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Juliusz L. KULIKOWSKI, Małgorzata PRZYTULSKA, Diana WIERZBICKA[1]

DISCRIMINATION OF BIOMEDICAL TEXTURES BASED ON LOGICAL SIMILARITY MEASURE

The paper presents an approach to discrimination of textures in radiological images based on multi-aspect similarity measures composed of logical tests. There are formulated basis assumptions for similarity measures which can be composed by products of partial (single-aspect) similarity measures. On the basis of similarity measures ε-similarity classes are defined. Next, two types: strong and weak similarity measures are defined. It is shown that they make possible to define similarity measures based on quality objects properties as well as on their numerical parameters. As an example of application of the general concept discrimination of normal and ill (lesions affected) tissues is considered. It is illustrated by analysis of USG images of liver tissues for which morphological spectra and their statistical parameters have been calculated. It is shown that the differences between values of some pairs of corresponding parameters can be used to a construction of an effective algorithm of textures discrimination. This algorithm takes into consideration both, numerical features of the texture samples and some qualitative data concerning the patients. Conclusions are formulated at the end of the paper.

1. INTRODUCTION

Discrimination of biomedical textures in radiological or microscopic images is a basis and a preliminary step to detection, localization and recognition of lesions in examined organs. We call *biomedical textures* collections of features and their characteristic parameters which observed and extracted from biomedical images make possible recognition of biologically different tissues, their localization and segmentation by contouring. For this purpose various features can be taken into consideration. The brightness level and color-based texture discrimination methods belong to the relatively simple ones. More sophisticated problems arise in monochromatic (USG, X-ray, MR, SPECT, PET, etc.) images analysis where characteristic textures' features in their micro-morphological structure are hidden. This is caused by the fact that biomedical tissues are not exactly regular and their textures rather as instances of random structures then as deterministic ones should be considered. In the literature concerning biomedical texture analysis probabilistic or statistical models play thus a dominant role [3,4,5,7]. Close to them are combined harmonic-statistical models [1,12,16], the models based on wavelets [2,17,21] and on fractal dimensions [9]. A large group of papers concerning texture analysis based on learning methods consists of those exploiting the artificial neural networks [10,14,15] and evolutionary algorithms [6,8,20]. In textures discrimination methods evaluation two basic criteria are used: discrimination *sensitivity* and discrimination *specificity*. Roughly speaking, the first one denotes ability of a method to detect difference between two samples of textures if in a certain, preliminarily defined sense they are *dissimilar*, while the second one means ability to recognize *similarity* of samples belonging to the same class and neglecting any existing between them non-substantial differences. In certain situations invariance of textures discrimination methods to image scaling and/or rotations is also required.

Discrimination of textures is a basic step to image segmentation, i.e. selection by contouring of image regions covered by textures corresponding to tissues being of interest (usually – to lesions) in a given examination problem. Segmentation is reached by integration of adjacent sub-areas in which the texture of interest by the discrimination procedure have been emphasized. However, despite a large class of texture discrimination methods and of their universality, in many cases no "pure" discrimination method as the most effective one for image segmentation can be recommended. Higher effectiveness can be expected due to using an alternative approach based on combinations of spectral, statistical,

[1] Nalecz Institute of Biocybernetics and Biomedical Engineering PAS, 4, Ks. Trojdena Str., 02-109 Warsaw, Poland.

morphological, etc. methods. A drawback of such approach consists in arising a problem of harmonization of various discrimination quality criteria. In this paper, a concept of overcoming this difficulty by using a *multi-aspect similarity measure based on logical tests* is proposed. The paper is organized as follows: in Sec. 2 basic notions of multi-aspect similarity measure based on logical tests are presented. In Sec. 3 the general concepts are applied to construction of a multi-aspect similarity measure of textures based on statistical parameters of their selected morphological spectral components. Some experimental results reached due to using the proposed method to analysis of ultrasound liver images are presented in Sec. 4. Sec. 5 contains concluding remarks.

2. MULTI-ASPECT SIMILARITY MEASURE BASED ON LOGICAL TESTS

2.1. SIMILARITY AND SIMILARITY MEASURES

It was mentioned above that similarity plays a substantial role in discrimination of textures. In general, it is a formal bi-variable reciprocal and symmetrical relation described in a set of objects. It does not satisfy a transitivity condition: if an object ω_1 is similar to ω_2 and ω_2 is similar to ω_3 then not obviously ω_1 is similar to ω_3; this in particular can be proven if ω_1, ω_2 and ω_3 denote samples of textures. On the other hand, image segmentation should lead to image partition into sub-areas covered by textures so that any three texture samples taken from them satisfy not only the reciprocity and symmetry but also the transitivity of similarity conditions. This apparent contradiction due to a concept of similarity measure can be overcome.

Definition 1:

Let Ω denote any set consisting of more than 2 elements (objects). We call *similarity measure* a function σ described on a Cartesian product Ω^2 satisfying the conditions:

i. $0 \le \sigma(\omega', \omega'') \le 1$,

ii. $\sigma(\omega', \omega') = 1$,

iii. $\sigma(\omega', \omega'') \equiv \sigma(\omega'', \omega')$,

iv. $\sigma(\omega', \omega'') \cdot \sigma(\omega'', \omega''') \le \sigma(\omega', \omega''')$

for any $\omega', \omega'', \omega''' \in \Omega$ •

The condition *iv* reminds a well-known "triangle inequality" in a definition of distance measure in a metric space [18]. Really, if Ω is also a metric space and $d(\omega', \omega'')$ denotes a distance measure between any two its elements then their similarity measure can be defined as

$$\sigma(\omega', \omega'') \equiv \exp[-\alpha \cdot d(\omega', \omega'')] \quad (1)$$

where α is a positive scaling coefficient. It can easily be proven that the conditions *i-iv* of Definition 1 are then satisfied; in particular, *iv* is satisfied due to the inequality:

$$d(\omega', \omega''') \le d(\omega', \omega'') + d(\omega'', \omega'''). \quad (2)$$

The set Ω with a defined in it similarity measure σ will be called a *similarity space.* On the basis of Definition 1 it can be formulated:

Definition 2:

Let Ω be a similarity space. Any non-empty subset $S_\varepsilon \subseteq \Omega$ such that $0 \le \varepsilon \le 1$ and any two its elements $\omega', \omega'' \in S_\varepsilon$ satisfy the condition $\sigma(\omega', \omega'') \ge \varepsilon$ will be called an *ε-similarity class* in Ω •

Evidently, in any ε-similarity class S_ε the ε-similarity of its elements is transitive by definition. The following theorem concerns extension of the ε-similarity classes:

Theorem 1:

Let S_ε be an ε-similarity class in Ω and let ε_{min} denoting a minimum similarity measure between any two elements of S_ε be such that $(\varepsilon_{min})^2 \ge \varepsilon$.. Then for any element $\omega^* \in \Omega$ not belonging to S_ε and

such that for an element $\omega \in S_\varepsilon$ it is $\sigma(\omega^*, \omega) = \varepsilon^* \geq \varepsilon_{min}$, the set $S_\varepsilon \cup \{\omega^*\}$ is also an ε-similarity class in Ω.

P r o o f. It follows from the property *iv* of similarity measure that in the given case, for any other $\omega' \in S_\varepsilon$, $\omega' \neq \omega$, it is:

$$\sigma(\omega^*, \omega') \geq \sigma(\omega^*,\omega)\cdot\sigma(\omega,\omega') \geq \varepsilon^*\cdot\varepsilon_{min} \geq (\varepsilon_{min})^2 \geq \varepsilon \quad (3)$$

Therefore, ω^* can be included into S_ε •

It can thus be concluded that there are some limits for extension of ε-similarity classes by joining to them new elements; proving their similarity to a selected element of the class is in general not sufficient if the set of the rest of elements is in their similarity not sufficiently compact.

The following property plays an important role in multi-aspect similarity detection.

Theorem 2:

If $\sigma^{(1)}$ and $\sigma^{(2)}$ are two similarity measures described on the same set of objects Ω are satisfying the conditions of Definition 1 then their product $\sigma = \sigma^{(1)} \cdot \sigma^{(2)}$ (calculated for the same pairs of corresponding variables) also satisfies the given conditions.

P r o o f. It follows directly from the form of algebraic conditions *i-iv* •

The Theorem 2 can easily be extended on any finite set of similarity measures. Its practical sense is that a multi-aspect similarity measure can be composed as a product of similarity measures defined for separately taken single-aspect similarity measures. The last Theorem concerns compositions of ε-similarity classes.

Theorem 3:

Let $S_{\varepsilon 1}, S_{\varepsilon 2},\ldots,S_{\varepsilon k}$ be *k* different *partial similarity classes* described in the same set Ω of objects. Then their product

$$S_\varepsilon = S_{\varepsilon 1} \cap S_{\varepsilon 2} \cap \ldots \cap S_{\varepsilon k} \quad (4)$$

is an ε-similarity class with $\varepsilon = \varepsilon_1 \cdot \varepsilon_2 \cdot \ldots \cdot \varepsilon_k$.

P r o o f: Any pair of elements belonging to all partial similarity classes is similar by ε_1 in the sense of $\sigma^{(1)}$, by ε_2 in the sense of $\sigma^{(2)}$, etc. Therefore, it is similar by $\varepsilon = \varepsilon_1 \cdot \varepsilon_2 \cdot \ldots \cdot \varepsilon_k$ in the sense of $\sigma = \sigma^{(1)} \cdot \sigma^{(2)} \cdot \ldots \cdot \sigma^{(k)}$ •

2.2. SIMILARITY MEASURES BASED ON LOGICAL TESTS

There are several ways the Definition 1 satisfying similarity measures can be established; one of them is based on logical tests [11]. this also in the form of a computer program has been implemented [18]. For this purpose: 1st it is necessary to define a set of *logical tests*

$$T_i: X_i \rightarrow \{0,1\} \quad (5)$$

where X_i, $i = 1,2,...,n$, denote some sets of parameters, and 2nd a *logical similarity function* on the basis of logical tests should be established. In [18] two types of logical tests have been defined:

- *Nominal tests* are defined on finite sets of the form $X_i = \{\xi_1, \xi_2,..., \xi_k\}$, called *quality attributes*, like: *color, staining* (of histological preparation), type of image preliminary *filtering*, etc.; $\xi_1, \xi_2,..., \xi_k$ denote values of the attributes. If $\Xi_i \subset X_i$ is a distinguished subset of the attribute X_i values then a nominal test takes the form:

$$T_i(\xi) = 1, \text{ if the observed value of the attribute } \xi \in \Xi_i,$$
$$T_i(\xi) = 0 \text{ otherwise.} \quad (6)$$

- *Interval tests* are defined on the sets X_i of the form of linearly ordered axes of natural or real numbers denoting the values of numerical parameters. If $\xi_{li}, \xi_{hi} \in X_i$, are some border (lowest and highest) values such that $\xi_{li} \leq \xi_{hi}$ then the following interval test can be defined:

$$T^{++}(\xi) = 1, \text{ if } \xi_{li} \le \xi \le \xi_{hi},$$
$$T^{++}(\xi) = 0 \text{ otherwise;} \quad (7)$$

Similarly, left-closed right-open $T^{+-}(\xi)$, left-open right-closed $T^{-+}(\xi)$ and left-open right-open $T^{--}(\xi)$ interval tests can be defined. In the above-given formulae the test values 0 and 1 can also be interpreted as Boolean, respectively, "*false*" and "*true*". On the basis of a set of logical tests a logical similarity measure in several ways can be defined. Two of them are shown below:

- Strong similarity function is given by the formula:

$$F(n,.m) = \frac{n-m}{n+m} \quad (8)$$

where n is the number of logical tests $T_1, T_2,..., T_n$ used to similarity assessment, while m, $0 \le m \le n$, denotes the number of tests whose assessed value is 0 ("*false*"). $F(n, m)$ for any natural n is a monotonically decreasing function of m, with decreasing decrements, taking value 1 for $m = 0$ and 0 for $m = n$ [20].

- *Weak similarity function* is defined as a weighed sum:

$$G(\boldsymbol{t};\boldsymbol{v}) = \sum_{i=1}^{n} t_i v_i \quad (9)$$

where $\boldsymbol{v} = [v_1, v_2,..., v_n]$ is a vector of non-negative weights whose sum equals 1, assigning relative *importance levels* to the corresponding logical tests' values $t_1, t_2,..., t_n$.

In stating similarity between two textures two situations should be considered. The first one arises when the properties of one texture (a *reference texture*) are a priori given and the similarity to it of the other one is to be stated. The second one arises when the properties of both textures are a priori not given and the problem consists in stating their similarity or dissimilarity. In medical applications both cases may arise; however, in this paper only the first one will be considered. In this case, the subsets Ξ_i in nominal tests as well as the intervals in interval tests describe the properties of the reference texture while the variables ξ denote the measured properties or parameters of the second, analyzed texture. In the second case the variables ξ should denote the pairs of properties or differences of parameter values corresponding to the compared textures. In both cases a result $T_i(\xi) = 1$ means that the given sample ξ to the particular, *i*-th strong similarity class. The conditions *i-iii* of the Definition 1 for the strong $F(n,m)$ and weak $G(\boldsymbol{t},\boldsymbol{v})$ similarity functions can easily be proven.

The proof of the condition *iv* is a little more sophisticated and is not presented in this paper. Below, it will be shown how the above-given general principles can be used to construct similarity functions for discrimination of textures.

3. SIMILARITY MEASURES FOR DISCRIMINATION OF TEXTURES

3.1. MORPHOLOGICAL SPECTRA AS CHARACTERISTICS OF TEXTURES

General backgrounds of morphological spectra as tools for textures characterization have been given in [13], some statistical properties of morphological spectra of biological textures have been described in [12]. Morphological spectra are systems of discrete 2D functions, related to Walsh functions, presented in the form of a multi-level hierarchical tree. The root of the tree (the k=0 level) corresponds to the bit-map of a monochromatic image. Each next k-th level consists of 4^k spectral components coded by k letters of the alphabet {*S, V, H, X* }. The symbols denote: *S* – assessment of mean pixel values, *V* - enhancement of vertical structures, *H* – enhancement of horizontal structures, *X* – enhancement of granular structures. Any k-th level spectral component is calculated on a square of $2^k \times 2^k$ pixels size. Therefore, calculation of an k-th level spectral component for full image needs partition of the images into

basic windows - squares of the above-mentioned size and the spectral component is given in the form of a matrix whose size corresponds to the basic windows' arrangement. Textures observed in radiological (USG, SPECT, MRI, etc.) images can be considered as instances of random fields rather than as regular, deterministic functions. Example of a liver ultrasonogram and of its selected spectral components *SS* and *SX*, as well as histograms of their spatial distribution values are shown in Fig. 1.

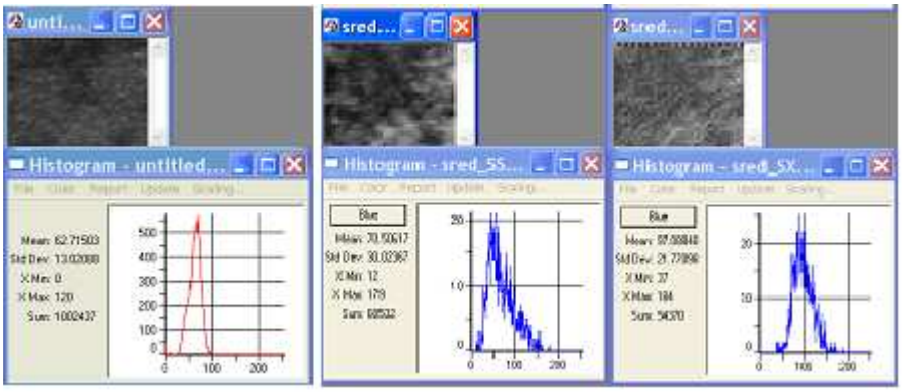

Fig. 1. Ultrasonogram of liver tissue and of its morphological spectral components *SS* and *SX*.

Statistical analysis of histograms of liver tissues' spectral components has shown that even in the case when no difference between normal and lesion-affected tissue by a naked eye could be remarked, evident differences between their statistical parameters occur. This is illustrated in Table 1 where several 2-nd level spectral components are analyzed. There were calculated: mean values, standard deviation, skewness, kurtosis and entropy of histograms taken over regions consisting of compact sets of 64 basic windows of 4×4 pixels size. Then, in order to make the results independent on average image luminance level, all parameters have been normalized by dividing by their mean values. The results are grouped in pairs: *h* – for normal (healthy) and *i* – for ill tissue for better illustration of their differences. It can be observed that certain parameters well discriminate normal and ill tissues: standard deviations of *SH* and *HH*, skewness of *HH*, *HV* and *HX*, kurtosis of *SH*, *HH*, *HV* and *HX*, entropy of *SS*, *SH* and *HH*. None of the mentioned parameters is sufficient to discriminate normal and ill tissues. However, they all can be used to construct of logical tests for a multi-aspect logical similarity measure.

Table 1. Normalized statistical parameters of selected spectral components of a liver ultrasonogram.

	SS	*SS*	*SH*	*SH*	*HS*	*HS*	*HH*	*HH*	*HV*	*HV*	*HX*	*HX*
	h	*i*	*h*	*i*	*h*	*i*	*h*	*i*	*h*	*i*	*h*	*i*
stdev	0.314	0.303	0.760	1.810	0.784	0.851	0.765	1.557	0.788	1.199	0.775	0.776
skew	0.000	0.003	0.024	0.020	0.011	0.023	0.016	0.040	0.060	0.134	0.092	0.017
kurt	0.000	0.000	0.019	0.152	0,012	0.023	0.014	0.114	0.078	0.167	0.144	0.067
entr	0.014	0.007	0.158	0.085	0.076	0.064	0.112	0.072	0.285	0.201	0.392	0.391

3.2. CONSTRUCTION OF A LOGICAL SIMILARITY MEASURE

As a basis for description of a "normal liver tissue" ω' for a given class of patients we can take the following quality features:

T_1: *sexuality – man,*
T_2: *aged – between 40 and 60 years,*
T_3: *vaccinated against type A jaundice – yes,*
T_4: *SH standard deviation level – 0.760 ±20%,*
T_5: *HH standard deviation level± 20%,*
T_6: *HH skewness level – 0.016± 20%,*

T_7: *HV skewness level – 0.060± 20%,*
T_8: *HX skewness level – 0.017± 20%,*
T_9: *SH kurtosis level – 0.019± 20%,*
T_{10}: *HH kurtosis level – 0.014± 20%,*
T_{11}: *HV kurtosis level – 0.078± 20%,*
T_{12}: *HX kurtosis level – 0.144± 20%,*
T_{13}: *SS entropy level – 0.014± 20%,*
T_{14}: *SH entropy level – 0.158± 20%,*
T_{15}: *HH entropy level – 0.112± 20%.*

For *healthy/ill* textures discrimination, where ω‘ denotes an examined texture, a composed similarity measure will be defined:

$$\sigma(\omega',\omega'') = \sigma^{(1)}(\omega',\omega'')\cdot\sigma^{(2)}(\omega',\omega'') \tag{10}$$

where, according to (9):

$$\sigma^{(1)}(\omega',\omega'') = 0.2T_1 + 0.6T_2 + 0.2T_3 \tag{11}$$

reflects relative values assigned to the partial similarity aspects T_1, T_2 *and* T_3, while $\sigma^{(2)}(\omega',\omega'')$ is given by the function *F(n,m)* calculated for the tests $T_4,\ldots, T_{15}$. Finally, a decision assigning an examined sample ω“ of texture to the class *healthy* (similar to ω‘) will take the form:

$$\begin{aligned} \omega' &\in \text{healthy if } \sigma(\omega',\omega'') \geq \gamma, \\ \omega' &\notin \textit{healthy} \text{ otherwise,} \end{aligned} \tag{12}$$

where $0 < \gamma \leq 1$ is a fixed threshold level.

4. CONCLUSIONS

Multi-aspect similarity measures based on logical tests are a flexible tool for description similarity classes of objects by taking into account combinations of their various qualitative features and numerical parameters. However, for this purpose some formal conditions by the similarity measure should be satisfied. Logical similarity may be combined with many other in pattern recognition used models like: spectral analysis (Fourier, wavelets, morphological etc.), geometry, fractals, statistics, color analysis, etc. In fact, using multi-aspect similarity measures in computer-aided pattern recognition makes it closer to natural visual perception which also is based on large classes of objects’ features and properties. Further investigation of this approach seems thus to be desirable.

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