, avoiding undesirable segments to appear as outputs of the network.

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