2006 IEEE International Conference on Fuzzy Systems
Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada
July 16-21, 2006

A Fuzzy Approach to Image Texture Representation Applied to Visual Coarseness Description

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***Abstract*— Although ”texture” is one of the most used features in image analysis, it is an ambiguous concept which, in many cases, is not easy to characterize. In this paper we face the problem of imprecision in texture description by proposing a methodology to represent texture concepts by means of fuzzy sets. Specifically, we model the concept of ”coarseness”, the most extended in texture analysis, relating representative measures of this kind of texture (usually some statistic) with its presence degree. To obtain these ”presence degrees” related to human perception, we propose a methodology to collect assessments from polls filled by human subjects, performing an aggregation of these assessments by means of OWA operators. Using as reference set a combination of some statistics, the membership function corresponding to the fuzzy set ”coarseness” will be modelled as the function which provides the best fit of the collected data. The proposed methodology could be extended to other types of texture concepts like orientation, roughness or regularity. The main novelty of this approach is the introduction of semantics in the texture analysis problem, by using linguistic labels represented by fuzzy sets in order to describe texture features.**

Keywords: Image features, texture features, fuzzy texture, visual coarseness.

I. Introduction

Most of the approaches that achieve automatic image analysis are mainly based on three visual features: colour, texture, and shape. Visual texture is one of the most difficult to be characterized due to the imprecission of the concept itself [1], [2], [3].

On the one hand, there is not an accurate definition for the concept of texture but some widespread intuitive ideas. In this way, texture is described by some authors as local changes in the intensity patterns or gray tones. This idea is used in opposition to the homogeneity one. Other authors consider texture as a set of basic items called *texels* (or texture primitives), arranged in a certain way. Thus, texture will be described by means of *gray tone* and *spatial arrangement* [4].

On the other hand, it is usual for humans to describe visual textures according to some ”textural concepts” like *coarseness*, *orientation*, *regularity* [5], [6], [7]. To describe such concepts, linguistic labels are used (e.g. coarse or fine can be used to describe coarseness), which can also be changed by linguistic modifiers (e.g. very fine or little fine).

The own imprecision of the concept of texture suggets to use representation models that incorporate the uncertainty. Nevertheless, the majority of the approaches found in the literature are crisp proposals [8], [9] where uncertainty is not properly taken into account. From these kind of approaches, two main groups of texture characterization methods may be considered [4]: *statistical methods* (which analyse gray tone spatial distribution by computing some statistics on pixels intensity) and *structural methods* (which characterize texture by means of *texels* arranged in a certain way given by a set of rules).

To deal with the imprecission relative to visual texture, there are some approaches which introduce the use of fuzzy logic [10], [11], [12], [13]. However, in many of them, fuzzy logic is usually applied just during the process but the output do not habitually model the imprecission (being often a crisp one). Other proposals use fuzzy logic allowing to manage semantic data by means of fuzzy sets for textural features [14], [15]. How these fuzzy sets are obtained is a matter of opinion, however.

In this paper, we propose to model textures by means of fuzzy sets to deal with the problem of imprecision found in texture characterization. To do this, two questions will be faced: what reference set should be used for the fuzzy set, and how to obtain the related membership functions. To solve the first question, a vector of measures will be automatically computed from the texture image. To answer the second question, functional relationship between a certain measure and the presence degree of a textural concept related to it will be learnt.

The rest of the paper is organized as follows. In section II we introduce the general model to obtain the fuzzy sets related to a textural concept. In this way, in section II-A we develop a methodology which allows to obtain assessments of the human perception according to different textural concepts and in section II-B we propose to fit functions as a way to obtain the membership functions. The general approach is particularly applied to the coarseness textural concept in section III. Finally, the main conclusions and future work are sumarized in section IV.

II. Image Texture Modelling

As mentioned in the above section, texture related concepts are *vague*. Therefore, it seems natural to model textural concepts by using any approach with the ability of representing the related uncertainty.

[1]This work has been partially supported by ”Instituto de Salud Carlos III” under FIS G03/185 project, ”Imagen Médica Molecular y Multimodalidad”

0-7803-9489-5/06/$20.00/©2006 IEEE

In this paper, we propose to model a *textural concept* as a fuzzy set. From now on, we shall denote $\mathcal{T}$ the textural concept we want to model. As reference set, a vector of K measures obtained by carrying out an analysis of the texture image is used. These measures should give reliable information about the presence degree of the textural concept under study. Thus, the model of the textural concept will be given by a fuzzy subset built on the domain of the chosen measures.

Furthermore, a membership function that models the textural concept for the fuzzy set is needed. In this paper we propose to obtain this function by learning a functional relationship between a certain set of measures and the presence degree of a textural concept.

To learn this relationship, we will use a set $\mathcal{I} = \{I_1, \dots, I_N\}$ of N images that fully represent the textural concept $\mathcal{T}$ to be learnt. Thus, for each image $I_i \in \mathcal{I}$, we will obtain (a) a vector of measures $\mathbf{M}^i = [m_1^i, \dots, m_K^i]$ and (b) an assessment v^i of the presence degree of the textural concept $\mathcal{T}$ under study. To get this assessment, a poll will be performed (section II-A). Once we have a multiset of valid pairs $\Psi = \{(\mathbf{M}^1, v^1), \dots, (\mathbf{M}^N, v^N)\}$, we shall estimate the membership function by fitting a suitable curve to the multiset of points Ψ (section II-B).

A. Assessment collection

In this section we will describe how to get, from the image set $\mathcal{I} = \{I_1, \dots, I_N\}$, a vector $\Gamma = [v^1, \dots, v^N]$ of the assessments of the presence degrees related to a certain textural concept $\mathcal{T}$.

Thus, firstly a criterion for choosing the image set $\mathcal{I}$ is needed (section II-A.1). After that, an assessment poll which allows to get assessments of the presence degree of the textural concept $\mathcal{T}$ will be designed. These assessments will be obtained for each image in $\mathcal{I}$ (section II-A.2). Finally, to be able to get just one assessment that summarizes the information given by inquired human subjects, an aggregation of the different assessments will be performed (section II-A.3).

1) The texture image set: Firstly, the image set $\mathcal{I} = \{I_1, \dots, I_N\}$ that fully represents the textural concept to be learnt must be chosen. Such set must satisfy the following properties:

- It must cover the different presence degrees related to the textural concept $\mathcal{T}$.
- The number of images for each presence degree of $\mathcal{T}$ must be representative enough.
- Each image must show, as far as possible, just one presence degree of $\mathcal{T}$; thus, it will be avoided the fact that a subject may have a different perception depending on what part of the image his/her attention is fixed on.

2) The poll: Given an image set $\mathcal{I}$ that satisfies the above mentioned properties, the next step is to obtain assessments about the perception of $\mathcal{T}$ from a set of subjects. From now on we shall denote $\Theta^i = [o_1^i, \dots, o_L^i]$ with $o_j^i \in [0, 1]$, the vector of assessments obtained from L subjects for image I_i. We have considered two alternatives to get Θ^i:

- To ask subjects about a presence degree between 0 and 1 for each image in the set.
- To ask subjects to assign images to classes, so that each class has associated a presence degree.
  In our proposal, the number of classes is fixed and an example image which represents the presence degree is associated to each class.

The first choice allows subjects to have more freedom to assess the presence degree of $\mathcal{T}$. However, according to our own experience, it is very difficult for a subject to assess a value between 0 and 1 that represents the presence degree of a certain concept (except in the case of both extremes: fulfillment of the concept -degree of 1- and unfulfillment of the concept -degree of 0).

Fortunately, this problem is solved by the second choice. The subject does not assess a value but classifies each image into a class. This choice still allows the subject to assess the presence degree of the concept $\mathcal{T}$. Another advantage is the possibility of using linguistic labels for each class, if desired. Because of this, we shall employ this alternative in this paper.

3) Assessment aggregation: Our aim at this point is to obtain, for each image in the set $\mathcal{I}$, one assessment that summarizes the assessments given by the different subjects.

To aggregate opinions we have chosen the use of OWA operator guided by a quantifier [16]. With these operators it can be represented the existing interval between logic *AND*, which allows for the representation of the quantifier *for all*, and logic *OR*, which allows for the representation of the quantifier *exists*.

Yager proposed in [16] the use of monotonically non-decreasing linguistic quantifiers. In particular, we can use quantifiers of the form:

$$Q(r) = \begin{cases} 0 & \text{if } r < a, \\ \frac{r-a}{b-a} & \text{if } a \le r \le b, \\ 1 & \text{if } r > b \end{cases} \tag{1}$$

being *a,b,r* $\in [0, 1]$. Depending on the values associated to the pair (a, b), the quantifier interpretation would be different. Thus, in [17] the quantifier *most* is associated to the pair (0.3, 0.8), the quantifier *at least half* (0,0.5) and the quantifier *as many as possible* (0.5,1).

Once the quantifier Q has been chosen, the weighting vector of the OWA operator can be obtained following Yager as $w_j = Q(j/L) - Q((j-1)/L), j = 1, 2, ..., L$. According to this, given a quantifier Q, for each image $I_i \in \mathcal{I}$ the vector Θ^i obtained from L subjects will be aggregated into one assessment v^i as follows:

$$v^i = w_1 \hat{o}_1^i + w_2 \hat{o}_2^i + ... + w_L \hat{o}_L^i \tag{2}$$

where $[\hat{o}_1^i, \dots, \hat{o}_L^i]$ is a vector obtained by ranking in nonincreasing order the values of the vector Θ^i.

B. Fitting the model

In this section we will deal with the problem of obtaining the membership function for a certain textural concept $\mathcal{T}$. To simplify the notation, as it is usual in the scope of fuzzy sets, we will use the same notation for the textural concept, for the fuzzy set which represents it and for the membership function that defines it. In this way, given a textural concept $\mathcal{T}$, it will be modelled by a membership function defined on a vector of K real measures, i.e.,

$$\mathcal{T} : \mathbb{R}^K \rightarrow [0, 1] \tag{3}$$

To estimate $\mathcal{T}$, the multiset $\Psi = \{(\mathbf{M}^1, v^1), \ldots, (\mathbf{M}^N, v^N)\}$ obtained in the previous section will be used. Since our aim is to find a function $\mathcal{T}$ (equation 3) which associates $\mathbf{M^i}$ and v^i, we propose to estimate $\mathcal{T}$ by fitting a suitable curve to the multiset of points Ψ.

Concretely, our approach calculates the membership function by means of a Least Squares Fitting of the multiset Ψ. If we consider a function $\mathcal{T}$ defined by D parameters $p_1, \ldots, p_D$, these parameters will be obtained as follows:

$$\underset{p_1,\ldots,p_D}{\operatorname{argmin}} \sum_{i=1}^{N} [v^i - \mathcal{T}(\mathbf{M}^i; p_1 \ldots p_D)]^2 \tag{4}$$

i.e. those that minimize the error function.

It should be noticed that there is an error related to the fitting. This error can also be viewed as a goodness measure of the measures used in this approach; according to this, different subsets of measures could be analyzed, so the subset which best minimizes the error will be chosen.

III. Application to Coarseness

Coarseness is one of the most used textural properties in the literature and allows to distinguish between fine and coarse textures. A *fine* texture can be considered as small texture primitives with big gray tone differences between neighbour primitives (e.g. the image in figure 1(A)). On the contrary, if texture primitives are bigger and formed by several pixels, it is a *coarse* texture (e.g. the image in figure 1(A)). In fact, an extremely coarse texture may be considered as a homogeneous texture and it must be noticed that coarse and fine textures imply the opposite extremes of the same textural concept.

It is usual that the texture concept is associated to the presence of fineness (from this point of view, texture is defined as local variations against the idea of homogeneity). Due to the importance of this type of texture, in this section we will model the "fineness" on the basis of the generic model proposed in section II so that a presence degree of 1 means fineness fullfillment and a degree of 0 means fineness unfullfillment.

A. Fineness measures

Different measures that characterize the presence of fine texture are found over the literature [5]. In this paper we have chosen simple measures which imply a low computational cost. We have specifically used three well known measures:

Fig. 1. Some examples of images with different degrees of fineness

- Range, measured as the difference between the minimum and the maximum values in the image. We will note $Range^i$ the range related to the image I_i
- Variance of the image gray tones. We will note Var^i the variance related to the image I_i
- Edge density, measured as the percentage of points which are an edge in the image, i.e. the number of points which are an edge divided by the total number of points in the image. In this paper, we have used the Canny Edge Detector [18]. We will note $EdgeDens^i$ the edge density related to the image I_i

B. Assessment collection

1) The fineness image set: In this paper, we have chosen a set $\mathcal{I}$ of $N = 80$ images representative of the concept of fineness. Figure 1 shows some images extracted from the set $\mathcal{I}$. The selection was done to cover the different presence degrees of fineness with a representative number of images.

Furthermore, we have selected images in which, as far as possible, just one degree of fineness is perceived.

2) The poll: To obtain assessments of the *fineness* perception for the set $\mathcal{I}$, we ask different subjects to assign images to classes. In particular, 20 subjects have participated in the poll and 9 classes have been considered. The first nine images in figure 1 show the nine representative images for each class used in this poll. It should be noticed that the images are decreasingly ordered according to the presence degree of the fineness concept. The first class (figure 1(A)), represents a presence degree of 1 while the ninth class (figure 1(I)), represents a presence degree of 0. The rest of the classes represent degrees in the interval (0,1).

Finally, a vector of 20 assessments $\Theta^i = [o_1^i, \dots, o_{20}^i]$ is obtained for each image $I_i \in \mathcal{I}$. The degree o_j^i associated to the assessment given by the subject S_j to the image I_i is computed as $o_j^i = (9-k)*0.125$, where C_k is the class to which the image is assigned.

3) Assessment aggregation: To aggregate the assessment of the vector Θ^i associated to the image $I_i \in \mathcal{I}$, we choose an OWA operator guided by the quantifier *the most*. This quantifier is defined using equation 1 with parameters $a = 0.5$ and $b = 0.75$. As the aggregation result, just one assessment v^i is obtained for each image I_i. This final assessment is computed by using equation 2. As an example, we obtain an aggregated value of 0.75 for the image in figure 1(I) where 15 subjects assessed a value o_j^i of 0.75 while 5 subjects assessed 0.875. The weighting vector obtained for 20 subjects which is used in equation 2 has a value of 0 for its ten first values and for its 5 last values, while the rest have a value of 0.2.

C. Fitting the model

Analyzing the values obtained when the measures of range and variance are applied over the image set $\mathcal{I}$, we observed a great data dispersion (this is not the same in the case of edge density measure). This fact suggests to exclude those two measures in the fitting step that will be just applied to the edge density.

At this point, as seen in section II-B, the aim is to obtain a membership function for the concept of texture $\mathcal{T}$=*Fineness*. To do it, we will use the multiset $\Psi = \{(\mathbf{M}^1, v^1), \dots, (\mathbf{M}^N, v^N)\}$ where $\mathbf{M}^i = [EdgeDens^i]$ (see section III-A) and v^i is the assessment related to I_i (see section III-B).

Then, the function is calculated by carrying out a Least Squares Fitting according to equation 4. In this paper, the fitting is done by means of an increasing linear function that cross the axis $Y = 0$ and $Y = 1$, so our membership function will be defined by parts and will have a graphical representation like the one shown in figure 2. The rationale behind this choice is to try to employ first a very simple function, and try more complex ones only if the results are

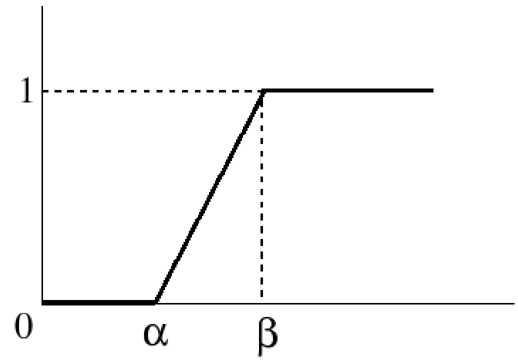

Fig. 2. Graphical representation of the kind of membership functions used in our *Fineness* modelling approach

not good enough. In this way, the function $\mathcal{T}$ is defined by two parameters α and β, as follows:

$$\mathcal{T}(\mathbf{M}^i) = \begin{cases} 0 & EdgeDens^i < \alpha, \\ \frac{EdgeDens^i - \alpha}{\beta - \alpha} & \alpha \le EdgeDens^i \le \beta, \\ 1 & EdgeDens^i > \beta \end{cases} \quad (5)$$

with $\mathbf{M}^i = [EdgeDens^i]$. The fitting parameters obtained in this paper have been $\alpha = 0.15$ and $\beta = 0.35$. Thus, the membership function related to the fuzzy set $\mathcal{T}$=*Fineness* is defined by equation:

$$\mathcal{T}(\mathbf{M}^i) = \begin{cases} 0 & EdgeDens^i < 0.15, \\ \frac{EdgeDens^i - 0.15}{0.2} & 0.15 \le EdgeDens^i \le 0.35, \\ 1 & EdgeDens^i > 0.35 \end{cases} \quad (6)$$

D. Results

Let's consider figure 3(A) corresponding to a mosaic made by several images, each one with a different increasing fineness presence degree. For each image in the mosaic, we apply the membership function defined in equation 6. The image 3(B) shows the edge map obtained from the original mosaic. This map is used to get the edge density which is the reference set of our fuzzy set. The fineness presence degree for each subimage is shown in figure 3(C) where a white grey level means maximum membership degree, while a black one corresponds to 0 membership degree (the numeric value is also shown on each subimage). It can be noticed that our model captures the evolution of the fineness degrees.

Table I shows a comparative between our model and the assessments obtained from subjects for the images in figure 3. To get such asessments, showed in the second column in table I, we have aggregated the assessments of 20 subjects following the steps explained in section III-B. The third column shows the fineness degree obtained by applying our model, the fourth column shows the difference between the computed degree and the human assessment. In the case of the fifth column we calculate the differences between the assessment given by each subject and the computed degree, and we obtain as

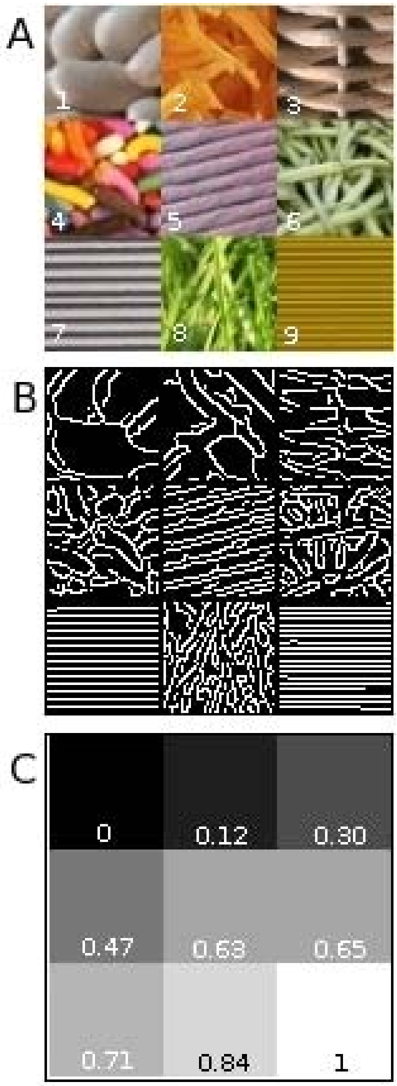

Fig. 3. Results for a mosaic image: (A) original mosaic image (B) edge map of the original images (C) presence degree of fineness textural concept obtained with the proposed model

Image	Human Assessment (H)	Estimated Value (V)	Error #1 ($\|H - V\|$)	Error #2
1	0	0	0	0
2	0.125	0.120	0.005	0.088
3	0.250	0.299	0.049	0.051
4	0.330	0.467	0.137	0.145
5	0.500	0.630	0.130	0.130
6	0.580	0.651	0.071	0.074
7	0.750	0.706	0.044	0.065
8	0.880	0.843	0.037	0.063
9	0.960	1.000	0.040	0.052
			Avg: 0.057	Avg: 0.074

TABLE I

ERRORS OBTAINED FROM MOSAIC IMAGE OF FIGURE 3

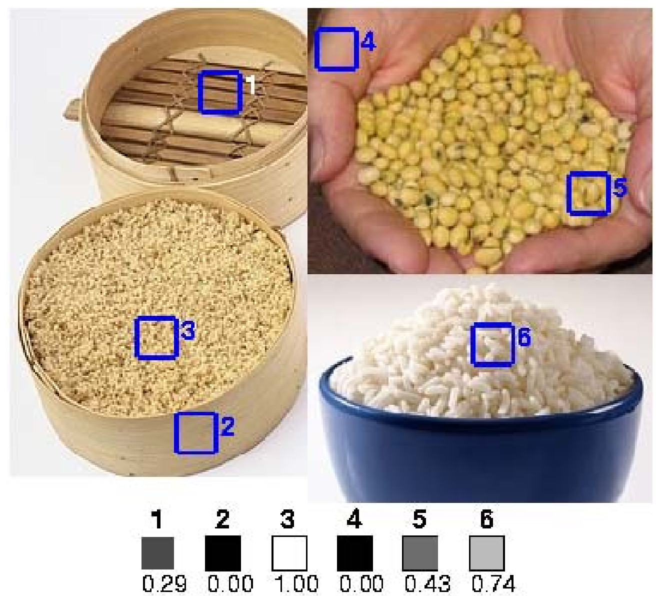

Fig. 4. Some examples of fineness degrees computed for six real subimages

error measure the mean from these 20 differences. Finally, the average errors shown in the last row with values of 0.057 and 0.074 show the goodness of our approach to represent the subjectivity found in fineness perception.

Figure 4 shows several real images where for each image, some windows have been selected corresponding to subimages with different fineness degree. We apply the model to each subimage, and the fineness degree obtained is shown at the bottom of figure 4. It can be noticed again that our model assesses high degrees to fine texture areas and also it assesses low degrees to coarse texture areas.

IV. CONCLUSIONS AND FUTURE WORKS

In this paper we have proposed a methodology to represent texture concepts by means of fuzzy sets. To define the membership function associated to the fuzzy set, the functional relationship between a certain measure (automatically computed over the image) and the presence degree of the textural concept has been learnt.

In order to obtain the perception degree of a certain textural concept, a group of human subjects have been polled and their assessments have been aggregated by means of OWA operators. After that, we have computed a membership function which fits the aggregated assessments, obtaining a fuzzy set that models the human perception for a certain textural concept.

This general methodology has been particularly applied to fineness. From the assessments given by 20 subjects and by using as reference set a group of very simple statistical measures, we have obtained a fuzzy set which models the human perception of fineness. The results given by our approach show a high level of connection with the assessments given by subjects.

As future work, the general methodology will be applied to other textural concepts like orientation or regularity. In the case of fineness, more complex statistical measures and non lineal fittings will be analyzed.

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