Visual and Semantic Similarity of Medical Image

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Abstract: This paper is a part of a complex study for automatic detection of medical image diagnostic. Thus, a method based on fuzzy clustering model is developed for medical image segmentation. At the end of this process, an image is represented as a collection of color regions and the visual features are mapped to semantic indicators. After that, the semantic rules are learned by applying the Apriori algorithm on a collection of diagnosed medical images. The experiments were realized on a medical database, which contains images obtained through different medical proceedings: endoscopy, radiology, magnetic resonance imaging etc.

Keywords: Image recognition, image segmentation, image color, image texture, image clustering.

1. INTRODUCTION

In medical domain, the physicians have to make feasible judgments on the diagnoses of patients by analyzing images offered by different technologies: endoscopy, radiology, magnetic resonance, etc. Therefore, strong methods are needed to support the physicians in making diagnosis decisions by dividing patients into different categories of risk.

Medical image content representation and retrieval is playing an increasing role in a large sphere of applications within the clinical process (Muller et al., 2004; Greenspan et al., 2007). For the clinical decision-making process it can be beneficial or even important to find other images of the same modality, the same anatomic region or the same disease.

Thus, a lot of researches were developed to investigate automated techniques for extracting the low-level features that could generate semantic descriptions of the medical image content. Among these techniques are the methods based on machine learning that manually annotate the test image datasets. Algorithms that recognize specific organs with different structures of the medical images are studied in (Hong et al., 2006). FIRE (Deselaers et al., 2004) application and IRMA (Lehmann et al., 2004) use with good results the sub-symbolic processing of images. Though, the actual methodologies of medical image analysis are not generically sufficient for interpreting different diseases. Their major problems are:

--The description of semantic concepts and the problem understanding-the relationships between the low-level features and semantic concepts are unclear in the actual developed methods. So detailed tests and analysis have to be realized to ensure which combinations of low-level features capture the best the semantic concepts.

--The generality of the application-in some of the previous researches, only certain semantic concepts could be learned, or the rule were generated of a fixed set of visual features.

The medical applications with automatic diagnosis capacity imply unique challenges, but at the same time new opportunities. In some way we understand an image from nature and in another way a medical image, if we are not physicians. On the other hand, there are a lot of formal representations of the medical knowledge that could be exploited to realize the automation of the medical diagnosis in any medical domain.

Also, in the medical domain, taxonomies, thesaurus and ontology were developed, varying from the general target, like UMLS (Bodenreider, 2004), SNOMED CT (Stearns et al., 2001), to the specific ones, like FMA (Rosse et al., 2003) for anatomy, RadLex (Langlotz, 2006) for radiology, and AIM (Rubin et al., 2009) is a new project developed at Stanford University.

The success of methods for medical image diagnosis depends on the quality of segmentation process, feature selection and rules generation. So, the objective of the current work is to improve the performance of existing approaches in the diagnosis of medical images. The first step of this complex study is the segmentation of medical images and computation of low-level features. The second step is the generation of semantic rules capable to identify diagnosis and the third step is the classification of new undiagnosed images.

2. FEATURE COMPUTATION AND MAPPING

From our experience we deduce that semantic concepts are very important for establishing image similarity (Ion, 2010). Although the semantic concepts are usually not directly related to the visual image features (color, texture, shape, position, dimension, etc.), these attributes capture information about the semantic meaning. Various low-level image features were tested for establishing their correlation with semantic categories. So, each semantic category is translated into computed image low-level features (Ion et al., 2010).

2.1 Image Segmentation by Color

A set of dominant colors for an image offers a compact description easy to be indexed. The image colors are clustered into a small number of representative colors. Before image clustering, the image is transformed from RGB color space to HSV color space. The image is described by a set of regions, one region for each dominant color. Each region is associated to a descriptor, which contains the color, the pixels percent, the spatial coherency, and the position of region centroid:

$$F= \{(c_i, p_i, s_i)\},$$

where i=1, 2,.., N, c_i is the color of the i region, p_i is the color percent of i region, s_i is the region spatial coherency.

The spatial coherency is a number that represents the spatial homogeneity of the dominant color in image. It is computed by identifying the pixels with the same color connected in groups, using four-connectivity. The number of dominant colors can vary from one image to other, and maximum 8 dominant colors are sufficient to represent an image.

The method we used for extracting the dominant colors is based on Fuzzy C-means clustering algorithm. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters (Bezdek, 1981). It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \qquad (1)$$

where m > 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i-th of d-dimensional measured image pixel, c_j is the d-dimension center of the cluster, and ||*|| is the Euclidian distance expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} as in (2) and the cluster centers c_j as in (3):

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \qquad (2)$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \qquad (3)$$

This iteration will stop, when $\max_{ij}\{\left| u_{ij}^{k+1} - u_{ij}^{k} \right|\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

The algorithm is composed of the following steps:

1. *Initialize $U=[u_{ij}]$ matrix, $U^{(0)}$*
2. *At k-step: calculate the centers vectors $C^{(k)}=[c_j]$ with $U^{(k)}$*

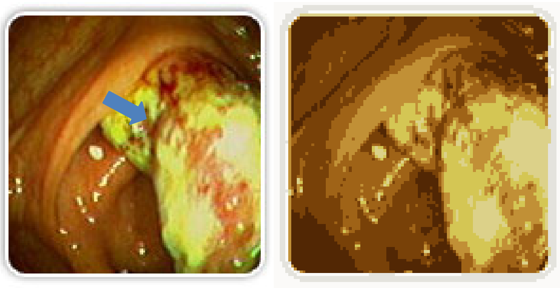
$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \qquad (4)$$

3. *Update $U^{(k)}$, $U^{(k+1)}$*

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \qquad (5)$$

4. *If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then STOP; otherwise return to step 2.*

The following figure illustrates the process of color image segmentation on medical image. The image from Figure 1 shows an advanced cancer in the right colon (Gastroenterology, 2010) and the sick region come in different yellow and brown hues. The segmentation results on this image can be observed in Figure 1.



(a) (b)

Fig.1. Results of segmentation on an image diagnosed with colon cancer: (a) Original image; (b) Image segmented with 8 regions

2.2 Region Texture

The texture is another feature that is taken into consideration for classifying and recognizing the material surfaces. A lot of descriptors are used for texture analysis. In this paper, we use the method based on co-occurrence matrices. The co-occurrence matrix is based on repeated occurrence of some configurations of pixels intensity in the image. These configurations vary with rapidity for thin texture and slower for roughly texture. The co-occurrence matrices can describe the occurrences of these intensity configurations, and in the case of color images, a matrix was computed for the index color of region.

The classification of texture is based on the characteristics extracted from the co-occurrence matrix (Udristoiu et al., 2010).
The vector of texture characteristics extracted from the co-occurrence matrix is created using 6 characteristics.

- The *maximum probability* detects the most frequent motif
- The *energy* describes the uniformity of the texture. In a homogeneous image, there are very few dominant grey-tone transitions; hence the co-occurrence matrix of this image will have fewer entries of large magnitude. So, the energy of an image is high when the image is homogeneous.
- The *entropy* measures the randomness of the elements in the matrix, when all elements of the matrix are maximally random, entropy has its highest value. So, a homogeneous image has lower entropy than an inhomogeneous image. In fact, when energy gets higher, entropy should get lower.
- The *contrast* is bigger for images with big contrast.
- *Cluster shade and Cluster prominence*: are measures of the skewness of the matrix, in other words the lack of symmetry. When cluster shade and cluster prominence are high, the image is not symmetric. In addition, when cluster prominence is low, there is a peak in the co-occurrence matrix around the mean values, for the image this means that there is little variation in grey-scales.
- *Correlation:* measures the correlation between the elements of the matrix. When correlation is high the image will be more complex than when correlation is low.

2.3 Region Shape

Shape is an important characteristic of an object. The goal of shape descriptors is to uniquely characterize the object shape. Two shape descriptors are used in our experiments:

- Eccentricity is the length ratio between the major and minor axes of the objects; smaller for rounded shapes and greater for distorting ones.
- Compactness is the ratio between the length of object's boundary and the object's area.

Because these two shape descriptors are developed from different rationales, we also use the combination of these features to do classification. We argue that they will complement one another and provide better performance than only using each of them.
In conclusion, the following visual features represent each region:

- The color of region– F1
- The region spatial coherency-F2
- The texture described by the vector of 6 features –F3
- The region area that represents the number of pixels (dimension) – F4
- The centroid coordinates on vertical (F5) and horizontal (F6) axis
- The region shape – F7

To map the mathematical values of the visual features, a vocabulary based on the concepts of semantic indicators is developed as in Figure 2. A syntax, which captures the basic models of human perception about patterns and diagnoses, is also developed.
The representation language is simple, because the syntax and vocabulary are elementary. The language elements are limited to the name of semantic indicators. Being visual elements, the semantic indicators and their values are: color (color-light-red), spatial coherency (spatial coherency-small, spatial coherency-medium, spatial coherency-big), texture (energy-small, energy-medium, energy-big, etc.), dimension (dimension-small, dimension-medium, dimension-big, etc.), position (vertical - upper, vertical - center, vertical - bottom,

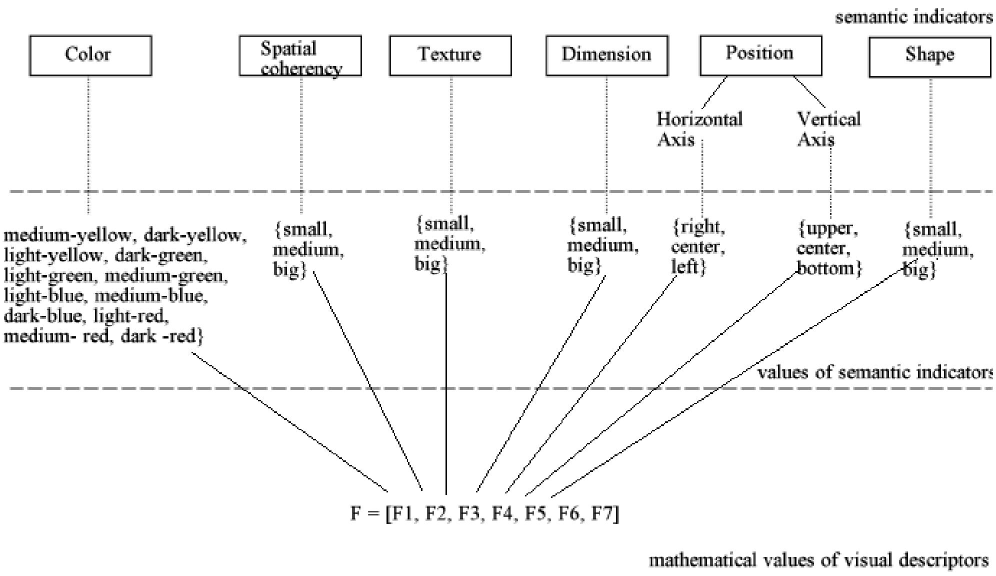


Fig. 2. Vocabulary Definition: mapping low level descriptors values to intermediate level descriptors values

horizontal-left, a.s.o.), shape (eccentricity-small, compactness - small, a.s.o.).

The values of each semantic indicator are mapped to a value domain, which corresponds to the mathematical descriptor. The syntax is represented by the model, which describes the images in the terms of semantic indicators values (Ion et al., 2010).

An image is represented in Prolog by means of the terms of form *figure(ListofRegions)*, where *ListofRegions* is a list of image regions.

The term *region(ListofDescriptors)* is used for image region representation, where the argument is a list of terms used to specify the semantic indicators. The term used to specify the semantic indicators is of form:

descriptor(DescriptorName, DescriptorValue).

The mapping between the values of low-level (mathematical) descriptors and the values of semantic indicators is based on experiments effectuated on images from different categories and the following facts are used:

mappingDescriptor(Name,SemanticValue,ListValues).

The argument *Name* is the semantic indicator name, *SemanticValue* is the value of the semantic indicator, *ListValue* represents a list of mathematical values and closed intervals, described by the following terms:

interval(InferiorLimit, SuperiorLimit).

The mapping mechanism has the following Prolog representation:

```
mapDescriptor(descriptor(Name,MathematicalValues),
descriptor(Name, SemanticValue)):-
mappingDescriptor(Name,SemanticValue,ListValues),
containValue(ListValues, MathematicalValue).

containValue([Value|_], Value).
containValue([interval(InferiorLimit,SuperiorLimit)|_],
Value):- InferiorLimit=<Value,Value=< SuperiorLimit.

containValue([_|ListValues], Value):-
containValue(ListValues, Value).
```

3. RULE BASED MEDICAL DIAGNOSIS

The component for medical image diagnosing includes the generation of semantic rules that discover the information about the sick regions that are frequent.

For this target, a medical image database, *DB*, is considered. The set $U = \{S_1,\ldots,S_n\}$, a subset of *DB*, which contains diagnosed image-examples, is used to train the system and generate semantic rules. A semantic rule determines the set of semantic indicators, which identify a diagnosis and has the form:

semantic indicators→ diagnosis

The learning process is resumed to the following steps:

- relevant images for each diagnosis are used for learning it.
- each image is automatically processed and segmented and the primitive visual features are computed.
- the primitive visual features of images are mapped to semantic indicators.
- the rule generation algorithms are applied to produce rules, which will identify each diagnosis from the database.

The algorithm for semantic rules generation is based on Apriori algorithm of finding the frequent itemsets (Udristoiu et al., 2010).

The scope of image association rules is to find semantic relationships between image objects. To generate association rules that discover the semantic information from images, the modeling of images in the terms of itemsets and transactions is necessary:

- the set of images within the same diagnosis represents the transactions set,
- the itemsets are the colors of image regions,
- the frequent itemsets represent the itemsets with support bigger or equal than the minimum support,
- the itemsets of cardinality between 1 and k are iteratively found (k-length itemsets),
- the frequent itemsets are used for rule generation.

The generated rules have the body composed by conjunctions of semantic indicators, while the head is the diagnosis. For each frequent color, all values of the other semantic indicators existed in the images are joined.

C_1 (union of semantic indicators of regions with color C_1) and ... and C_n (union of semantic indicators of regions with color C_n)→diagnosis.

So, a semantic rule describes the most frequent characteristics of a diagnosis.

The rules are represented in Prolog as facts of the form:

rule(Category, Score, ListofRegionPatterns).

The patterns from *ListofRegionPatterns* are terms of the form:

regionPattern(ListofPatternDescriptors).

The patterns from the descriptors list specify the set of possible values for a certain descriptor name. The form of this term is:

descriptorPattern(descriptorName,ValueList).

The values list has the same form as the argument used for mapping the semantic descriptors.

One of the semantic rules used to identify the colon cancer diagnosis is illustrated bellow. This rule has the score (confidence) equal to 100%.

```
rule(colon cancer,100,
[regionPattern([
        descriptorPattern(color,[medium-brown]),
```

```
        descriptorPattern(horizontal-position,[center,
        right]),
        descriptorPattern(vertical-position,[center,
        middle, down]),
        descriptorPattern(dimension,[big, medium]),
        descriptorPattern(eccentricity-shape,[small]),
        descriptorPattern(texture-probability,[medium]),
        descriptorPattern(texture-
        inversedifference,[medium]),
        descriptorPattern (texture-entropy,[big]),
        descriptorPattern (texture-energy,[big]),
        descriptorPattern (texture-contrast,[big]),
        descriptorPattern (texture-correlation, [big])])],
[regionPattern ([
        descriptorPattern(color,[medium-yellow]),
        descriptorPattern(horizontal-position,[center,
        right]),
        descriptorPattern (vertical-position,[center,
        bottom]),
        descriptorPattern(dimension,[medium, small]),
        descriptorPattern(eccentricity-shape,[small]),
        descriptorPattern(texture-probability,[big]),
        descriptorPattern(texture-
        inversedifference,[big]),
         descriptorPattern (texture-entropy,[medium]),
        descriptorPattern (texture-energy,[big]),
        descriptorPattern (texture-contrast,[medium]),
        descriptorPattern (texture-correlation,[big])])],
  [regionPattern ([
        descriptorPattern(color,[light-yellow]),
        descriptorPattern (horizontal-position,[right]),
        descriptorPattern (vertical-position,[bottom]),
        descriptorPattern(dimension,[small, medium]),
        descriptorPattern(eccentricity-shape,[big]),
        descriptorPattern(texture-probability, [medium]),
        descriptorPattern(texture-inversedifference,
        [big]),
        descriptorPattern (texture-entropy,[big]),
        descriptorPattern (texture-energy,[big]),
        descriptorPattern (texture-contrast,[small]),
        descriptorPattern (texture-correlation, [big] )])]).
```

The learning of semantic rules is continuously made, because when a diagnosed image is added in the learning database, the system continues the process of rules generation.

The component of medical image diagnosing includes the classification of new unlabeled images.

The classification process can be resumed to the next steps:

- each new image is processed and segmented in regions,
- for each new image the low-level characteristics are mapped to semantic indicators,
- the classification algorithm is applied for identifying the image diagnosis.

The classifier represents the set of semantic rules. So, being given a new image, the classification process searches in the rules set for finding its most appropriate diagnosis. Images are processed and are represented by means of semantic indicators as Prolog facts. The semantic rules are applied on the set of images facts, using the Prolog inference engine. A semantic rule matches an image if all characteristics, which appear in the body of the rule, also appear in the image characteristics.

4. EXPERIMENTS AND CONCLUSION

In the experiments realized through this study, two databases are used for testing the learning process. The database used to learning the correlations between images and semantic concepts contains 200 images from digestive diagnosis (Gastrolab, 2010; Gastroenterology, 2010). The database used in the learning process is categorized into the following diagnoses: ulcer, polyp and rectocolitis. The system learns each concept by submitting about 20 images per diagnosis. For each diagnosis, the following metrics are computed: accuracy, sensitivity, and specificity as in (6), (7), (8).

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{6}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$specificity = \frac{TN}{TN + FP} \tag{8}$$

where TP represents the number of true positives (images correctly diagnosed with the searched diagnosis), FP represents the number of false positives (images incorrectly diagnosed with the searched diagnosis), TN represents the number of true negatives (images correctly diagnosed with a different diagnosis, FN represents the number of false negatives (images incorrectly diagnosed with a different diagnosis.

The results of the presented methods are very promising, being influenced by the complexity of endoscopic images as can be observed in Table 1. Improvements can be brought using a segmentation method with greater semantic accuracy.

Table 1. Results recorded by the annotation methods.

Diagnosis	***Accuracy***	***Sensitivity***	***Specificity***
Ulcer	95.9%	91%	68.5%
Polyps	96.4%	91.5%	69.1%
Esophagitis	95.3%	89%	69%
Rectocolitis	95.8%	91.5%	71.5%

In this study we propose a system that could assist physicians by doing automatic diagnosis based on visual content of medical images. For establishing correlations with diagnoses, we experimented and selected some low-level visual characteristics of images. So, each diagnosis is translated in visual computable characteristics and in terms of sick regions. The language used for rules representation is Prolog. The advantages of using Prolog are its flexibility and simplicity in representation of rules and it is not a big time consumer.

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