

Medical Image Analysis Through A Texture Based Computer Aided Diagnosis Framework

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Abstract

Current medical imaging scanners allow to obtain high resolution digital images with a complex informative content expressed by the textural aspect of the membranes covering organs and tissues (hereinafter objects). These textural information can be exploited to develop a descriptive mathematical model of the objects to support heterogeneous activities within medical field. This paper presents a framework based on the texture analysis to model the objects contained in the layout of diagnostic images. By each specific model, the framework automatically also defines a connected application supporting, on the related objects, different targets, such as: segmentation, mass detection, reconstruction, and so on. The framework is tested on MRI images and results are reported.

Keywords: Medical Imaging, Texture Analysis, Pattern Recognition, Feature Extraction, Framework, Classification, Segmentation, CAD.

1. INTRODUCTION

Current medical imaging scanners, as Magnetic Resonance Imaging (MRI), Position Emission Tomography (PET), or Computer Tomography (CT), allow to obtain digital images with high level detail having a complex informative content that goes beyond the simple visual representation. By observing the relationships between clusters of pixels (i.e., the texture) of the membranes covering objects, meaningful features can be derived to describe the morphological structures of the objects themselves. These features (i.e., textural information) are exploited to develop mathematical models of the objects to support different activities within medical field.

In the last years, there have been many efforts to conceive intelligent and automated systems to support critical diagnostic tasks (e.g., analysis, masses identification). Current Decision Support Systems (DSSs), better known as Computer Aided Diagnosis (CAD) systems, are still not completely effective tools. There is an extensive literature focused on the different aspects of the medical image processing. A first remarkable image analysis approach is shown in [1], where the authors describe an automatic segmentation framework, for brain MRI, based on the combination of atlas registration, fuzzy connectedness segmentation, and parametric bias field correction. Another work that has supported some aspects related to the textural image filters is detailed in

[2], presenting a novel co-occurrence matrices based approach to discriminate textures belonging to different kinds of images by considering statistical representation of the structural texture primitives (i.e., textons). Another useful approach is presented in [3], where an approach to automate the myocardial contours detection, to optimize detection and tracking of the grid of tags within myocardium, is described. A further interesting work, [4], presents a real mixed statistical model based on a region-driven curve evolution algorithm. An original approach is described in [5], presenting a novel algorithm to achieve automatic texture based segmentation of organs in MRIs of the abdomen. A robust multi-resolution statistical shape model algorithm is detailed in [6]. A last meaningful paper [7], explores the use of the co-occurrence matrixes to extract textural features from medical images. These approaches are based on several principles related to the image understanding, but there are no works to exploit the morphological structure (given by the texture analysis) of the objects with the aim to provide both their descriptive mathematical model and related dedicated *Texture based Computer Aided Diagnosis (T-CAD)* Framework.

This paper presents some basic technical and methodological advancements of our developed T-CAD Framework which was implemented to perform the texture analysis and reconstruction activities of brain MRI images [8]. These improvements are based on a conceptual generalization of our previous experiences in mathematical modeling of the brain [9], [10] and [11]. More specifically, in this paper we detail the restyled ability of our T-CAD Framework which, on one side, supports the mathematical modeling process of each object represented inside the image layout and, on the other hand, automatically defines, for each model, an ad-hoc application to support a set of fixed targets to aid the medical specialist in a specific context (e.g., craniopharyngioma identification on brain MRI images). Observe that each mathematical model (e.g., craniopharyngioma model) computed during the modeling process is defined one and for all. The effectiveness of the restyled approach is shown both on experimental data (MRI images) and on ad-hoc model-driven applications.

The paper is organized as follows. Section 2 illustrates the main architectural aspects of the described T-CAD Framework. Section 3 introduces and discusses the main experimental results, highlighting a specific case study. Section 4 presents the conclusions and plans the future work.

2. THE T-CAD FRAMEWORK ARCHITECTURE

The developed T-CAD Framework is a smart tool that allows skilled user to define a texture based *Mathematical Model* (MM) of each object represented inside a cluster of diagnostic images representing a volume (in this case, the application is relative to MRI images). A specific MM (e.g., of the brain) is simply the set of formalized mathematical classes representing different basic objects contained in the related image (e.g., cerebral tissue, abnormal mass, background). For each MM the framework supports the building of a dedicated T-CAD system to support a specific medical image analysis process (e.g., image segmentation and mass recognition). The next two sub-sections show the general approach, and the main textural filters used within the framework, respectively.

2.1 The Region Based Algorithm

The *Region Based Algorithm* (RBA) represents the core of the T-CAD Framework. Actually, its main aspect regards the building of the mathematical classes constituting a specific MM, as the dedicated system generation is only a technical application of the related MM on a dataset of source images. For this reason, the definition of the MM will be first detailed, and finally the system generation process will be described. Figure 1 shows the basic architecture of the RBA.

The *first panel* (MRI Scanner and DBs) highlights that the framework works on two kinds of databases (DB). The first (**TR**aining-**DB**) is used when the skilled user has to build a new MM. For this reason, the population of the TR-DB follows a rigid protocol which has to ensure the fulfillment of different qualitative and quantitative requirements relatively to the informative content of the related images. The second (**SouR**ce-**DB**) points out that, once obtained the related MM, it is possible to analyze each kind of source image coming directly from the MRI scanner.

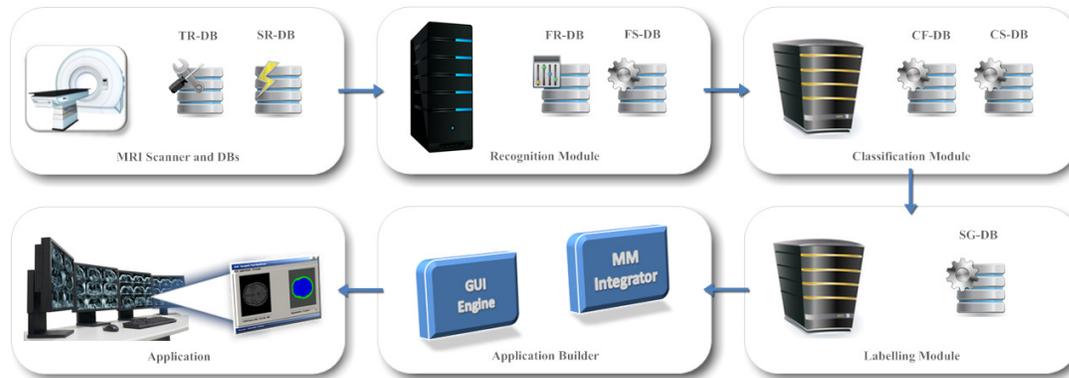


FIGURE 1: Region Based Algorithm Architecture.

The **second panel** (Recognition Module) highlights the recognition process on each image belonging to the TR-DB, where an adaptable elaboration window runs across the image to perform a feature extraction process based on a suitable set of textural filters (i.e., features vector). It is divided in two steps, the first one, supported by two specific filters, **Entropy** and **Homogeneity** (see next sub-section), is to fix the window size both to maximize the number of image zones with high entropy levels and to minimize the number of neighboring heterogeneous zones. The second step is to exploit the found fixed window to analyze, by the features vector (filters are stored in the **Filter-DB**), each image area (in top-bottom and left-right way). For each image the analysis produces a feature map, the set of feature maps defines a feature space (stored in the **FeatureSpace-DB**) that, suitably interpreted, provides the mathematical class of each chosen basic object. In fact, by analyzing the correlation related to all feature spaces of each basic object, a preliminary mathematical model of everyone can be defined. Here, there is the main innovation of the current framework with respect the old one. In the first release of the framework the building of the feature space and the comparison between them were performed in supervised-way. This means that a skilled user followed the whole process, supported by analytical tools (e.g., histograms, statistical computational), to manually define feature maps and spaces. In the current version we have implemented a machine-learning like approach to automatically build them. In a first phase the approach builds the feature maps refining the values extracted by each zone image. The first obtained measurements fix the interval of values of a map (according to a specific filter), each new measurement limits or expand the previous interval. When particular values are computed in less than 15% of the available image areas these values are discarded to avoid introducing noise within the map creation process. Afterwards, the exhaustive comparison of each different preliminary model allows to find the textural relationships to univocally describe each basic object. This description is the MM, which can be considered as the set of the mathematical classes defining itself. Also this aspect has been changed in this last release where a semi-automatic mechanism has substituted a whole skilled user based approach. In particular, the implemented method automatically compares the preliminary models highlighting the overlap of intervals (if any). In this case the skilled user can decide to follow or not the indications of the monitoring system. Note that the described process only occurs when a skilled user wants to build a new MM.

The **third panel** (Classification Module) points out the classification process which uses the MM found in the previous module (and stored in the **ClassFormat-DB**) to analyze the source images coming from the MRI scanner (SR-DB). This process follows the same approach shown in the recognition module, but its purpose is to classify any zone of each source image according to a selected MM. The module works following two different steps. During the first, any image zone is analyzed (by using the mentioned elaboration window) to classify it according to one of the formalized mathematical classes belonging to the related MM. Afterwards, homogeneous image zones are suitably marked and merged. During the second step the module assigns to one of the

formalized classes, by a statistical distribution algorithm, the remaining zones that have been not classified at all. Each classified image is stored in a new database (**ClasSified-DB**).

The **fourth panel** (Labelling Module) highlights the labelling process where every classified source image is properly labelled to provide an immediate visual impact to the user. Each segmented image is arranged in a suitable database (**SeGmented-DB**).

The **fifth panel** (Application Builder) points out the ad-hoc application builder. In particular, the MM Integrator includes the definition of the selected MM inside the application. Observe that the framework allows user to include more than one specific MM. The GUI Engine highlights that the main mechanisms related to the data presentation (e.g., visualization engine, interaction properties) are the same independently from the specific application.

The **sixth panel** (Application) shows an example of a created application. In this case it is referred to the segmentation of a MRI image of the brain.

2.2 Textural Image Filters

The image filters adopted to support the RBA have been suitably chosen and/or created to define the basic textural informative content of the objects composing the human body. Actually, our strong belief is to have found a general approach adoptable for every object represented by MRI images, which, at the moment, has been refined to define the textural morphological structures of four specific objects: brain, heart, liver and bones. Our approach divides the image filters into three different graphical classes, each able to characterize a specific informative layer of the mentioned objects: **informative class**, **texture class** and **pattern class**.

The **informative class** is composed by those first order statistic image filters which distinguish between zones with and without relevant information content. In our experience, the following two set of filters represent the main best suitable ones: *N-Order Moment* (M_{n_1}) and *N-Order Central Moment* (C_{n_2}):

$$M_{n_1} = \sum_{i=0}^N i^{n_1} \cdot p(i), C_{n_2} = \sum_{i=0}^N (i - M_{n_1})^{n_2} \cdot p(i) \quad (1)$$

where: $p(i)$ represents the probability that the gray level i appears inside the elaboration window. The following constraints must hold:

$$0 \leq p(i) \leq 1 \forall i \in [0..255] \subset \mathbb{N}, \sum_{i=0}^N p(i) = 1, n_1, n_2 \in \mathbb{N}, N = 255 \quad (2)$$

M_{n_1} and C_{n_2} measure respectively, on different textural graphical layers, the consistent quantity and the semantic readability of the information related to different image zones.

The **texture class** is composed by those second order statistic image filters measuring macro and micro textural structures. Our empirical studies allowed to detect the following four set of filters: *Homogeneity* ($Hg(d)$), *Contrast* ($Ct(d)$), *Inverse Difference* ($Id(d)$) and *Entropy* ($En(d)$):

$$Hg(d) = \sum_{i=0}^N \sum_{j=0}^N [p_d(i, j)]^h, Ct(d) = \sum_{i=0}^N \sum_{j=0}^N |i - j|^k \cdot [p_d(i, j)]^l \quad (3)$$

$$Id(d) = \sum_{i=0}^N \sum_{j=0}^N \frac{[p_d(i, j)]^m}{1 + (i - j)^s}, En(d) = - \sum_{i=0}^N \sum_{j=0}^N p_d(i, j) \cdot \log_n(p_d(i, j)) \quad (4)$$

where: $p_d(i,j)$ represents the probability that two points with distance d have respectively i and j gray value. The following constraints must hold:

$$0 \leq p_d(i, j) \leq 1 \forall (i, j) \in [0..255] \times [0..255] \subset \mathbb{N}^2 \quad (5)$$

$$\sum_{i=0}^N \sum_{j=0}^N p_d(i, j) = 1, d \in [1..8] \subset \mathbb{N}, h, k, l, m, n, s \in \mathbb{N}, N = 255 \quad (6)$$

$Hg(d)$ measures the degree of uniformity of the different image zones, where high or low values within the feature maps highlight light or wide changes of the textural structures, respectively. $Ct(d)$ expresses roughly how the mentioned structural changes occur. High values of the related feature maps, point out fast continuous changes within the image zones. On the contrary, slow changes are highlighted by low values. $ld(d)$ provides the measure of the transition between different basic objects, where low values typically highlight a boundary zone. $En(d)$ is used to detect the randomness level within the considered image zone, where the complex changes in the random distribution of the grey levels are directly proportional to the given values.

The **pattern class** is composed by those second order statistic image filters measuring pattern structures. Experimental observations allowed to identify the following two set of filters: *Correlation* ($Cr(d)$) and *Difference Entropy* ($De(d)$):

$$Cr(d) = \sum_{i=0}^N \sum_{j=0}^N \frac{(i - \mu_x) \cdot (j - \mu_y) \cdot p_d(i, j)^p}{(\sigma_x \cdot \sigma_y)^a}, De(d) = - \sum_{i=0}^N p_{x-y}(i) \log_n [p_{x-y}(i)] \quad (7)$$

where:

$$\mu_x = \sum_{i=0}^N \sum_{j=0}^N i \cdot (p_d(i, j)), \sigma_x = \sqrt{\sum_{i=0}^N \sum_{j=0}^N (i - \mu_x)^2 \cdot (p_d(i, j))} \quad (8)$$

$$\mu_y = \sum_{i=0}^N \sum_{j=0}^N j \cdot (p_d(i, j)), \sigma_y = \sqrt{\sum_{i=0}^N \sum_{j=0}^N (j - \mu_y)^2 \cdot (p_d(i, j))} \quad (9)$$

and, in addition to the constraints shown in (5) and (6), the following ones must hold:

$$p_{x-y}(k) = \sum_{i=0}^N \sum_{j=0}^N [p_d(i, j)]^g, |i - j| = k, p, a, n, g, k \in \mathbb{N} \quad (10)$$

$Cr(d)$ is usually used to recognize definite patterns within texture zones previously identified, while the $De(d)$ is adopted to detect the different components (i.e., parts of a same pattern) of different basic objects.

Each class of filters is based on the variation of the current co-occurrence matrix concept, where the elaboration process considers all the search directions. In particular, each couple of pixels, able to increase a coefficient of the matrix, is chosen considering a pixel (i.e., the center of a circle) within the elaboration window and the connected pixel which is at the boundary of the circumference related to the fixed radius (i.e., the d parameter). The parameters belonging to the set of filters are customized, within the recognition process, according to the specific contextual medical domain and related tasks. Besides, the shown filters are often used on more than one level of the Gaussian Pyramid [12] to enrich the resolution of the texture described by the MMs.

3. EXPERIMENTAL RESULTS AND A CASE STUDY

This section summarizes the experimental results regarding the analysis of MRI images of different body districts: brain, heart, liver and bones. To explain the experimental session, the following three general tasks have been selected according to the present medical image analysis process: *task 1* - layout segmentation, *task 2* - abnormal mass or lesion detection, *task 3* - textural characterization.

Table 1 reports the experimental session which has been divided in two different phases. The first, regarding MRI image recognition, has concerned the selection of patients (455) to define the set of training images (1850) and to build the four basic MMs. The second, regarding the MRI image classification and segmentation, has concerned the selection of patients (615) to obtain a set of images (2565) to test each MM on the mentioned tasks.

Medical Domain	Training Patients	Testing Patients	Training DB Images			Source DB Images			Partial Images
			Task 1	Task 2	Task 3	Task 1	Task 2	Task 3	
Brain	270	385	450	680	60	975	775	40	2980
Heart	75	100	150	80	35	170	100	25	560
Liver	60	80	70	100	30	135	90	20	445
Bones	50	50	70	85	40	100	100	35	430
Total Images	-----	-----	740	945	165	1380	1065	120	4415

TABLE 1: Main Case Studies: Training and Source DB.

Actually, the best qualitative results (more than 90% of success rate) come from the brain MM which has a large amount of training and test images. Moreover, it has been our historical first study case. Also the remaining three models have a high success rate (between the 65% and 80%), but they need for wider experimental sessions. In fact, the accuracy of the MM is strongly tied to the amount of training images used to refine the mathematical classes.

To show more details about a specific segmentation process next sub-section shows a case study regarding the segmentation of the brain images.

3.1 Case Study: MRI Brain Images

This section shows a concrete case study in which a suitable mathematical model is defined according to specific targets, and where a model-based application is created to support the related image analysis process. Actually, the framework produces the same application in which only the mathematical model is replaced each time.

The morphological structures of objects are very different, each of them can be better emphasized according to a specific kind of MRI image (e.g., T_1 , T_2 , Proton Density (PD)). For this reason, a brief specification of the DICOM (Digital Imaging and Communication in Medicine) image format is given in relation to a specific case study.

The *Brain Mass Identification* (BMI) application has been created to aid medical specialists during the mass identification within the brain MRI images. In particular, the following targets were established:

- a. **segmentation** of the image layout in three basic objects: cerebral tissue, rest of the image (i.e. muscular and bones) and background;
- b. **identification** within the cerebral tissue of abnormal masses (e.g., gliomas, craniopharyngiomas, medulloblastomas);
- c. **classification** of the found abnormal masses distinguishing them from other kinds of primary cerebral tumors.

A careful analysis of the set of pixels composing brain MRI images detected in the transversal T_1

weighted the more suitable ones to better highlight the textural morphological structures of the objects, according to the fixed targets. Table 2 shows the main technical features of the images.

Main Technical Features	Resolution		Category		Pre-Processing		Scanning Anatomic Plan
	Spatial	Gray Scale	Primary Type	Secondary Types	Local Application	Global Application	
MRI Brain Images	512x512	256 (8 bit)	T1 (weighted and not weighted)	T2 and PD (weighted and not weighted)	Anti-Spurious Filter	Anti-Aliasing Filter	Transversal

TABLE 2: MRI Brain Images: Main Technical Features.

Images belonging to the others categories have been used to refine and optimize the textural feature extraction methodology. Table 2 also shows that two different kinds of pre-processing filters have been applied on the related source images to normalize the original gray levels. The mentioned filters do not alter the quality of the original source image, they are used to improve the image zones affected by lack of information (i.e., localized noise).

The two screenshots reported in Figure 2 point out the segmentation process of the BMI application on two MRI brain images. In particular, the first screenshot (left) shows an image in which the three layers related to basic objects are found. The second one (right) highlights the recognition of four layers where an abnormal mass classified as craniopharyngioma it is also identified.

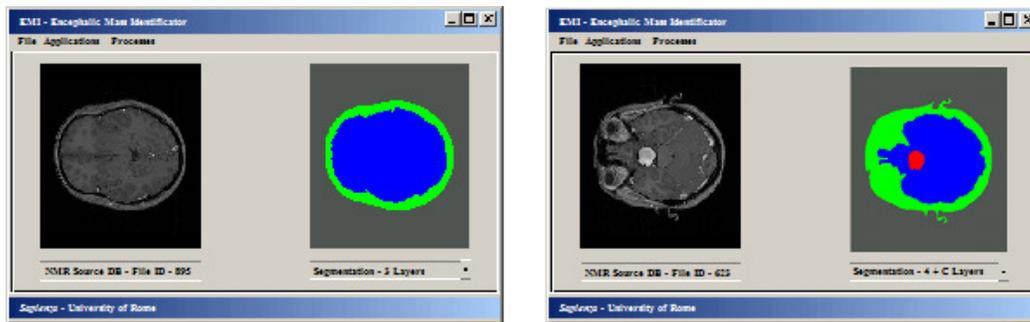


FIGURE 2: BMI Application: Segmentation Results.

The abnormal mass identification has required, first, the construction of the Abnormal Mass Mathematical Model (AB-MM) (see [9] for the model), and then the construction of the Craniopharyngioma Mathematical Model (CPH-MM) (see [10] for the model). These two models have been used to build the recognition engine of the BMI application.

Note that the MMs, on one side, define the formalized mathematical classes to represent the basic objects. On the other hand, they support a first step inside the 3D reconstruction and rendering environment. In fact, the provided classes have an exhaustive informative content. A skilled user can already exploits the mathematical classes on different anatomic scanning plans to infer complex information, one of our next steps is to implement a visual 3D rendering engine.

4. CONCLUSION AND FUTURE WORK

This paper describes the main aspects of an innovative T-CAD Framework, that exploits textural information that covers organs and tissues, tested within the MRI context. The skilled user, once established both the contextual medical domain (e.g., brain analysis) and the specific task (e.g., craniopharyngioma recognition) can build the related MM (i.e., the set of suitable mathematical classes) to describe the basic objects (i.e., cerebral tissue, rest of the image, abnormal masses, craniopharyngioma and background) useful to the achievement of the required task (i.e., craniopharyngioma recognition on any compatible image dataset). To achieve the task, the framework allows user to create a suitable application based on the related MM. Note that each

MM is defined once and for all. At the moment, our main work is to refine the MM of the following organs and tissues: brain, heart, liver and bones. Another goal is the development of a rendering engine to renderize and visualize 3D objects reconstruction.

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