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A Dialectical Method to Classify Alzheimer's Magnetic Resonance Images

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1. Introduction

It is largely known that a great amount of current methods of analysis in image analysis and processing is based on parametric statistics. Alternatively, several approaches in Computational Intelligence, and particularly in Evolutionary Computation, are inspired by biology and other social-based sciences, like the ones based on the movement of flocks and birds, particularly particle swarm optimization, that tend to approximate this basic social behaviour present in inferior animals to the searching process to find a global optimum in a determined objective functions. However, it notorious that just a few approaches, to be optimistic, and almost none to be realistic, are inspired in Philosophy.

Herein this work we claim that Philosophy can be also considered as a source of inspiration to build new tools for analysis in Computational Intelligence, in particular, and in image processing and analysis, in general. This chapter presents the Objective Dialectical Method (ODM): an evolutionary method for classification based on the Philosophy of Praxis, a philosophical approach that considers parts of reality as complex systems composed by basic units called poles, where such units are involved in conflict, affecting each other and generating more poles or eliminating others, as this dynamics proceeds.

Alzheimer's disease is the most common cause of dementia, both in senile and presenile individuals, observing the gradual progress of the disease as the individual becomes older (Ewers et al., 2006). The major manifestation of Alzheimer's disease is the diminution of the cognitive functions with gradual loss of memory, including psychological, neurological and behavioral symptoms indicating the decline of the daily life activities as a whole. Alzheimer's disease is characterized by the reduction of gray matter and the growth of cerebral sulci. However, the white matter is also affected, although the relation between Alzheimer's disease and white matter is still unknown (Friman et al., 2006).

Acquisition of diffusion-weighted magnetic resonance images (DW-MR images) turns possible the visualization of the dilation of the lateral ventriculi temporal corni, enhancing the augment of sulci, related to the advance of Alzheimer's disease (Haacke et al., 1999). Therefore, volumetrical measuring of cerebral structures is very important for diagnosis and

evaluation of the progress of diseases like Alzheimer's (Ewers et al., 2006), especially the measuring of the volumes occupied by sulci and lateral ventriculi, turning possible the addition of quantitative information to the qualitative information expressed by the DW-MR images (Hayasaka et al., 2006).

Usually, the evaluation of the progress of Alzheimer's disease using image analysis of DW-MR images is performed after acquiring at least three images of each slice of interest, generated using the sequence spin-echo Stejskal-Tanner with different diffusion exponents, where one of the exponents is 0 s/mm², that is, a T2-weighted spin-echo image (Haacke et al., 1999). Then, a fourth image is calculated: the Apparent Diffusion Coefficient Map, or ADC map, where each pixel is associated to the corresponding apparent diffusion coefficient of the associated voxel: the brighter the pixels, the greater the corresponding apparent diffusion coefficients (Haacke et al., 1999).

The dialectical conception of reality is a kind of philosophical investigative method for analyzing processes present in nature and in human societies. Its origins are connected to the philosophy of the ancient civilizations of Greece, China and India, closely connected to the thoughts of Heraclite, Plato, and the philosophies of Confucionism, Buddhism, and Zen. As a general analysis method, dialectics has experienced considerable progress due to the development of German Philosophy in the 19th century, with Hegel's dialectics and, in the 20th century, the works of Marx, Engels, and Gramsci. All those philosophers produced seminal works on the dynamics of contradictions in nature and class-based societies, giving rise to the Historical Materialism (Marx, 1980; Engels, 1975; Gramsci, 1992a; Gramsci1992b; Bobbio, 1990).

The dialectical method of Historical Materialism is a tool for studying systems by considering the dynamics of their contradictions, as dynamic processes with intertwined phases of *evolution* and *revolutionary crisis*. It has inspired us to conceive an evolutionary computational intelligent method for classification that is able to solve problems commonly approached by neural networks and genetic algorithms.

Each of the most common paradigms of Computational Intelligence, namely neural networks, evolutionary computing, and culture-inspired algorithms, has its basis in a kind of theory intended to be of general application, but in fact very incomplete; e.g. the neural networks approach is based on a certain model of the brain; evolutionary computing is based on Darwin's theory; and cultural-inspired algorithms are based on the study of populations, such as those of ant colonies.

However, it is important to notice that it is not necessarily the case (and indeed it may be impossible) that the theories an algorithm are based on have to be complete. For example, neural networks utilize a well-known incomplete model of the neurons. This is a strong reason for investigating the use of Philosophy as a source of inspiration for developing computational intelligent methods and models to apply in several areas, such as pattern recognition.

Thornley and Gibb discussed the application of Dialectics to understand more clearly the paradoxical and conceptually contradictory discipline of information retrieval (Thornley & Gibb, 2007), while Rosser Jr. attempted to use some aspects of Dialectics in nonlinear dynamics, comparing some aspects of Marx and Engel's dialectical method with concepts of Catastrophe Theory, Emergent Dynamics Complexity and Chaos Theory (Rosser Jr., 2000). However, there are no works proposing a mathematical approach to establish the fundamentals of Dialectics as a tool for constructing computational intelligent methods.

This work presents the Objective Dialectical Method (ODM), which is an evolutionary computational intelligent method, and the Objective Dialectical Classifier (ODC), an instance of ODM that operates as a non-supervised self-organized map dedicated to pattern recognition and classification. ODM is based on the dynamics of contradictions among dialectical poles. In the task of classification, each class is considered as a dialectical pole. Such poles are involved in pole struggles and affected by revolutionary crises, when some poles may disappear or be absorbed by other ones. New poles can emerge following periods of revolutionary crisis. Such a process of pole struggle and revolutionary crisis tends to a stable system, e.g. a system corresponding to the clusterization of the original data.

This chapter presents a relatively new approach to evaluate the progress of Alzheimer's disease: once the ADC map usually presents pixels with considerable intensities in regions not occupied by the head of patient, a degree of uncertainty can also be considered in the pixels inside the sample. Furthermore, the ADC map is very sensitive to noisy images (Haacke et al., 1999; Santos et al., 2007a). Therefore, in this case study, images are used to compose a multispectral image, where each diffusion-weighted image is considered as a spectral band in a synthetic multispectral image. This multispectral image is classified using the Objective Dialectical Classifier, a new classification method based on Dialectics as defined in the Philosophy of Praxis.

Herein this chapter ODM is used to generate an adaptative image classifier able to start the classification process with a determined initial number of classes and, after a determined period of evolution, to find a suboptimum number of classes according to classification performance. These results were generated using an image database composed by real Alzheimer's magnetic resonance images, to get synthetic multispectral images. The classification results were compared with results generated using image classifiers based on Kohonen's self-organized maps, fuzzy c-means and k-means. ODM demonstrated to be instrumental in assembling evolutionary mathematical tools for the analysis of multispectral images. A 2-degree polynomial network with supervised training is used to generate the ground truth image. The classification results are used to improve the usual analysis of magnetic resonance images based on diffusion tensors in clinical analysis of Alzheimer's disease. The results are compared to ground-truth images produced by polynomial networks using a morphological similarity index.

2. Materials and methods

2.1 DW-MR images and ADC maps

The DW-MR images used in this work were acquired from the clinical images database of the Laboratory of MR Images, at the Department of Physics of Universidade Federal de Pernambuco, Recife, Brazil. This database is composed by clinical images acquired from Alzheimer's volunteers, using clinical 1.5 T MR imaging systems. We used 60 cerebral DWMR images corresponding to male patients with Alzheimer's disease. To perform the training of the proposed analysis, we chose the MR images corresponding to the 13th slice, showing the temporal corni of the lateral ventriculi, to furnish a better evaluation for specialists and facilitate to stablish correlations between data generated by the computational tool and *a priori* specialist knowledge.

An image can be considered as a mathematical function, where its domain is a region of the plane of the integers, called grid, and its counterdomain is the set of the possible values occupied by the pixels corresponding to each position on the grid.
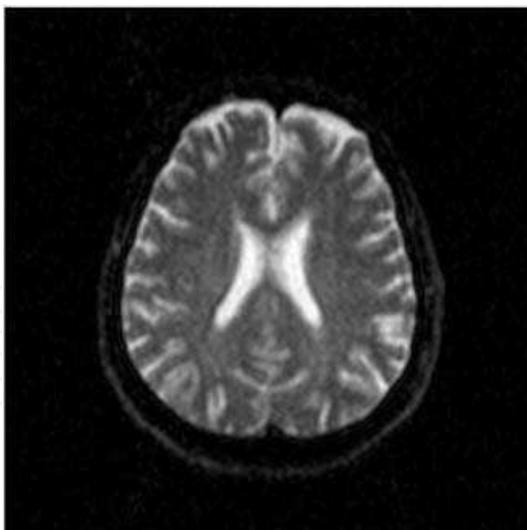
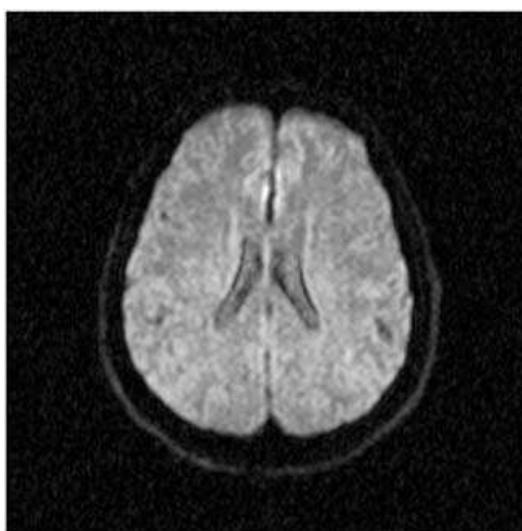Fig. 1. Axial diffusion-weighted image with exponent diffusion of 0 s/mm²

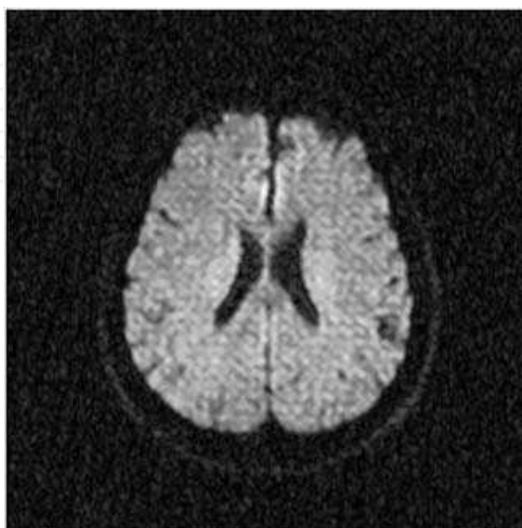Fig. 2. Axial diffusion-weighted image with exponent diffusion of 500 s/mm²

Fig. 3. Axial diffusion-weighted image with exponent diffusion of 1000 s/mm²

Let $f_i : S \rightarrow W$ be the set of the diffusion-weighted MR images, where $1 \leq i \leq 3$, $S \subseteq \mathbf{Z}^2$ is the grid of the image f_i, where $W \subseteq \mathbf{R}$ is its codomain. The synthetic multispectral image $f : S \rightarrow W^3$ composed by the MR images of the figures 1, 2 and 3 is given by:

$$f(\mathbf{u}) = (f_1(\mathbf{u}), f_2(\mathbf{u}), f_3(\mathbf{u}))^T \tag{1}$$

where $\mathbf{u} \in S$ is the position of the pixel in the image f, and f_1, f_2 and f_3 are the diffusion-weighted MR images. Considering that each pixel $f_i(\mathbf{u})$ is approximately proportional to the signal of the corresponding voxel as follows (Castano-Moraga et al., 2006):

$$f_i(\mathbf{u}) = K\rho(\mathbf{u})e^{-T_E/T_2(\mathbf{u})}e^{-b_i D_i(\mathbf{u})}, \tag{2}$$

where $D_i(\mathbf{u})$ is the nuclear spin diffusion coefficient measured after the i-th experiment, associated to the voxel mapped in the pixel in position $\mathbf{u}$; $\rho(\mathbf{u})$ is the nuclear spin density in the voxel; K is a constant of proportionality; $T_2(\mathbf{u})$ is the transversal relaxation time in the voxel; T_E is the echo time and b_i is the diffusion exponent, given by (Haacke et al., 1999):

$$b_i = \gamma^2 G_i^2 T_E^3/3, \tag{3}$$

where γ is the gyromagnetic ratio and G_i is the gradient applied during the experiment . Figures 1, 2 and 3 show images with diffusion exponents 0 s/mm², 500 s/mm² and 1000 s/mm², respectively.

The analysis of DW-MR images is often performed using the resulting ADC map $f_{ADC}: S \rightarrow W$, which is calculated as follows (Basser, 2002):

$$f_{ADC}(\mathbf{u}) = \frac{C}{b_2} \ln\left(\frac{f_1(\mathbf{u})}{f_2(\mathbf{u})}\right) + \frac{C}{b_3} \ln\left(\frac{f_1(\mathbf{u})}{f_3(\mathbf{u})}\right), \tag{4}$$

where C is a constant of proportionality.

Considering n experiments, we can generalize equation 4 as follows:

$$f_{ADC}(\mathbf{u}) = \sum_{i=2}^{n} \frac{C}{b_i} \ln\left(\frac{f_1(\mathbf{u})}{f_i(\mathbf{u})}\right). \tag{5}$$

Thus, the ADC map is given by:

$$f_{ADC}(\mathbf{u}) = C\bar{D}(\mathbf{u}), \tag{6}$$

where $\bar{D}(\mathbf{u})$ is an ensemble average of the diffusion coefficient $D(\mathbf{u})$ (Fillard et al., 2006).

Therefore, pixels of the ADC map are proportional to diffusion coefficients in the corresponding voxels. In figure 4 can be seen several artifacts associated to presence of noise. In regions of image where signal-to-noise ratio is poor (let us say, $s/n \approx 1$), the ADC map produces artifacts as consequence of the calculation of logarithms (see equations 4 and 5). Consequently, pixels of the ADC map not necessarily correspond to diffusion coefficients but *apparent* diffusion coefficients, once several pixels indicate high diffusion rates in voxels in empty areas or in very solid areas, e.g. bone in the cranial box, as can be seen in figure 4. This fact generates a considerable degree of uncertainty about the values inside brain area.
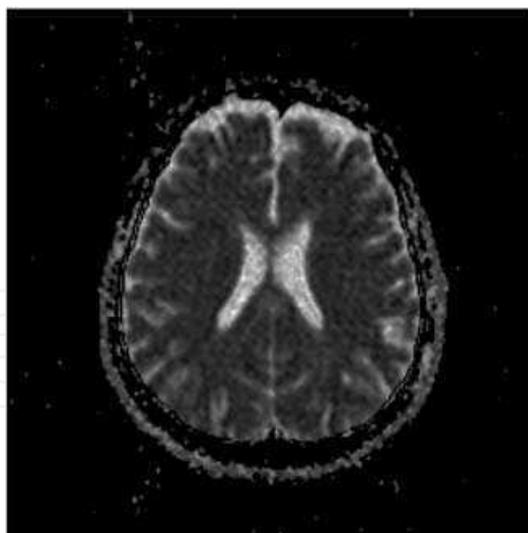
Fig. 4. ADC map calculated from the three diffusion images

In this work we present an alternative to the analysis of the ADC map: the multispectral analysis of the image $f: S \to W^3$ using methods based on neural networks as an alternative that could be easily extended to other diffusion-weighted images than cerebral ones. The proposed analysis is performed using the Objective Dialectical Classifier, presented in the following section.

2.2 Classification using the Objective Dialectical Method

Objective Dialectical Classifiers (ODC) are an adaptation of Dialectics, as defined in the Philosophy of Praxis, to tasks of classification (Gramsci, 1992a; Gramsci, 1992b). This means that the feature vectors are mounted and considered as vectors of conditions. Specifically, once they are applied to the inputs of the dialectical system, their coordinates will affect the dynamics of the contradictions among the integrating dialectical poles. Hence, the integrating poles model the recognized classes at the task of non-supervised classification (Santos et al., 2008a).

Therefore, an ODC is in fact an adaptable and evolutionary-based non-supervised classifier where, instead of supposing a predetermined number of classes, we can set an initial number of classes (dialectical poles) and, as the historical phases happen (as a result of pole struggles and revolutionary crises), some classes are eliminated, others are absorbed, and a few others are generated. At the end of the training process, the system presents a number of statistically significant classes present in the training set and, therefore, a feasible classifier associated to the final state of the dialectical system (Santos et al., 2008a).

To accelerate the convergence of the dialectical classifier, we have removed the operator of pole generation, present at the revolutionary crises. However, it could be beneficial to the classification method, once such operator is a kind of diversity generator operator. The solution found can then be compared to other sort of evolutionary-based image classifiers (Santos et al., 2008a).

The following algorithm is a possible implementation of the training process of the objective dialectical classifier, used in this work (Santos et al., 2008a):

1.   Set the following initial parameters:
    1.1   Number of historical phases, n_P;

    1.2 Length of each historical phase, n_H;

    1.3 Desired final number of poles, $n_{C,f}$;

    1.4 Step of each historical phase $0 < \eta(0) < 1$;

    1.5 Maximum crisis, $0 \leq \chi_{max} \leq 1$;

    1.6 Initial number of poles $\# \Omega(0) = n_C(0)$, defining the initial set of poles:

$$\Omega(0) = \{C_1(0), C_2(0), \ldots, C_{n_C(0)}(0)\}.$$

2.   Set the following thresholds:

    2.1 Minimum force, $0 \leq f_{min} \leq 1$

    2.2 Minimum contradiction, $0 \leq \delta_{min} \leq 1$

3.   Initialize the weights $\omega_{i,j}(0)$, where $1 \leq i \leq n_C(0)$ and $1 \leq j \leq n$.

4.   Let $\# \Omega(t)$ be the cardinality of $\Omega(t)$, repeat until n_P iterations or $\# \Omega(t) = n_{C,f}$:

    4.1 Repeat until n_H iterations:

        4.1.1 Initialize the measures of force $f_i = 0$, for $1 \leq i \leq n_C(t)$.

        4.1.2 For all vectors of conditions

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$$

of the input set $\Psi = \{\mathbf{x}^{(l)}\}_{l=1}^{L}$, repeat:

        4.1.2.1 Compute the values of the anticontradiction functions:

$$g_i(\mathbf{x}) = e^{-\|\mathbf{x} - \mathbf{w}_i\|}$$

where $1 \leq i \leq n_C(t)$.

        4.1.2.2 Calculate g_{max}:

$$g_{max} = \max\{g_1(\mathbf{x}), g_2(\mathbf{x}), \ldots, g_{n_C(t)}(\mathbf{x})\}.$$

        4.1.2.3 Calculate the index $k(t)$ of the winner class:

$$g_i = g_{max} \Rightarrow k(t) = i.$$

        4.1.2.4 Adjust the weights of the winner pole:

$$w_{i,j}(t+1) = \begin{cases} w'_{i,j}(t), & i = k(t) \\ w_{i,j}(t), & i \neq k(t) \end{cases}$$

where

$$w'_{i,j}(t) = w_{i,j}(t) + \eta(t)(x_j(t) - w_{i,j}(t)).$$

        4.1.2.5 Update the measure of force of the integrating poles:

$$f_i(t+1) = \begin{cases} f_i(t) + 1, & i = k(t) \\ f_i(t), & i \neq k(t) \end{cases}.$$

        4.1.3 Quantitative changing: $\Omega(t+1) = \Omega(t)$,

    4.2 Calculate the normalized measures of force:

$$\bar{f}_i(t) = \frac{f_i(t)}{\max\{f_j(t)\}_{j=1}^{n_C(t)}},$$
for $1 \leq i \leq n_C(t)$.

4.3 Compute the contradictions:

$$\delta_{i,j} = 1 - g_i(\mathbf{w}_j),$$

where $2 \leq j \leq n_C(t)$, $1 \leq i \leq j$ and find the maximum contradiction

$$\delta_{\max} = \max\{\delta_{i,j}, i \neq j\},$$

for $j = 2,3,\ldots, n_C(t)$ and $i = 1,2,\ldots, j - 1$.

4.4 Qualitative changing: compute the new set of poles, $\Omega (t + 1)$:

$$\bar{f}_i(t) > f_{\min} \Rightarrow C_i(t) \in \Omega(t + 1),$$

where $1 \leq i \leq n_C(t)$ and

$$\delta_{i,j} \geq \delta_{\min} \Rightarrow C_i(t), C_j(t) \in \Omega(t + 1),$$
$$\delta_{i,j} < \delta_{\min} \Rightarrow C_i(t) \in \Omega(t + 1),$$
$$\delta_{i,j} = \delta_{\max} \Rightarrow C_q \in \Omega(t + 1),$$

where $2 \leq j \leq n_C(t)$, $1 \leq i \leq j$, $q = n_C(t)+1$, and

$$w_{q,k}(t+1) = \begin{cases} w_{i,k}(t + 1), & k \bmod 2 = 1 \\ w_{j,k}(t + 1), & k \bmod 2 = 0 \end{cases},$$

for $k = 1,2,\ldots, n$.

4.5 Add the crisis effect to the weights of the new integrating poles of the dialectical system:

$$w_{i,j}(t + 2) = w_{i,j}(t + 1) + \chi_{\max}G(0, 1),$$
$$\text{for } 1 \leq i \leq n_C(t + 1), 1 \leq j \leq n \text{ and } \Omega(t + 2) = \Omega(t + 1).$$

Once the training process is complete, ODC behavior occurs in the same way as any non-supervised classification method. This is clear if we analyze the training process when $n_P = n_H = 1$. This transforms the ODC into a k-means method (Santos et al., 2008a).

The classification is performed in the following way: given a set of input conditions

$$\mathbf{x} = (x_1, x_2, \ldots, x_n)^T,$$

if the dialectical system reaches stabilization when $\Omega=\{ C_1, C_2,\ldots, C_n\}$, then we apply the following classification rule:

$$g_k(\mathbf{x}) = \max\{g_1(\mathbf{x}), g_2(\mathbf{x}),\ldots, g_{n_C}(\mathbf{x})\} \Rightarrow \mathbf{x} \in C_k,$$

where $1 \leq k \leq n_C$.

2.3 Classification using neural networks

Let the universe of classes of interest be defined as $\Omega=\{C_1, C_2, C_3\}$, C_1 represents the cerebrospinal fluid; C_2, the white and the gray matter, as they cannot be distinguished using diffusion images, because their diffusion coefficients are very similar; and C_3 corresponds to the image background.

For the multispectral analysis using neural nets, the inputs are associated with the vector $\mathbf{x} = (x_1, x_2, x_3)^T$, where $x_i = f_i(\mathbf{u})$, for $1 \leq i \leq 3$. The net outputs represent the classes

of interest and are associated with the vector $\mathbf{y} = (y_1, y_2, y_3)^T$, where each output corresponds to the class with the same index. The decision criterion employed in this analysis was the Bayes criterion: the output with greater value indicates the most probable class (Duda et al., 2001; Duda & Hart, 1972; Sklansky & Wassel, 1981). The training set and the test set were built using specialist knowledge during the selection of the regions of interest (Haykin, 1999). The synthetic multispectral image was classified using the following methods:

- Kohonen Self-Organized Map (SOM) classifier: 3 inputs, 3 outputs, maximum of 200 iterations, initial learning rate η_0 = 0.1, circular architecture, Gaussian function of distance;
- Fuzzy c-means classifier: 3 inputs, 3 outputs, maximum of 200 iterations, initial learning rate η_0 = 0.1;
- Radial Basis Function (RBF) network: layer 1: a k-means clustering map with 3 inputs, 18 outputs, maximum of 200 iterations, initial learning rate η_0 = 0.1; layer 2: an one-layer perceptron with 18 inputs, 3 outputs, 75 iterations, training error of 5%, initial learning rate η_0 = 0.1.

To make comparisons between the proposed multispectral approach and the ADC map, we performed a monospectral non-supervised classification of the ADC map using a clustering-based method (Li et al., 2006; Bartesaghi & Nadar, 2006). We chose a Kohonen SOM classifier (KO-ADC) with 3 inputs, 3 outputs, maximum of 200 iterations, and initial learning rate η_0 = 0.1.

These methods were chosen in order to evaluate the behavior and performance of a classical neural network (RBF network) and well-known clustering-based networks (Kohonen SOM and fuzzy c-means) executing the task of classification of the synthetic multispectral image. Their initial learning rates and number of iterations were empirically determined.

3. Discussion and results

The ground-truth image was built by the use of a two-degree polynomial network to classify the multispectral image. The training set was assembled using anatomic information obtained from T1, T2 and spin density MR images.

The ODC was trained using an initial system of 10 integrating classes, affected by 3 input conditions, studied during 5 historical 100-length phases, with an initial historical step η_0 = 0.1. At the stages of revolutionary crisis we considered a minimum measure of force of 0.01, minimum contradiction of 0.25 and maximum crisis of 0.25. The stop criterion was the final number of classes, in our case, 4 classes. The input conditions are the values of pixels on each of the 3 bands.

ODC training resulted in 6 classes, reduced to 4 classes after a manual post-labeling that merged the 3 classes external to the cranium, i.e. background, noise and cranial box, into a single class, namely background. This post-labeling was performed manually because the 3 populations are statistically different and only conceptually can they be reunited in a unique class. Figures 5 and 6 show the resulting classification by ODC before and after manual post-labeling, respectively.

From Figure 6 we can see that ODC was able to make a distinction between white and gray matter, the latter present in the interface between cerebrospinal fluid and white matter. Notice that an increased damaged area is highlighted. The classification fidelity was measured using the morphological similarity index, with structure element square 3×3, and Wang's index (Wang & Bovik, 2002), yielding 0.9877 and 0.9841, respectively.
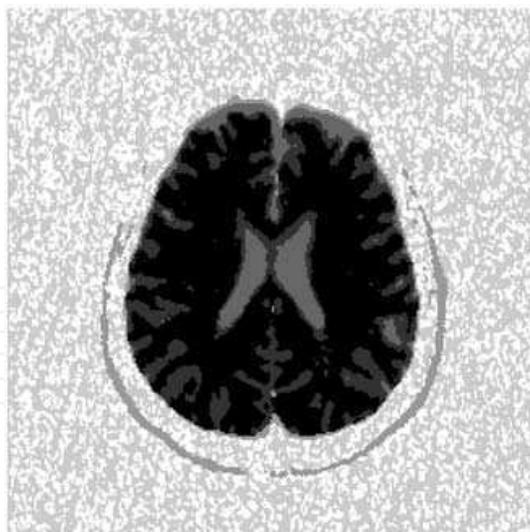
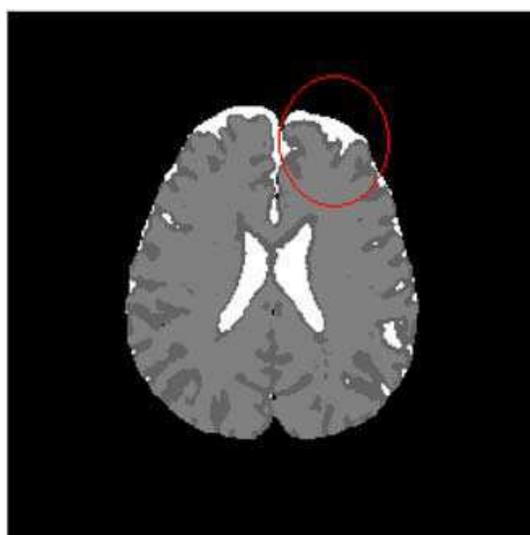Fig. 5. Classification result by ODC before manual post-labeling

Fig. 6. Classification result by ODC after manual post-labeling. White areas are indication of cerebrospinal fluid, once gray and dark gray areas indicate white and gray matter, respectively. The damaged area is emphisized.

Figures 7, 8, and 9 show classification results obtained by the use of classifiers based on Kohonen SOM (KO), RBF networks (RBF), and fuzzy c-means (CM), respectively, considering a fixed number of classes, namely white and gray matter, cerebrospinal fluid and background (Santos et al., 2008b; Santos et al., 2007a; Santos et al., 2007b; Santos et al., 2007c; Santos et al., 2007d). Figure 10 shows the result of the classification of the ADC map using the Kohonen SOM classifier (KO-ADC) (Santos et al., 2007d). However, these visual results are evidence that, using such an approach, it is not possible to distinguish between white and gray matter in multispectral DW-MR Alzheimer's images.

The objective dialectical classifier could identify statistically significant classes in situations where the initial number of classes is not well known. It makes possible the detection of relevant classes and even singularities beyond the initial prediction made by the medical specialist. It is also able to aid the medical specialist to measure the volumes of interest, in an attempt to establish a correlation of such measuring with the advance of
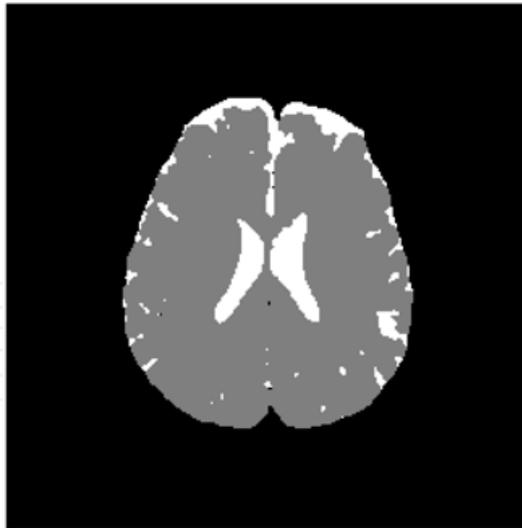
Fig. 7. Classification result by Kohonen SOM after manual post-labeling
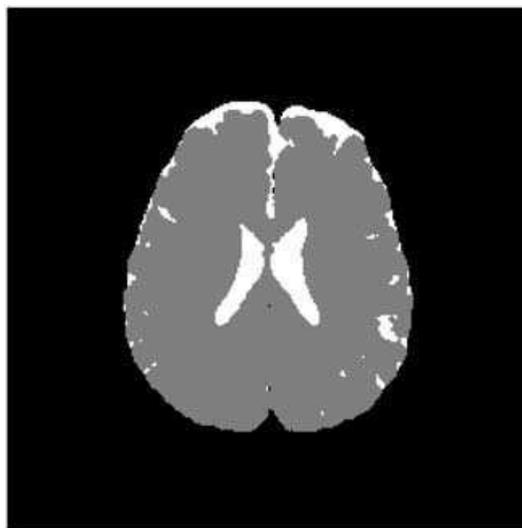

Fig. 8. Classification result by the RBF network classifier
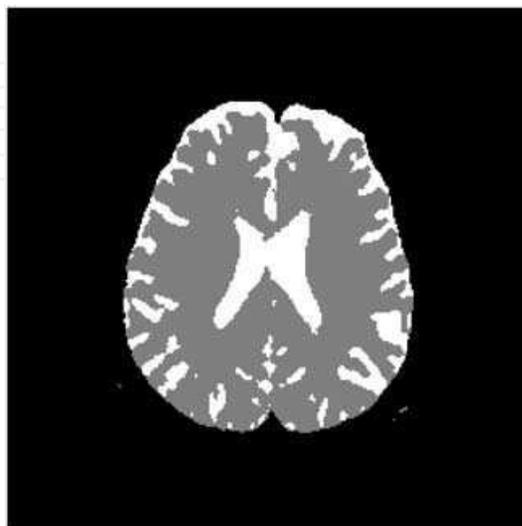

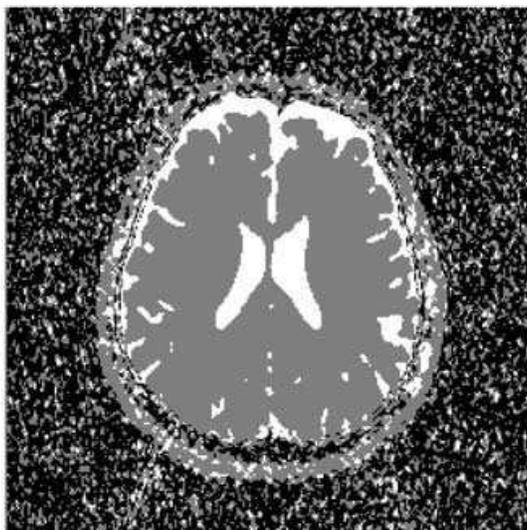Fig. 9. Classification result by fuzzy c-means after manual post-labeling

Fig. 10. Classification of ADC map by Kohonen SOM

neurodegenerative diseases, such as Alzheimer's, and to differentiate significant alterations in the values of the measured diffusion coefficients. ODC can qualitatively and quantitatively improve the analysis of the human medical specialist.

In summary, the objective dialectical classifier can be used in problems where the number of statistically significant classes is not well known, or in problems where we need to find a sub-optimum clustering map to be used for classification. The task of finding a suboptimum clustering map is empirical, once it is necessary to analyze the behavior of the training process as a function of the several parameters of the method, namely the minimum force, the minimum contradiction, the initial number of classes, the number of historical phases, the duration and the historical step of each historical phase, that is, all the initial parameters of the proposed segmentation algorithm. Nevertheless, it is important to emphasize that, as the number of initial parameters is given, the classification performance of the dialectical classifiers is highly dependent on these initial parameters.

The objective dialectical method inaugurates a new family of evolutionary methods inspired in the Philosophy, especially the Philosophy of Praxis, which can be used to solve both classical and new image analysis problems, such as the one presented in our case study, that is, biomedical image analysis and processing.

We conclude by stating that philosophical thought is a great source of inspiration for constructing new computational intelligent methods highly applicable to Biomedical Engineering problems, since we are simply returning to our original source of knowledge: Philosophy as an important tool to a better understanding of nature and ourselves in a larger sense.

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Evolutionary Computation

Edited by Wellington Pinheiro dos Santos

This book presents several recent advances on Evolutionary Computation, specially evolution-based optimization methods and hybrid algorithms for several applications, from optimization and learning to pattern recognition and bioinformatics. This book also presents new algorithms based on several analogies and metafores, where one of them is based on philosophy, specifically on the philosophy of praxis and dialectics. In this book it is also presented interesting applications on bioinformatics, specially the use of particle swarms to discover gene expression patterns in DNA microarrays. Therefore, this book features representative work on the field of evolutionary computation and applied sciences. The intended audience is graduate, undergraduate, researchers, and anyone who wishes to become familiar with the latest research work on this field.

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