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Fast and effective characterization for classification and similarity searches of 2D and 3D spatial region data

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Abstract

We propose a method for characterizing spatial region data. The method efficiently constructs a k -dimensional feature vector using concentric spheres in 3D (circles in 2D) radiating out of a region's center of mass. These signatures capture structural and internal volume properties. We evaluate our approach by performing experiments on classification and similarity searches, using artificial and real datasets. To generate artificial regions we introduce a region growth model. Similarity searches on artificial data demonstrate that our technique, although straightforward, compares favorably to mathematical morphology, while being two orders of magnitude faster. Experiments with real datasets show its effectiveness and general applicability.

Keywords

Characterization; Regions of Interest; Feature extraction; Classification; Similarity searches; Region growth model

1. INTRODUCTION

Spatial region data, referred to in certain cases as spatial Regions of Interest (ROIs), are encountered in several domains, including medical images, satellite data, and thematic maps in geographical databases. Current technological advances, such as remote sensing technology, satellite imagery devices and high-resolution medical image acquisition devices, have allowed a wide range of spatial region data to be collected in large data repositories. Most of the recent applications that utilize these region data (i.e., sets of objects/regions in the space) require efficient access to these data repositories. Content-based retrieval and classification capabilities are of great need. Methods employed for this type of content-based access rely heavily on effective and efficient techniques for feature extraction [1]. These features should be simple enough to allow fast automated computation. Nevertheless, they should also be descriptive and meaningful in order to effectively capture a region's properties. These features usually provide some quantitative information with respect to size, shape, texture or other discriminative properties of a region.

Most of the characterization techniques are based on extracted global visual features that refer to the entire image (or volume) content [2–3] rather than to regions that are of interest. However, analysis of region data in certain fields, such as meteorology and medical imaging, require focusing on specific regions that are of particular interest, in order to analyze critical information [4–8]. Examples of such ROIs are highly populated areas in geographic maps,

regions with high levels of precipitation or temperature-relative humidity in meteorological maps, brain activation regions during a particular task in fMRI¹ and lesions or tumors in MRI². Figure 1 shows examples of such regions in medical and meteorological images. When characterizing these types of ROIs, highly informative quantitative features need to be extracted. These features can be employed for classification, in order to indicate associations among spatial characteristics and non-spatial attributes, such as the development of a disease or climatic changes over time.

One of the main concerns of the region based analysis techniques is to delineate and characterize the shape of a ROI. Representing the shape of ROIs has been the main issue of various attempts to characterize region data [9–10]. Shape is the geometrical information that remains when location, scale and rotational effects are filtered out from an object [11]. Shape representation and analysis has generated a rich array of approaches from simpler ones that use anatomical or mathematical landmarks, simpler shapes [12–13] and polygonalization [13] to more advanced ones that extend to obtaining numerical vectors from various transformations of the boundary. Such techniques include the Fourier transform [14–17], wavelet transform [18–21], moments of inertia [22] or extraction of self-similarity properties expressed by fractal dimension [23–24].

Concepts from mathematical morphology, namely the “pattern spectrum” of a shape, have also been used to map the shape of a ROI to a point in a k -dimensional space [25], performing effective characterization and classification [26]. In this technique, mappings are defined in terms of a structural element, a “small” primitive shape that interacts with the input image (via morphological operators like dilation, erosion, opening ($\circ$), and closing ($\bullet$)) to transform it and in the process, extract useful information about its geometrical and topological structure [27]. The morphological distance between two objects x_1 and x_2 is defined as:

$$d_{morph}^E(x_1, x_2) = \left(\sum_{m=-M}^M |d^*(f_m^E(x_1), f_m^E(x_2))|^p \right)^{1/p} \quad (1.1)$$

with

$$f_m^E(x) = \begin{cases} x \ominus mE, & 1 \leq m < M \\ x, & m = 0 \\ x \oplus mE, & -M \leq m \leq -1 \end{cases} \quad (1.2)$$

where E is some structuring element, M is the maximum radius used to construct E (circle or sphere), d^* is the area of the symmetric set difference distance measure defined as $d^*(x_1, x_2) = |x_1 \cup x_2| - |x_1 \cap x_2|$ after the objects have been optimally aligned via registration, and p denotes the particular norm used (e.g., $p=2$, for the Euclidean distance). The morphological distance, as defined by equations (1.1) and (1.2) has been used to effectively quantifying shape dissimilarity of homogeneous objects [26]. These equations can be also used for non-homogeneous regions; in this case the standard morphological operators (i.e., dilation, erosion, opening ($\circ$), and closing ($\bullet$)) are extended to take into consideration the pixel values of the internal region content [28].

The idea of using a structural element that interacts with a ROI to extract information has been used in several other approaches as well. Sholl initially proposed using concentric circles to characterize tree-like structures [29]. In the context of dendritic trees, his technique involved

¹Functional-Magnetic Resonance Imaging: shows physiological activity in brain.

²Magnetic Resonance Imaging: shows soft-tissue structural information.

a set of concentric circles (shells in 3-D) radiating out from the root through the rest of the tree (see Figure 2.a). During this process, information was extracted to obtain a characterization vector. Sholl showed that the number of dendritic branches per unit area decreased as an exponential function of the distance from the cell body (tree root) by counting the number of dendrites in each annular region (see Figure 2.b). His method has been used in neuroscience databases [30–31].

Shape characterization techniques can be utilized to represent the boundaries of region structures and have been primarily employed for 2D shape analysis [9,13–14,20–21]. Unfortunately, most of these 2D methods do not generalize directly to 3D shape characterization and similarity assessment [10], while being also computationally expensive. For example, 3D shape descriptors based on 3D Fourier transform require canonical coordinate normalization, coarse 3D surface discretization and complex number computations that are time consuming and not straightforward to implement [16–17]. Some work has also been done in utilizing the wavelet transform for 3D shape matching [21]. All these approaches have been mostly applied to extract features that characterize the periphery of a region. This is the dominating property when dealing with homogeneous regions (e.g., binary images) [26]. On the other hand, properties of the internal volume need to be considered as well when analyzing non-homogeneous regions, where intensity variability of the volume elements (voxels in 3D or pixels in 2D) is a critical property.

In this paper, we propose a method to quantitatively characterize spatial region data acquired by modern imaging modalities, such as meteorological images collected by sensors that measure temperature and precipitation, satellite geophysical data, or medical images acquired by MRI (Magnetic Resonance Imaging), fMRI (functional Magnetic Resonance Imaging), and CT (Computed Tomography) (see Figure 1). Our approach extracts signatures from 2D as well as 3D regions, operating directly on the 3D space without loss of information or significant computational overhead. The proposed methodology also applies to both homogeneous and non-homogeneous regions. The extracted features capture properties of the boundaries and patterns of voxel (pixel) value variability in the internal volume of the ROI. Our approach being simple performs rapid feature computation and it is faster than existing techniques. This advantage makes it suitable for approximate searches of similar regions in large image databases. In the sections that follow, we present a detailed description of the proposed methodology (Section 2). We describe in detail the datasets used for the evaluation of our proposed approach (Section 3) as well as the experiments performed and the results obtained (Section 4). We also present a discussion based on our experimental evaluation and future extensions of our proposed approach (Section 5). Finally we present our concluding remarks (Section 6).

2. METHODOLOGY

In order to characterize ROIs we extend the original idea of Sholl's analysis [29] proposed in 1953 for tree-like structures to non-tree like structures in order to obtain a characterization vector of k attributes mapping a ROI to a point in the k -dimensional space. Figure 3 illustrates the main idea. We propose a quantitative characterization technique that can be applied to both homogeneous and non-homogeneous regions [32]. Although the characterization of ROIs is of particular interest in meteorological [33] or medical image databases [6], the methodology we propose here can be applied to other types of image data as well.

The region data (in 3D volumes or 2D images) we consider can be defined as sets of (often connected) voxels (volume elements) that form structures or objects. We deal with the characterization of two different types of regions: (a) homogeneous, where all the voxels that form the regions have the same value which is different from the background (binary data) and

(b) non-homogeneous, where the values of voxels that form the regions can range while they are still different from the background (non-binary data, e.g., gray scale images). Another way to view non-homogeneous regions is that the voxel values reflect a probability that the voxels belong to a ROI as in the case of statistical parametric maps [34] obtained from analysis of fMRI activations, or in the case of uncertainty in delineating the boundaries of certain structures in medical images. We will refer to this value of a voxel in non-homogeneous regions as *density content* of a voxel.

In certain applications, necessary preprocessing steps for the characterization and classification of ROIs are the segmentation and the registration of the corresponding images. Segmentation is required to delineate the particular regions that are of interest while registration is required to bring the regions into spatial coincidence with a template, which is also referred to as spatial normalization. Our method focuses solely on the characterization process assuming that, in cases required, these preprocessing steps have been applied.

The basic problem we are addressing here is the following: Given a homogeneous or non-homogeneous ROI, effectively extract useful features so that characterization, classification and retrieval of similar regions can be performed efficiently. The proposed method for characterization is based on representing the voxel *density content* of each ROI with identifying signatures.

Let Θ denote a ROI constructed by a set of voxels $V = \{v_i, i = 1, \dots, z\}$. Consider m to be the center of mass of Θ . We indicate as R a sub-region of Θ that extends over a radius r from the center of mass m . For characterizing Θ we define the *radial voxel counting function* as

$$N_{\Theta}(m, r) = |\{v_i \in R\}|, \text{ where } \forall i, v_i \in R : |m - v_i| \leq r. \quad (2.1)$$

The radial voxel counting function $N_{\Theta}(m, r)$ counts the number of voxels v that belong to the sub-region R . In other words, this function enumerates the voxels v that belong to the intersection of a sphere of radius r (circle for 2D ROIs) and the ROI Θ .

For the non-homogeneous regions the contribution of each voxel is determined by its *density content*. Hence, the alternative *radial voxel density counting function* for the non-homogeneous ROIs is defined as:

$$N_{\Theta}(m, r) = \sum_i \text{density content}(v_i), \text{ where } \forall i, v_i \in R : |m - v_i| \leq r. \quad (2.2)$$

This alternative *density counting function* calculates the sum of the *density content* of each voxel v_i that belongs to the sub-region R defined by the intersection of a sphere of radius r (circle for 2D ROIs) and the ROI Θ .

The proposed characterization process is as follows: Using the center of mass m as center, construct a series of $i = 1, \dots, k$ concentric spheres S_i in 3D (or circles in 2D) with regular increments inc of their radius r_i . For each sphere S_i (or circle) calculate the $N_{\Theta}(m, r_i)$ where $i = 1, \dots, k$. For each radius r_i measure the following quantities (i.e., features):

$$f_s(i) = \frac{N_{\Theta}(m, r_i)}{N_{SPHERE}(m, r_i)} \quad (2.3)$$

and

$$f_r(i) = \frac{N_{\Theta(m, r_i)}}{N_{\Theta(m, r_k)}} \quad (2.4)$$

forming respectively feature vectors f_s and f_r of size k . The features of vector f_s measure the fraction of the sphere (or circle) occupied by the ROI (Eq. 2.3) at each radius r_i . On the other hand, the features of vector f_r measure the fraction of the ROI occupied by the sphere (or circle) (Eq. 2.4). These are expressed using the total voxel count for homogeneous ROIs or the overall voxel *density content* for non-homogeneous ROIs respectively. Table 1 outlines the characterization algorithm for a 3D ROI in pseudocode. Figure 3.b illustrates the characterization process by capturing snapshots of the intersection between the concentric spheres and a 3D ROI that is being analyzed. The sensitivity of the characterization depends largely on the radius increment r_i . Complex or not very distinctive ROIs require a small radius increment in order to be represented efficiently by the constructed feature vectors.

The constructed f_s and f_r feature vectors represent the initial region in a compact form, mapping the entire ROI to a point in the k -dimensional space. As the results in our experimental evaluation demonstrate, these features can be utilized effectively for classification and similarity searches. For projecting the characterization vectors to a lower dimensionality space, we propose the use of dimensionality reduction techniques, such as the Karhunen-Loeve (K-L) transform or Singular Value Decomposition (SVD). K-L or SVD attempt to rotate the coordinate system of the initial vector space so that projections into the new space are calculated from uncorrelated features [35]. A feature selection approach based on a Markov Chain Monte Carlo (MCMC) framework suitable for this kind of ROI characterization ROIs has also been proposed [36].

3. EVALUATION DATASETS

In this section we present a detailed description of the datasets used in the evaluation of the proposed methodology. We experimented with both artificial and real region data. The artificial ROIs were generated using a parametric region growth model which is described in Section 3.1. This model was employed in order to simulate spatial regions with predefined controllable structural patterns (i.e., when their characteristics follow certain distributions). The artificial datasets are described in detail in Section 3.2. For evaluating the effectiveness of our approach on real data, we considered 2D meteorological images representing temperature variations as well as 3D medical images depicting activity in the human brain during a series of cognitive tests. These real datasets are described in detail in Section 3.3.

3.1 Generation of artificial regions

We developed a discrete-time region growth model for the generation of artificial regions with predetermined characteristics. This model is based on a 2D model originally proposed by Eden [37] which has been used in studies of similarity searches [26]. The growth (infection) process begins with one initial voxel (or cell) at time $t=0$ and progresses using the following rule: each infected cell may infect its non-diagonal neighbors with some probability.

We have extended this initial model by allowing the probability thresholds to be different for each direction. For example, in 3D, given a probability threshold vector $p = [p_E, p_W, p_N, p_S, p_U, p_D]$, an infected voxel may infect its six non-diagonal neighboring voxels with probabilities p_E, p_W, p_N, p_S, p_U , and p_D where the probabilities are not necessarily equal. These probability thresholds can be adjusted properly for each direction, in order to obtain regions of a desired shape, or even change with time in order to obtain even more complex structures. Each region is grown until it reaches a certain volume calculated by the total number of voxels, which is a parameter in our model.

We are also modeling the degree of infection. In non-homogeneous regions the distribution of *density content* (value) of the voxels in the region follows the behavior of a usually monotonic decreasing (with the number of epochs) function, simulating the intensity of a certain property for the internal area of the region. In this case, voxel values can also be considered as probabilistic values indicating the presence of a property or inclusion of the voxel in the region of interest. This property of our model can be utilized for simulating complex regions, such as ROIs encountered in meteorological visualizations or in medical images. For example, tumors or lesions in medical images are often considered to be homogeneous regions for simplicity although in most cases these are non-homogeneous regions with boundaries that are difficult to identify. One can use probability distributions collected from real data to model the structural properties of these ROIs, their spatial arrangement, the size of sub-regions, the direction of growth of each sub-region in various stages, the depth of growth, the degree of infection, etc. This model can be employed to generate a large number of realistic regions.

3.2 Artificial data

Basic 2-Class datasets—These datasets consist of artificial ROIs. Each set includes regions of two distinct spatial patterns (classes) generated by the proposed growth model. Each class consists of 50 ROIs that were generated using a total number of 15 epochs and different probability thresholds for each class. We consider homogeneous and non-homogeneous 2D and 3D structures. More specifically the sets are the following: (a) **2DHom** set: 2D Homogeneous 50x50 pixel images. One class of circular and another class of elongated to two opposite directions (north-south) ROIs (Figure 4.a). The corresponding probability vectors were $p_{class\ 1} = [0.5\ 0.5\ 0.5\ 0.5]$ and $p_{class\ 2} = [0.2\ 0.2\ 0.8\ 0.8]$ for the two classes; (b) **2DNonHom** set: 2D Non-Homogeneous 50x50 pixel images. One class of ROIs elongated to one direction (north) and another class of ROIs elongated to two opposite directions (north-south) ROIs. The corresponding probability vectors were $p_{class\ 1} = [0.2\ 0.2\ 0.5\ 0.8]$ and $p_{class\ 2} = [0.2\ 0.2\ 0.8\ 0.8]$ for the two classes (Figure 4.b); (c) **3DHom** set: 3D Homogeneous 50x50x50 voxel images having the same properties as the ROIs in the 2DHom set; (d) **3DNonHom** set: 3D Non-Homogeneous 50x50x50 voxel images having the same properties as the ROIs in the 2DNonHom set.

Large Scale 5-Class dataset—This dataset is used to evaluate the scalability of the proposed technique. It consists of 5000 sample 2D 100x100 pixel images, each belonging to one of five distinct classes of 1000 2D circular non-homogeneous spatial ROIs. To make the dataset challenging, the probability vector was the same for all five classes and equal to $p = [0.5\ 0.5\ 0.5\ 0.5]$. The distinction among the classes is based on the fact that ROIs in each class are generated according to a different distribution with respect to the voxels' *density content*; they follow a different function modeling their degree of intensity spread over the number of growth epochs. More specifically, the voxel values are modeled by the following function:

$$voxelvalue = \frac{40}{39 + epoch} + (5 - StepF_{class_i}(epoch)) \times 0.01 + 0.005, \text{ where } epoch = 1, \dots, 40$$

In the above formula, $StepF_{class_i}(epoch)$ is a step function that models the spread of the degree of intensity and is different for each class. Figure 4.c shows sample ROIs from each class, illustrating the differences among the classes as well as the within class variation. Figure 4.d shows the corresponding step functions used for generating the ROIs in each class.

3.3 Real Data

In order to demonstrate the applicability of our methodology to a diverse range of actual applications we experimented with real ROIs, such as the ones shown in Figure 1. We evaluated our technique both on 2D meteorological and on 3D medical image data.

2D Meteorological Data—This dataset has been collected from the National Oceanic and Atmospheric Administration (NOAA) web data services. We used the Climate Visualization service (<http://www.ncdc.noaa.gov/oa/climate/onlineprod/drought/xmgr.html>), an interactive on-line graphing tool designed to allow visual browsing of the data available on-line at the National Climatic Data Center (NCDC). Tabular raw mean temperature measurement data are also available by NOAA (http://www5.ncdc.noaa.gov/climate normals/hcs/HCS_41.pdf). We experimented with geographical regions and certain time periods (e.g., months or seasons), where the raw temperature measurements suggest similar weather conditions. Our intention was to demonstrate that our proposed approach is capable of indicating discriminative spatial temperature patterns even in the cases where the raw annotated temperature measurements (including first and second order statistics) imply resembling climatic environment.

We selected the state of Arizona (AZ) for which, as shown in the raw mean temperature monthly measurements available by NOAA (http://www5.ncdc.noaa.gov/climate normals/hcs/HCS_41_seq.txt), the months of November and March have very similar average temperature measurements during a 70 year range period (1931–2000). More specifically, the months of November 1963 and March 1953 have the exact average temperature of 50.7° F. We collected 2D contour images visualizing minimum and maximum daily temperature measurements for these two months, segmenting the exact region boundaries of AZ State. To be consistent with the average temperature measurements used to make this image selection, we constructed the actual mean temperature images by averaging (pixel-wise) the corresponding minimum and maximum temperature images. Hence, the dataset used in the evaluation of the proposed approach consisted of 2 classes (November 1963 vs. March 1953) of 30 2D daily average temperature contour 797x556 pixel images. Figures 5.a and 5.b show sample images from each class, illustrating different climatic patterns despite the similar temperature average. These examples are indicative of the within class variation of these data sets.

3D Medical Image Data—To evaluate the applicability of the proposed technique on real data we experimented using ROIs extracted from 3D fMRI brain activation contrast maps. The fMRI scans were obtained from a study designed to explore neuroanatomical correlates of semantic processing in Alzheimer's disease [38]. The brain activation levels were measured for 9 control and 9 patient samples while they were asked to participate in a series of semantic tasks. These tasks were selected to differentially probe semantic knowledge of categorical, functional, and phonological congruence between word pairs. More specifically, we considered four datasets of fMRI contrast maps acquired during the following cognitive tests: (a) Category exemplar (catx): identify word pairs with correct category exemplar relationships from among incorrect ones, (b) Category function (catf): identify word pairs with correct category function relationships from among incorrect ones, (c) Nonsense pairs (nonpr): listen to nonsense pseudo-word pairs and decide if they are the same or different, and (d) Episodic recognition memory task (imprec): identify formerly heard words and pseudowords encountered in catx and catf tasks above versus new foils.

Prior to the application of the proposed technique, preprocessing was applied, using SPM99 [34] to bring homologous regions into spatial coincidence (through spatial normalization). We also removed the effect of the background noise and masked the data using a binary mask extracted from the T1 [39] anatomical atlas, which was used as the template to register the data. Only signal within the binary mask was included in the analysis. The preprocessed dataset is available at http://denlab.temple.edu/data_repository.

For the experiments presented here, we focused on a number of specific sub-regions in the brain. These are ROIs that have been identified as being highly discriminative with respect to the development of Alzheimer's disease [40]. More specifically, these regions have p-values < 0.001 when using statistical tests such as t-test and ranksum test to determine the significance

of their association with Alzheimer's disease. Figure 6.a shows one of these selected regions in consecutive 2D slices of the 3D volume on the T1 canonical atlas. Figures 6.b and 6.c illustrate the corresponding actual fMRI contrast ROI for a control and a patient sample. In total, we experimented with 7 datasets of fMRI contrast activation map ROIs, each consisting of 9 control and 9 patient samples. It is worth mentioning that even though the size of the fMRI datasets is small compared to the artificial and meteorological data used in our experimental evaluation, it is considered to be a sufficient sample for an fMRI study, since such 3D brain scans are difficult and costly to acquire. The dataset is highly heterogeneous with an intrinsic difficulty in finding any pattern.

4. EXPERIMENTAL RESULTS

In this section we present the experimental evaluation of the proposed methodology on the datasets described in Section 3. We apply the characterization technique on a wide range of spatial ROIs and evaluate its effectiveness with experiments on classification and similarity searches. These experiments demonstrate the ability of our technique to provide efficient representation (characterization) of the ROIs included in the datasets. We used Neural Networks as classifiers, constructed by one hidden layer of 5 neurons, inputs equal to the number of features of the characterization vectors and one output node indicating the class label. Depending on the size and the nature of each dataset we used either back-propagation or the Levenberg-Marquardt algorithm for training. We also compared our approach to mathematical morphology. The implementation was carried out in MATLAB Version 6.1.0.450 Release 12.1 using the PRTools toolbox for pattern recognition [41] and the SDC Morphology Toolbox v.1.1 [42]. The SDC Morphology toolbox applies the extended morphological operations for the analysis of non-homogeneous ROIs [43]. All the experiments were performed on a two Pentium III Xeon processor workstation with 1 Gigabyte of RAM running Linux Release 9.

4.1 Results on artificial data

Experiments with the Basic 2-Class datasets—These sets provide an initial basic framework for evaluation. We obtained both f_s and f_r signatures, using a radius increment of 1 and 2 pixels for the characterization process. Figure 7.a shows the variation of the f_s signatures for the 3DHom dataset. As illustrated in the figure, ROIs belonging to the same class have similar characterization signatures that tend to cluster, indicating structural differentiation among classes.

For the classification experiments, the training was performed using the Levenberg-Marquardt optimization to reduce the training epochs. The training set size ranged from 60% to 80% of the total available samples (two classes of 50 ROIs each in every set). Table 2 shows the classification accuracy and standard deviation averaged over 40 repetitions using the f_r vectors, for all sets and experimental settings. The performance obtained on the test set was very good in all the cases, reaching up to approximately 100% with very low standard deviation over all the training-testing trials.

We also performed similarity searches comparing our approach with mathematical morphology (see Section 1). Similarity between ROIs was assessed using the Euclidean distance metric when using our proposed characterization signatures, contrary to the morphological distance when using morphological operators to characterize the ROIs. The structural element used in calculating the morphological distance was a disk where M (the maximum radius used) was equal to 20. The morphological distance calculation between two 3D ROIs took approximately 11 minutes (660 seconds) while our proposed method for characterization, including the calculation of the Euclidean norm, took 7 seconds on the workstation we used. Hence, due to time constraints imposed by the morphological distance

calculation, we could perform experiments only with the 2D sets (2DHom and 2DNonHom). For each of these two sets, we selected one region from each class as the query ROI and calculated its distance to all the ROIs in the same set (for both classes). Our approach was two orders of magnitude faster in performing the similarity calculations. Also, as illustrated in Figure 8, Euclidean distances based on our signatures provided comparable similarity estimates to those of mathematical morphology. In the case of non-homogeneous ROIs, our approach was more robust, differentiating more effectively than morphology ROIs of the contrasting classes (Figures 8.c vs. Figure 8.g., Figure 8.d. vs. Figure 8.h). In general, morphology has been used mostly in studies regarding homogeneous 2D ROIs where shape was the most important region property [25–26]. Its applicability has not been demonstrated efficiently for 3D ROIs and non-homogeneous data, where properties of the internal region need to be considered as well. Our approach demonstrates an advantage over morphology operating faster for 3D ROIs and being also more robust for non-homogeneous region characterization.

Classification and similarity search experiments with the Large Scale 5-Class dataset—We applied the proposed characterization approach to the 5000 ROIs of the large scale 5-class dataset, constructing characterization vectors (f_r) of 39 attributes, with a radius increment of 1 pixel. The time required to characterize each ROI was 0.14 seconds. For the classification, training was performed using the back-propagation algorithm. The training set size ranged from 60% to 80% of the total available samples (five classes of 1000 ROIs each). We performed 35 training-testing trials. In every repetition, the training set was generated at random from the total available dataset. The training set generation was performed with replacement and for every run the larger training sets included the smaller ones. Testing was performed on all the available samples. Table 3 shows the obtained classification accuracies and standard deviations. The very good performance indicates that the proposed characterization approach can be robust even when the ROIs have not easily observable dissimilarities, as in the case of the internal volume properties for this dataset.

We also evaluated the performance of our characterization technique on similarity searches. More specifically, we randomly selected one query ROI from each class and calculated its Euclidean distance from all the 5000 ROIs of the dataset. Table 4 illustrates the precision results for each of the query ROIs and different number of ROIs retrieved. The precision is the fraction of the ROIs retrieved by the similarity search that are relevant (this is defined as the number of ROIs retrieved that are relevant over the number of ROIs retrieved). Precision of 100% denotes that there are no false alarms. The reported precision is quite high, which is very impressive taking into consideration the obvious structural similarity of the 5 classes (see Figure 4.c). These results, considering as well the very small amount of time required to acquire the characterization signatures, demonstrate the scalability of the proposed technique to large datasets and its ability to enhance retrieval response.

4.2 Results on real data

Experiments with 2D Meteorological Data—We applied the proposed characterization approach on each mean temperature image of the meteorological dataset using a radius increment of 2, 5 and 10 pixels. The characterization for each ROI took approximately 7 seconds when using a radius increment of 2 pixels, 3 seconds for radius increment of 5 pixels and 1.5 seconds when using an increment of 10 pixels. We constructed f_r and f_s signatures with 150, 60 and 30 features respectively for each different increment. Samples of these signatures are shown in Figure 7.b. We performed classification experiments using the Levenberg-Marquardt training optimization algorithm for Neural Networks in order to reduce training epochs due to the high dimensionality. The training set size scaled from 60% up to 85% of the total available dataset. We performed 35 training-testing trials and averaged the classification accuracy. As Table 5 illustrates, the performance ranged between 80% – 86%. These results

verify that the proposed approach has the ability to extract powerful characterization vectors, which have the ability to discriminate between region data patterns that are not distinguishable using simple annotated attributes and characteristics. Such cases occur very often in large publicly available data repositories where browsing and selection capabilities for the user are based on annotated features. Most of the traditional characterization techniques would not be suitable to be applied to such large scale data archives. For example, the wavelets or the Fourier transform would be computationally expensive to operate on a voxel-by-voxel level required for this type of analysis. Morphology would also be difficult to apply on such highly non-homogeneous data. Finally, techniques such as color histogram estimation would not be able to capture discriminative properties, since the overall histogram statistics are similar for the two classes. The proposed approach demonstrates an advantage over these techniques, being very fast and producing compact representations that can improve indexing, storage and retrieval capabilities.

Experiments with fMRI data from an Alzheimer's disease study—We applied the proposed characterization technique to the ROIs of our fMRI datasets. These real fMRI contrast activation maps are considered to be highly non-uniform data. As a consequence, the total 3D ROI volume calculation, using the weighted voxel contribution required for the f_r vector denominator, varies greatly among subjects. For this purpose, we used only the f_s vectors. We experimented with radius increments of 0.2 and 0.5 of a volume element (voxel) for the growth of the concentric spheres. Selecting such a fractional radius increment provides more detailed characterization which is very desirable for such very small and highly heterogeneous ROIs. These fractional increments of 0.2 and 0.5 correspond to 0.4mm and 1mm respectively in the actual fMRI brain volume. Samples of these signatures are shown in Figure 7.c. Despite this high level of detail and the fact that our approach operates directly on the 3D domain, the characterization ranged approximately from 3 up to 7 seconds for each region, depending on the number of features extracted and the size of the ROI. Other characterization approaches would be quite inefficient to apply on these data. Wavelets and the Fourier transform would be very computationally expensive for voxel-wise analysis due to the large number of voxels forming the 3D volumes. Morphological distance calculations would be at least two orders of magnitude slower and more complex since the data are 3-dimensional and non-homogenous.

In this particular application, the curvature of the signatures conveys information for the activation patterns of the original data. As we observed, signatures of different classes tend to cluster and follow similar behavior, indicating the activation level differentiation between controls and patients. This information provides valuable insight when interpreting and predicting the development of the disease. For the classification experiments, in order to avoid overfitting due to a small training dataset, we applied one-layer perceptron networks trained by the Pocket algorithm [44]. The leave-one-out approach was employed to evaluate the classification performance [35,45]. More specifically, the training set consisted of patients and controls with indices $1, 2, 3, \dots, i-1, i+1, \dots, 9$ and testing was performed on patient and control with an index i , where $i=1, \dots, 9$. Table 6 summarizes the results for all the different experimental settings. The classification accuracy ranged from 73% – 84% in discriminating controls from patients. These results are very encouraging taking into consideration the limited size of the dataset and the complexity of interpreting fMRI activation studies. They also demonstrate that the proposed technique has great potential for providing efficient characterization of highly non-uniform ROIs, capturing their structural patterns and information content. Within the specific medical imaging application domain, our methodology can contribute to a framework that supports medical decision making and diagnosis.

5. DISCUSSION AND FUTURE WORK

We presented an approach that efficiently characterizes spatial Regions of Interest (ROIs). The main idea was to construct characterization signatures using concentric circles (or spheres in 3D) as structural elements that operate with the region to extract informative features. These features form a k -dimensional feature vector that maps the ROI into the k -dimensional space.

Many of the region structures found in nature follow a behavior that cannot be modeled by the traditional Euclidean geometry [24]. More specifically, these structures are not restricted to an integer numbered dimensionality and exhibit degrees of self-similarity described by fractal geometry. Several techniques have been proposed in order to quantitatively characterize these properties. In the context of characterizing spatial self-similar ROIs an informative metric is the *fractal mass dimension*. The mass dimension, d_m , of an object is defined as follows: (i) locate a point P inside the object (near the middle), (ii) denote by $M(r)$ the amount of mass of the ROI inside the sphere (circle if the ROI is in the 2D) of radius r and centered at P . If the power law relation $M(r) = c r^d$ holds over some range of r values, then the mass dimension $d_m = d$. Assuming that the ROI has finite extent, the power relation holds only for a range of r values. The *fractal mass dimension* has been used to characterize the texture of region structures in medical imaging [46]. The proposed characterization approach can be viewed as having a relation to this concept, being able to convey some self-similarity properties. When dealing with ROIs, the amount of mass $M(r)$ is the number of voxels, since a voxel is defined as the primitive volume element. In the special case of non-homogeneous ROIs, the contribution of each voxel is weighted probabilistically according to its *density content*. Equations (2.3) and (2.4) measure features that correspond to fractional volumes. In the corresponding signatures, such as the ones shown in Figure 7, one can identify segments, between not necessarily consecutive radius increments, where the slope of the curve seems to be constant (stable). This constant curvature slope is an indication that a power relation holds and that the corresponding concentric region segments could exhibit a degree of self-similarity.

Work in progress includes the extension of the proposed characterization method so that it can be applied to non-homogeneous regions with more than one initial growing point. We are also considering the application of dimensionality reduction techniques for the selection of the most discriminative features that can be used for classification. Further research is also required in order to determine specific parameters, such as radius increment, when applying the proposed approach on real data. Adaptive characterization could be of particular interest in this case. Regions with high information content should be characterized using smaller radius increments than the ones that do not convey critical information. Other concentric structures could be utilized as well for characterization, such as cubes, which could result in reducing the running time of the algorithm even more, since generating a sphere is always more time consuming. Finally, we believe there is an implicit connection between our proposed approach and *fractal mass dimension* that can be quantitatively formulated, revealing information related to non Euclidean characteristics of the regions, such as their self-similarity (fractal) properties.

6. CONCLUSIONS

In this paper we presented an approach for fast and effective characterization of 3D (and 2D) homogeneous and non-homogeneous ROIs. The method, although straightforward, achieves competent classification and retrieval accuracy and compares favorably to alternative methods. Moreover, it is simpler to implement and run. The main idea of the approach is to construct k -dimensional vectors by extracting quantitative fractional volume measurements, using concentric spheres as structuring elements that interact with the ROI. The major contributions of our methodology are:

1. It considers both structural shape information, as well as properties of the internal region (volume) space. Hence, it can be applied effectively both on homogeneous and non-homogeneous ROIs. The extracted signatures can be used to compare the distributions of voxel *density content* among different classes. Other techniques, such as wavelets, Fourier transform and morphology, have been employed mostly for characterizing the shape rather than the region content patterns. On the other hand, techniques such as histograms focus solely on voxel value properties, without taking into consideration neither the voxels' spatial distribution nor the boundary structure of the region.
2. It is applicable both to 2D and 3D region data operating directly on the 3D space without significant computational overhead or loss of the spatial locality information. Other techniques, such as morphology, wavelets and Fourier transform operate either on a 2D basis, or require significant computational overhead in order to operate directly in 3D. When selected to operate on a 2D slice basis in order to analyze 3D data, these techniques fail to preserve the spatial locality of voxels.
3. It is very fast, even up to two orders of magnitude when compared to methods such as mathematical morphology and can be used to enhance retrieval performance in large region data repositories.

We provided evaluation with experiments involving both artificial and real datasets. More specifically, we conducted classification using Neural Networks and similarity searches utilizing the extracted signatures. The overall accuracies were very high, ranging from 90% to 100% for synthetic data and from 73% to 86% for different cases of real data. These results demonstrate that the proposed approach has the ability to efficiently characterize spatial regions. The proposed technique is also more robust and faster, by two orders of magnitude, than mathematical morphology that has been extensively used in this context.

VITAE

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References

1. Smeulders AWM, Worring M, Santint S, Gupta A, Jain R. Content-Based Image Retrieval at the End of the Early Years. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2000;22:1349–1380.
2. A. Pentland, R. W. Picard, S. Sclaroff, Photobook: tools for content-based manipulation of image databases, in *Proc. of SPIE Conf., Storage and Retrieval of Image and Video Databases II*, San Jose, CA, 1994, pp. 34–47.
3. Flickner M, Sawhney H, Niblack W, Ashley J, Huang Q, Dom B, Gorkani M. Query by image and video content: the QBIC system. *IEEE Computer* 1995;28(9):23–32.
4. J. G. Dy, C. E. Brodley, A. C. Kak, C. Shyu, L. S. Broderick, The Customized-Queries Approach to CBIR, in *Proc. of the IS&T/SPIE Electronic Imaging Conf.: Storage and Retrieval for Image and Video Databases VII*, 1999, pp. 3656:22–32.
5. T. Lehmann, B. Wein, J. Dahmen, J. Bredno, F. Vogelsang, M. Kohnen, Content-Based Image Retrieval in Medical Applications: A Novel Multi-Step Approach, in: M. M. Yeung, B-L Yeo, C. A. Bouman (Eds.), in *Proc. of SPIE Storage and Retrieval for Media Databases 2000*, vol. 3972, 2000, pp. 312–320.
6. Megalooikonomou V, Ford J, Shen L, Makedon F, Saykin A. Data mining in brain imaging. *Statistical Methods in Medical Research* 2000;9(4):359–394. [PubMed: 11084713]
7. V. Megalooikonomou, D. Pokrajac, A. Lazarevic, Z. Obradovic, Effective classification of 3-D image data using partitioning methods, in *Proc. of the SPIE 14th Annual Symposium in Electronic Imaging: Conference on Visualization and Data Analysis*, San Jose, CA, 2002, pp. 62–73.
8. R. Weber, M. Mlivoncic, Efficient region-based image retrieval, in *Proc. of the twelfth International Conference on Information and Knowledge Management (CIKM)*, New Orleans, USA, 2003, pp. 69–76.
9. Loncaric S. A Survey of Shape Analysis Techniques. *Pattern Recognition* 1998;31:983–1001.
10. N. Iyer, K. Lou, S. Jayanti, Y. Kalyanaraman, K. Ramani, Three Dimensional Shape Searching: State-of-the-art Review and Future Trends, *Computer Aided Design* (2004) (in press).
11. I.L. Dryden, K. V. Mardia, *Statistical Shape Analysis*, Wiley and Sons, 1998.
12. Zhou Y, Toga A. Efficient skeletonization of volumetric objects. *IEEE Transactions on Visualization and Computer Graphics* 1999;5:196–209.
13. Deseilligny MP, Stamon G, Suen CY. Veinerization: a new shape description for flexible skeletonization. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1998;20:505–521.
14. Pesoon E, Fu K. Shape discrimination using Fourier descriptors. *IEEE Transactions on SMC* 1997;7:170–179.
15. Wallace T, Wintz P. An efficient three-dimensional aircraft recognition algorithm using normalized fourier descriptors. *Computer Graphics and Image Processing* 1980;13:99–126.
16. D. V. Vranic, D. Saupe, 3D Shape Descriptor Based on 3D Fourier Transform, in *Proc. of the EURASIP Conference on Digital Signal Processing for Multimedia Communications and Services (ECMCS 2001)*, Budapest, Hungary, 2001, pp. 271–274.
17. J. Sijbers, T. Ceulemans, D. Van Dyck, Algorithm for the computation of 3D Fourier descriptors, in *Proc. of 16th International Conference on Pattern Recognition*, vol. 2, Quebec City, Canada, 2002, pp. 790–793.
18. Mallat S. A theory for multiresolution signal decomposition: the wavelet representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1989;11:2091–2110.
19. R. M. Rao, A. S. Bopardikar, *Wavelet Transforms: Introduction to Theory and Applications*, Addison Wesley Longman, 1998.
20. Dinggang S, Horace HS. Discriminative wavelet shape descriptors for recognition of 2-D patterns. *Pattern Recognition* 1999;32(2):151–165.

21. Paquet E, Murching A, Naveen T, Tabatabai A, Rioux M. Description of shape information for 2-D and 3-D objects. *Signal Processing: Image Communication* 2000;16:103–122.
22. Hu MK. Visual pattern recognition by moment invariants. *IRE Transactions on Information Theory* 1962;8:179–187.
23. Penn AI, Bolinger L, Schnall MD, Loew MH. Discrimination of MR Images of Breast Masses with Fractal-Interpolation Function Models. *Academic Radiology* 1999;6:156–163. [PubMed: 10898034]
24. B. Mandelbrot, *Fractal Geometry of Nature*, W. H. Freeman, New York, 1977.
25. Maragos P. Morphological skeleton representation and coding of binary images. *IEEE Transactions on Acoustics, Speech and Signal Processing* 1986;34:1228–1244.
26. Korn F, Sidiropoulos N, Faloutsos C, Siegel E, Protopapas Z. Fast and effective retrieval of medical tumor shapes. *IEEE Transactions on Knowledge and Data Engineering* 1998;10:889–904.
27. J. Serra, *Image Analysis and Mathematical Morphology*. Academic Press, New York. 1982.
28. Bangham JA, Marshall S. Image and signal processing with mathematical morphology. *Electronics and Communication Engineering Journal* 1998;10(3):117–128.
29. Sholl D. Dendritic Organization in the Neurons of the Visual and Motor Cortices of the Cat. *Journal of Anatomy* 1953;87:387–406. [PubMed: 13117757]
30. H. J. Karten, P. Kelly, Content-Based Query and Retrieval in Neuroscience Databases <http://www-cajal.ucsd.edu/Pages/Database/ContentBased/contentBased.html>
31. Jacobs GA, Theunissen FE. Extraction of Sensory Parameters from a Neural Map by Primary Sensory Interneurons. *Journal of Neuroscience* 2000;20:2934–2943. [PubMed: 10751446]
32. V. Megalooikonomou, H. Dutta, D. Kontos, Fast and Effective Characterization of 3D Region Data, In Proc. of the IEEE Intl. Conf. on Image Processing (ICIP), Rochester, NY, 2002, pp. 421–424.
33. Jones E, Roydhouse A. Intelligent retrieval of archived meteorological data. *IEEE Expert* 1995;10(6):50–57.
34. Friston KJ, Holmes AP, Worsley KJ, Poline JP, Frith CD, Frackowiak RSJ. Statistical parametric maps in functional imaging: a general linear approach. *Human Brain Mapping* 1995;2:189–210.
35. R. Duda, P. Hart, D. Stork, *Pattern Classification*, John Wiley and Sons, NY, 2000.
36. D. Kontos, V. Megalooikonomou, M. J. Sobel, Q. Wang, An MCMC Feature Selection Technique for Characterizing and Classifying Spatial Region Data, in Lecture Notes in Computer Science 3138, Springer-Verlag, in Proc. of the International Workshop on Syntactical and Structural Pattern Recognition (SSPR 2004) and Statistical Pattern Recognition (SPR 2004), Lisbon, Portugal, 2004, pp. 379–387.
37. M. Eden, A two-dimensional growth process, in Proc. of the Fourth Berkeley Symposium on Mathematics, Statistics and Probability, Berkeley, CA, 1961, pp. 223–239.
38. Saykin AJ, Flashman LA, Frutiger SA, Johnson SC, Mamourian AC, Moritz CH, O’Jile JR, Riordan HJ, Santulli RB, Smith CA, Weaver JB. Neuroanatomic substrates of semantic memory impairment in Alzheimer’s disease: Patterns of functional MRI activation. *Journal of the International Neuropsychological Society* 1999;5:377–392. [PubMed: 10439584]
39. J. Talairach , P. Tournoux , Co-planar stereotaxic atlas of the human brain, Thieme, Stuttgart, 1988.
40. D. Kontos, V. Megalooikonomou, D. Pokrajac, A. Lazarevic, Z. Obradovic, J. Ford, F. Makedon, A.J. Saykin, “Extraction of Discriminative Functional MRI Activation Patterns and an Application to Alzheimer’s Disease”, in: Lecture Notes in Computer Science 3216, Springer-Verlag, in Proc. of the 7th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI), Rennes - Saint- Malo, France, 2004, pp. 727 – 735.
41. R.P.W.Duin, PRTools 4.0, A Matlab Toolbox for Pattern Recognition, 2004 (www.prtools.org).
42. SDC Morphology toolbox for Matlab Version 1.3, 2004 (<http://www.mmmorph.com>).
43. E. R. Dougherty, R.A. Lotufo, *Hands-on Morphological Image Processing*, SPIE Press, 2003.
44. Gallant SI. Perceptron-Based Learning Algorithms. *IEEE Transactions on Neural Networks* 1990;1(2):179–191.
45. K. Fukunaga, *Introduction to Statistical Pattern Recognition*, Academic Press, San Diego, 1990.
46. Chen C, Daponte JS, Fox MD. Fractal Feature Analysis and Classification in Medical Imaging. *IEEE Transactions on Medical Imaging* 1989;8(2):133–142.

Fig. 1.

Examples of 2D and 3D spatial ROIs in medical (brain) and geospatial images: (a) a voxel-based analysis p-value volume for the development of Attention Deficit Hyperactivity Disorder (ADHD), (b) a 2D MRI image showing a brain tumor, (c) a 2D slice from a 3D fMRI volume showing brain activity during cognitive tests, (d) temperature and (e) precipitation contour maps in meteorological images.

Fig. 2. Sholl's analysis of tree-structures: (a) concentric circles radiating out from the root of a dendritic tree to its leaves, (b) number of branches with respect to distance from the root of the tree.

Fig. 3. Extension of Sholl's analysis to (a) regular (i.e., non-tree-like) shapes in 2D and (b) intersecting concentric spheres with a 3D ROI being characterized.

Fig. 4. 2D samples of (a) homogeneous and (b) non-homogeneous ROIs used in the Basic 2-Class datasets, (c) sample ROIs from each of the 5 classes of the Large Scale 5-Class dataset and (d) the corresponding step functions used for generating the ROIs of each class in the Large Scale 5-Class dataset.

Fig. 5. Various example mean temperature images of Arizona (AZ) state for (a) November 1963 and (b) March 1953, indicating the range of variation of spatial patterns within each class.

Fig. 6.

(a) A sample discriminative area selected for applying the proposed characterization technique, shown in consecutive 2D slices on the T1 canonical brain atlas. 2D slices of the actual contrast fMRI ROI for (b) a control and (c) a patient.

Fig. 7. Sample characterization signatures from artificial and real data; (a) the f_s vectors for the 3DHom set, (b) the f_s vectors obtained for radius increment of 2 for the Meteorological data and (c) the f_s vectors for a ROI selected from the fMRI dataset (*IMPREC* cognitive test).

Fig. 8.

Euclidean distances based on the f_r feature vectors between (a) a spherical query ROI, (b) an elongated query ROI and all the ROIs of the 2DHom dataset. Euclidean distances based on the f_s feature vectors and (c) a north-elongated ROI, (d) a north-south-elongated ROI and all ROIs of the 2DNonHom dataset. Corresponding morphological distances (e), (f), (g), (h), for the same query ROIs and datasets. In all cases the horizontal axis refers to the 100 ROIs in each set. The first 50 ROIs belong to the one class and the remaining 50 ROIs to the other class (two classes in each set). The vertical axes correspond to the calculated distance.

Table 1
The outline of the algorithm for characterization of a 3D ROI

Algorithm Characterize_3D_ROI
<p>Input: ROI Θ formed by voxels v Θ center of mass m initial radius r_0 constant radius increment inc total number of features k</p> <p>Output: Feature vectors f_s and f_r $r = r_0$ # initialization of radius</p> <p>if Θ is homogeneous # calculate the total ROI volume (number of voxels that form Θ) TotalROIVolume = $N_{\Theta}(m, r_k) = \{v \in \Theta\}$ else TotalROIVolume = $N_{\Theta}(m, r_k) = \sum_i density_content(v_i), v_i \in \Theta$ end</p> <p>for $i = 1, \dots, k$ # repeat for total number of features $S_i = CreateSphere(m, r)$ # create a sphere with m as center and r as radius TotalS_iVolume = $N_{S_i}(m, r) = \{v_{sphere} \in S_i\}$ # number of voxels that form the <i>sphere</i> $R = \Theta \cap S_i$ if Θ is homogeneous $N_{\Theta}(m, r) = \{v_i \in R\}$ else $N_{\Theta}(m, r) = \sum_i density_content(v_i), v_i \in R$ end</p> <p>$f_s(i) = \frac{N_{\Theta}(m, r_i)}{TotalS_iVolume}$ $f_r(i) = \frac{N_{\Theta}(m, r_i)}{TotalROIVolume}$ $r = r + inc$ # increase radius by a standard increment</p> <p>end</p>

Table 2

Classification accuracies and standard deviations (in parenthesis) averaged over 40 repetitions for the Basic 2-Class sets using the f_r vectors

Dataset	Classification Accuracy (<i>Standard Deviation</i>)		
	60 %	Training set size 70 %	80 %
2DHom	98.25 % (0.022)	98.33 % (0.027)	98.87 % (0.021)
2DNonHom	98.56 % (0.027)	98.25 % (0.023)	98.12 % (0.033)
3DHom	99.56 % (0.009)	99.75 % (0.008)	99.75 % (0.011)
3DNonHom	98.25 % (0.079)	99.66 % (0.010)	99.25 % (0.024)

Table 3

Classification accuracies and standard deviations (in parenthesis) averaged over 35 repetitions for the Large Scale 5-Class dataset using the f_r vectors and the back-propagation algorithm

Dataset	Classification Accuracy (<i>Standard Deviation</i>)		
	60 %	Training set size 70 %	80 %
<i>Large Scale 5-Class</i>	89.54 % (<i>0.043</i>)	97.68 % (<i>0.012</i>)	94.97 % (<i>0.030</i>)

Table 4

Similarity retrieval precision (%) for different number of similar ROIs retrieved (Large Scale 5-Class dataset)

	Precision for similarity retrieval Objects Retrieved				
	100	200	300	400	500
Query ROI for Class 1	100.00%	100.00%	100.00%	90.50%	78.60%
Query ROI for Class 2	100.00%	92.00%	80.67%	69.75%	59.40%
Query ROI for Class 3	100.00%	88.50%	65.67%	52.25%	45.40%
Query ROI for Class 4	100.00%	100.00%	99.33%	83.75%	72.20%
Query ROI for Class 5	100.00%	98.00%	74.33%	60.25%	50.80%

Table 5

Classification results for the 2D Meteorological dataset

Radius Increment	Number of Features	Type of Signature	Classification Accuracies Training Set Size		
			60%	70%	80%
2	150	f_r	81.24 %	86.43 %	86.29 %
		f_s	80.86 %	83.71 %	86.00 %
5	60	f_r	81.81 %	84.43 %	84.86 %
		f_s	81.90 %	85.86 %	86.29 %
10	30	f_r	81.62 %	84.43 %	85.43 %
		f_s	83.33 %	85.14 %	85.71 %

Table 6

Classification results using the signatures extracted from the fMRI ROIs of the Alzheimer dataset

ROI Type	Radius Increment (number of features)	Control	Classification Accuracy		Total
			Patient		
CATF ROI p-value = 7.8157e-004	0.5 (20 features)	72.38 %	74.29 %		73.33 %
	0.2 (50 features)	73.97 %	76.83 %		75.40 %
CATF ROI p-value = 0.0045	0.5 (22 features)	81.59 %	77.78 %		79.68 %
	0.2 (56 features)	77.14 %	73.33 %		75.24 %
CATX ROI p-value = 0.0012 & 0.0025	0.5 (16 features)	82.54 %	86.03 %		84.29 %
	0.2 (40 features)	83.49 %	85.08 %		84.29 %
IMPREC ROI p-value = 0.0036	0.5 (8 features)	76.83 %	87.94 %		82.38 %
	0.2 (20 features)	77.78 %	88.25 %		83.02 %
IMPREC ROI p-value = 0.0012	0.5 (6 features)	73.97 %	84.44 %		79.21 %
	0.2 (15 features)	74.60 %	84.13 %		79.37 %
NONPR ROI p-value = 7.4204e-004	0.5 (12 features)	78.10 %	67.62 %		72.86 %
	0.2 (30 features)	78.41 %	68.89 %		73.65 %
NONPR ROI p-value = 7.4430e-004	0.5 (8 features)	69.84 %	88.89 %		79.37 %
	0.2 (20 features)	73.65 %	88.89 %		81.27 %