Defining A Fuzzy Partition for Coarseness Modelling in Texture Images

J. Chamorro-Martínez, P. Martínez-Jiménez[1] J.M. Soto-Hidalgo [2]

1.Department of Computer Science and Artificial Intelligence, University of Granada
Granada, Spain
2.Department of Computer Architecture, Electronics and Electronic Technology, University of Córdoba
Córdoba, Spain
Email: {jesus,pedromartinez}@decsai.ugr.es, jmsoto@uco.es

Abstract— *In this paper, the texture feature "coarseness" is modelled by means of a fuzzy partition on the domain of coarseness measures. The number of linguistic labels to be used, and the parameters of the membership functions associated to each fuzzy set are calculated relating representative coarseness measures (our reference set) with the human perception of this texture property. A wide variety of measures is studied, analyzing its capability to discriminate different coarseness categories. Data about the human perception of fineness is collected by means of a pools, performing an aggregation of their assessments by means of OWA operators. This information is used to obtain a fuzzy partition adapted to the human perception of coarseness-fineness*

Keywords— Coarseness, fineness, fuzzy partition, fuzzy texture, image features, texture features.

1 Introduction

For analyzing an image several kind of features can be used. From all of them, texture is one of the most popular and, in addition, one of the most difficult to characterize due to its imprecision. For describing texture, humans use vague textural properties like *coarseness/fineness*, *orientation* or *regularity* [1, 2]. From all of them, the *coarseness/fineness* is the most common one, being usual to associate the presence of fineness with the presence of texture. In this framework, a *fine* texture corresponds to small texture primitives (e.g. the image in figure 1(A)), whereas a *coarse* texture corresponds to bigger primitives (e.g. the image in figure 1(I)).

There are many measures in the literature that, given an image, capture the fineness (or coarseness) presence in the sense that the greater the value given by the measure, the greater the perception of texture [3]. However, given a certain measure value, there is not an immediate way to decide whether there is a fine texture, a coarse texture or something intermediate; in other words, there is not a textural interpretation.

To face this problem, fuzzy logic has been recently employed for representing the imprecision related to texture. In many of these approaches, fuzzy logic is usually applied just during the process, being the output a crisp result [4, 5]. Other approaches try to model the texture and its semantic by means of fuzzy sets defined on the domain of a given texture measure. In this last framework, some proposals model the texture property by means of an unique fuzzy set [6], and other approaches define fuzzy partitions providing a set of linguistic terms [7, 8].

Focusing our study in the last type of approaches, two questions need to be faced for defining properly a fuzzy partition: (i) the number of linguistic labels to be used, and (i) the parameters of the membership functions associated to each fuzzy set (and, consequently, the kernel localization). However, these question are not treat properly in the literature. Firstly, the number of fuzzy sets are often chosen arbitrarily, without take into account the capability of each measure to discriminate between different categories. Secondly, in many of the approaches, just an uniform distribution of the fuzzy sets is performed on the domain of the measures, although is wellknown that measure values corresponding to representative labels are not distributed uniformly. In addition, from our knowledge, none of the fuzzy approaches in the literature considers the relationship between the computational feature and the human perception of texture, so the labels and the membership degrees do not necessarily will match with the human assessments.

In this paper, we propose a fuzzy partition taking into account the previous questions. Firstly, in order to select the number of linguistic labels, we analyze the ability of each measure to discriminate different coarseness categories. For this purpose, data about the human perception of fineness is collected by means of a pools. This information is also used to localize the position and size of the kernel of each fuzzy set, obtaining a fuzzy partition adapted to the human perception of coarseness-fineness

The rest of the paper is organized as follows. In section 2 we present our methodology to obtain the fuzzy partition. Results are shown in section 3, and the main conclusions and future work are sumarized in section 4.

2 Fuzzy Partitions for Coarseness

As it was pointed, there is not a clear perceptual interpretation of the value given by a fineness measure. To face this problem, we propose to define a fuzzy partition on the domain of a given fineness measure. For this purpose, several questions will be faced: (i) what reference set should be used for the fuzzy partition, (ii) how many fuzzy sets will compound the partition, and (ii) how to obtain the membership functions for each fuzzy set.

Concern to the reference set, we will define the partition on the domain of a given coarseness-fineness measure. From now on, we will note $\mathcal{P} = \{P_1, \ldots, P_K\}$ the set of K measures analyzed in this paper, Π_k the partition defined on the domain of $\mathcal{P}_k$, N_k the number of fuzzy sets which compounds the partition Π_k, and $\mathcal{T}_k^i$ the i-th fuzzy set in Π_k. In this paper, the set $\mathcal{P} = \{P_1, \ldots, P_K\}$ is formed by the $K = 17$ mea-

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Figure 1: Some examples of images with different degrees of fineness

sures shown in the first column of table 1. It includes classical statistical measures, frequency domain approaches, fractal dimension analysis, etc. All of them are automatically computed from the texture image.

With regard to the number of fuzzy sets which compounds the partition, we will analyze the ability of each measure to distinguish between different degrees of fineness. This analysis will based on how the human perceives the fineness-coarseness. To get information about human perception of fineness, a set of images covering different degrees of fineness will be gathered. This images will be used to collect, by means of a pool, human assessments about the perceived fineness. From now on, let $\mathcal{I} = \{I_1, \ldots, I_N\}$ be the set of N images representing fineness-coarseness examples, and let $\Gamma = \{v^1, \ldots, v^N\}$ be the set of perceived fineness values associated to $\mathcal{I}$, with v^i being the value representing the degree of fineness perceived by humans in the image $I_i \in \mathcal{I}$. The way to obtain Γ will be describe in section 2.1

Using the data about human perception, and the measures values obtained for each image $I_i \in \mathcal{I}$, we will apply a set of multiple comparison tests in order to obtain the number of fineness degrees that each measure can discriminate (section 2.2). In addition, with the information given by the tests, we will define the fuzzy sets which will compund the partition (2.3).

2.1 *Assessment collection*

In this section, the way to obtain the set $\Gamma = \{v1, \ldots, v^N\}$ of perceived fineness values associated to $\mathcal{I}$ will be described. For this purpose, firstly the image set $\mathcal{I}$ will be selected. After that, a poll for getting assessments about the perception of fineness will be designed. Finally, for a given image, the assessments of the different subjects will be aggregated.

2.1.1 *The texture image set*

A set $\mathcal{I} = \{I_1, \ldots, I_N\}$ of $N = 80$ images representative of the concept of *fineness* has been selected. Figure 1 shows some images extracted from the set $\mathcal{I}$. Such set has been selected satisfying the following properties:

1. It covers the different presence degrees of fineness.
2. The number of images for each presence degree is representative enough.
3. Each image shows, as far as possible, just one presence degree of fineness.

Due to the third property, each image can viewed as ”homogeneous” respect to the fineness degree represented, i.e., if we select two random windows (with a dimension which does not ”break” the original texture primitives and structure), the perceived fineness will be the same for each window (and also respect to the original image). In other words, we can see each image $I_i \in \mathcal{I}$ as a set of lower dimension images (windows) with the same fineness degree of the original one.

As we explained, given an image $I_i \in \mathcal{I}$, a set of measures $\mathcal{P}$ will be applied on it. In fact, and thanks to the third property, we really can apply these measures for each subimage, assuming that the human assessment associated to that subimage will be the human assessment associated to the whole image. From now on, we will note as $\mathbf{M}^i_w = [m^{i,w}_1, \ldots, m^{i,w}_{K'}]$ the vector of measures for the w-th window of the image I_i, with $m^{i,w}_k$ being the result of applying the measure $P_k \in \mathcal{P}$ to the w-th window of the image I_i.

2.1.2 *The poll*

Given the image set $\mathcal{I}$, the next step is to obtain assessments about the perception of fineness from a set of subjects. From now on we shall note as $\Theta^i = [o^i_1, \ldots, o^i_L]$ the vector of assessments obtained from L subjects for the image I_i. To get Θ^i, subjects will be asked to assign images to classes, so that each class has associated a perception degree of fineness. 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 degree of fineness.

As result, a vector of 20 assessments $\Theta^i = [o^i_1, \ldots, o^i_{20}]$ is obtained for each image $I_i \in \mathcal{I}$. The degree o^i_j associated to the assessment given by the subject S_j to the image I_i is computed as $o^i_j = (9 - k) * 0.125$, where $k \in \{1, \ldots, 9\}$ is the index of the class C_k to which the image is assigned by the subject.

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Algorithm 1 Distinguishable clusters selection

Input:
  $Part^0 = C_1, C_2, \ldots, C_n$: Initial Partition
  δ: distance function between clusters
  ϕ: Set of multiple comparison tests
  NT: Number of positive tests to accept distinguishability
1.-Initialization
  $k = 0$
  $distinguishable = false$
2.- While (distinguishable = false) and (k < n)
  Apply the multiple comparison tests ϕ to $Part^k$
  If for each pair $C_i, C_j \in Part^k$ more than NT of the multiple comparison tests ϕ show distinguishability
    $distinguishable = true$
  Else
    Search for the pair of clusters C_r, C_{r+1}, verifying
    $\delta(C_r, C_{r+1}) = \min\{\delta(C_i, C_{i+1}), C_i, C_{i+1} \in Part^k\}$
    Join C_r and C_{r+1} on a cluster $C_u = C_r \cup C_{r+1}$
    $Part^{k+1} = Part^k - C_r - C_{r+1} + C_u$
    $k = k + 1$
3.- Output: $Part_k = C_1, C_2, \ldots, C_{n-k}$

2.1.3 *Assessment aggregation*

Our aim at this point is to obtain, for each image in the set $\mathcal{I}$, one assessment v^i that summarizes the assessments Θ^i given by the different subjects about the presence degree of fineness.

To aggregate opinions we have used an OWA operator guided by a quantifier [9]. Concretely, the quantifier "the most" has been employed, which allows to represent the opinion of the majority of the polled subjects. This quantifier is defined as

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

with $r \in [0, 1]$, $a = 0.3$ and $b = 0.8$. Once the quantifier Q has been chosen, the weighting vector of the OWA operator can be obtained following Yager [9] as $w_j = Q(j/L) - Q((j-1)/L), j = 1, 2, ..., L$. According to this, 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:

$$v^i = w_1\hat{o}^i_1 + w_2\hat{o}^i_2 + ... + w_L\hat{o}^i_L \quad (2)$$

where $[\hat{o}^i_1, \ldots, \hat{o}^i_L]$ is a vector obtained by ranking in nonincreasing order the values of the vector Θ^i.

2.2 *Distinguishability Analysis of the Fineness Measures*

As it was expected, some measures have better ability to represent fineness-coarseness than the others. To study the ability of each measure to discriminate different degrees of fineness-coarseness (i.e. how many classes can P_k actually discriminate), we propose to analyze each $P_k \in \mathcal{P}$ by applying a set of multiple comparison tests following the algorithm 1. This algorithm starts with an initial partition[1] and iteratively joins clusters until a partition in which all classes are distinguishable is achieved. In our proposal, the initial partition will be formed by the 9 classes used in our poll (where each class will contain the images assigned to it by the majority of the subjects), as δ the Euclidean distance between the centroids of the involved classes will be used, as ϕ a set of 5 multiple comparison tests will be considered (concretely, the tests of Scheffé, Bonferroni, Duncan, Tukey's least significant difference, and Tukey's honestly significant difference [10]), and finally the number of positive tests to accept distinguishability will be fixed to $NT = 3$.

[1] Let us remark that this partition is not the "fuzzy partition". In this case, the elements are measure values and the initial clusters the ones given by the pool

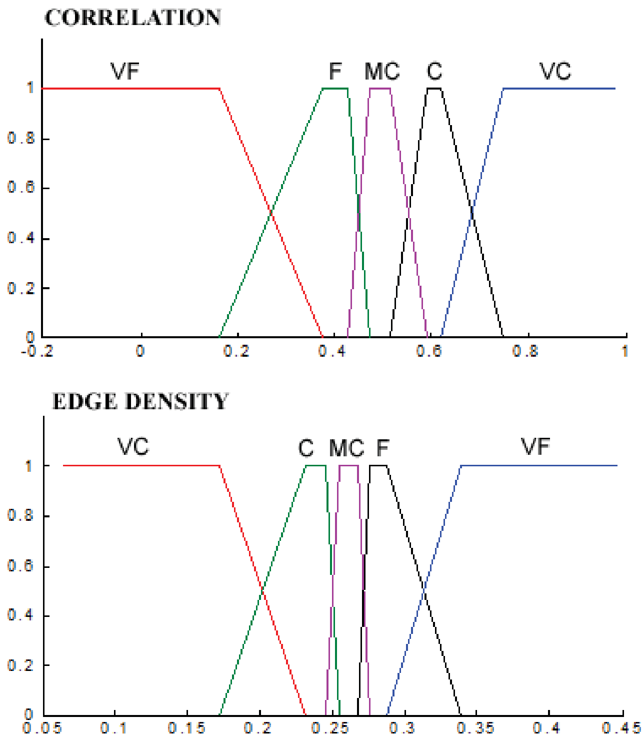

Figure 2: Fuzzy partitions for the measures Correlation and Edge Density. The linguistic labels are VC = very coarse, C = coarse, MC = medium coarse, F = fine, VF = very fine

From now on, we shall note as $\Upsilon_k = C^k_1, C^k_2, \ldots, C^k_{N_k}$ the N_k classes that can be discriminated by P_k. For each C^k_r, we will note as $\bar{c}^k_r$ the class representative value. In this paper, we propose to compute $\bar{c}^k_r$ as the mean of the measure values in the class C^k_r.

Table 1 shows the parameters obtained by applying the proposed algorithm 1 with the different measures considered in this paper. The second column of this table shows the N_k classes that can discriminated each measure and the third column shows how the initial classes have been grouped. The columns from fourth to eighth show the representative values $\bar{c}^k_r$ associated to each cluster.

2.3 *The Fuzzy Partitions*

In this section we will deal with the problem of defining the membership function for each fuzzy sets compounding the partition. As it was explained, the number of fuzzy sets will be given by the number of categories that each measure can discriminate.

In this paper, trapezoidal functions are used for defining the

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Table 1: Result obtained by applying the algorithm 1

Measure	N_k	Classes	$\bar{c}_5 \pm KW_5/2$	$\bar{c}_4 \pm KW_4/2$	$\bar{c}_3 \pm KW_3/2$	$\bar{c}_2 \pm KW_2/2$	$\bar{c}_1 \pm KW_1/2$
Correlation [3]	5	{1,2-4,5-6,7-8,9}	0.122±0.038	0.403±0.0272	0.495±0.0225	0.607±0.0133	0.769±0.0210
ED [11]	5	{1,2,3-5,6-8,9}	0.348±0.0086	0.282±0.0064	0.261±0.0063	0.238±0.0066	0.165±0.0061
Abbadeni [12]	4	{1,2-6,7-8,9}	-	5.672±0.2738	9.208±0.4247	11.12±0.2916	25.23±1.961
Amadasun [1]	4	{1,2-6,7-8,9}	-	4.864±0.271	7.645±0.413	9.815±0.230	19.62±1.446
Contrast [3]	4	{1,2-5,6-8,9}	-	3312±265.5	2529±295.5	1863±94.84	790.8±129.4
FD [13]	4	{1,2,3-8,9}	-	3.383±0.0355	3.174±0.0282	2.991±0.0529	2.559±0.0408
Tamura [2]	4	{1,2-6,7-8,9}	-	1.540±0.0634	1.864±0.0722	2.125±0.0420	3.045±0766
Weszka [14]	4	{1,2-6,7-8,9}	-	0.153±0.0064	0.113±0.0093	0.099±0.0036	0.051±0.0041
DGD [15]	3	{1,2-8,9}	-	-	0.020±0.0010	0.038±0.0017	0.091±0.0070
FMPS [16]	3	{1,2-8,9}	-	-	0.256±0.0477	0.138±0.0122	0.0734±0.0217
LH [3]	3	{1,2-8,9}	-	-	0.023±0.0010	0.052±0.0025	0.127±0.0096
Newsam [17]	3	{1,2-6,7-9}	-	-	0.1517±0.0425	0.2654±0.0466	0.4173±0.0497
SNE [18]	3	{1,2-8,9}	-	-	0.879±0.0182	0.775±0.0087	0.570±0.0232
SRE [19]	3	{1,2-8,9}	-	-	0.995±0.00026	0.987±0.00066	0.966±0.0030
Entropy [3]	2	{1,2-9}	-	-	-	9.360±0.124	8.656±0.301
Uniformity[3]	2	{1,2-9}	-	-	-	$1.3E^{-4} \pm 2.6E^{-5}$	$3.9E^{-4} \pm 1.9E^{-4}$
Variance[3]	1	-	-	-	-	-	-

membership functions. In addition, a fuzzy partition in the sense of Ruspini is proposed. Figure 2 shows some examples of the type of fuzzy partition used. To establish the localization of each kernel, the representative value $\bar{c}_r^k$ will be used (in our case, the mean). Concretely, this value will be localized at the center position of the kernel.

To establish the size of the kernel, we propose a solution based on the multiple comparison tests used in section 2.2. As it is known, in these tests confidence intervals around the representative value of each class are calculated (being accomplish that these intervals do not overlap for distinguishable classes). All values in the interval are considered plausible values for the estimated mean. Based on this idea, we propose to set the kernel size as the size of the confidence interval.

The confidence interval CI_r^k for the class C_r^k is defined as

$$CI_r^k = \bar{c}_r^k \pm 1.96 \frac{\bar{\sigma}_r^k}{\sqrt{||C_r^k||}} \tag{3}$$

where $\bar{c}_r^k$ is the class representative value, and $\bar{\sigma}_r^k$ is the estimated standard deviation for the class. Thus, the kernel size KW_r^k is

$$KW_r^k = 3.92 \frac{\bar{\sigma}_r^k}{\sqrt{||C_r^k||}} \tag{4}$$

and the endpoints of the kernel will be given by $\bar{c}_r^k \pm KW_r^k/2$ Table 1 shows these values for each measure and each class.

Figure 2 shows the fuzzy partitions for the measures of correlation and ED (the ones with higher capacity to discriminate fineness clases).

3 Results

In this section, the fuzzy partition defined for the measure ”Correlation” (showed in Figure 2) will be applied in order to analyze the performance of the proposed model.

Let’s consider Figure 3(A) corresponding to a mosaic made by several images, each one with a different increasing degree of fineness. Figure 3(B-F) shows the membership degree to the fuzzy sets ”very coarse”, ”coarse”, ”medium coarse”, ”fine” and ”very fine”, respectively, using the proposed model. For each pixel in the original image, a centered window of size 32×32 has been analyzed and its membership degree to each fuzzy set has been calculated. Thus, Figure 3(B) represents the degree in which the texture is perceived as ”very coarse”, with a white level meaning maximum degree, and a dark one meaning zero degree. It can be noticed that our model captures the evolution of the perception degrees of fineness.

Figure 4 presents an example where the proposed fuzzy partition has been employed for pattern recognition. In this case, Figure shows a microscopy image (Figure 4(A)) corresponding to the microstructure of a metal sample. The lamellae indicates islands of eutectic, which are to be separated from the uniform light regions. The brightness values in regions of the original image are not distinct, so texture information is needed for extracting the uniform areas. This fact is showed in Figure 4(B1,B2), where a thersholding on the original image is displayed (homogeneous regions cannot be separated from the textured ones as they ”share” brightness values). Figure 4(C1) shows a mapping from the original image to its membership degree to the fuzzy set associated ”very coarse”. Thus, Figure 4(C1) represents the degree in which the texture is perceived as ”very coarse” and it can be noticed that uniform regions correspond to areas with the maximum degree (bright grey levels), so if only the pixels with degree upper than 0.9 are selected, the uniform light regions emerge with ease (Figure 4(C2,C3)).

4 Conclusions and future works

In this paper, a fuzzy partition for representing the fineness/coarseness concept have been proposed. The number of fuzzy sets and the parameters of the membership functions have been defined relating fineness measures with the human perception of this texture property. Pools have been used for collecting data about the human perception of fineness, and the capability of each measure to discriminate different coarseness degrees has been analyzed. The results given by our approach show a high level of connection with the human perception of fineness/coarseness. As future work, the perfor-

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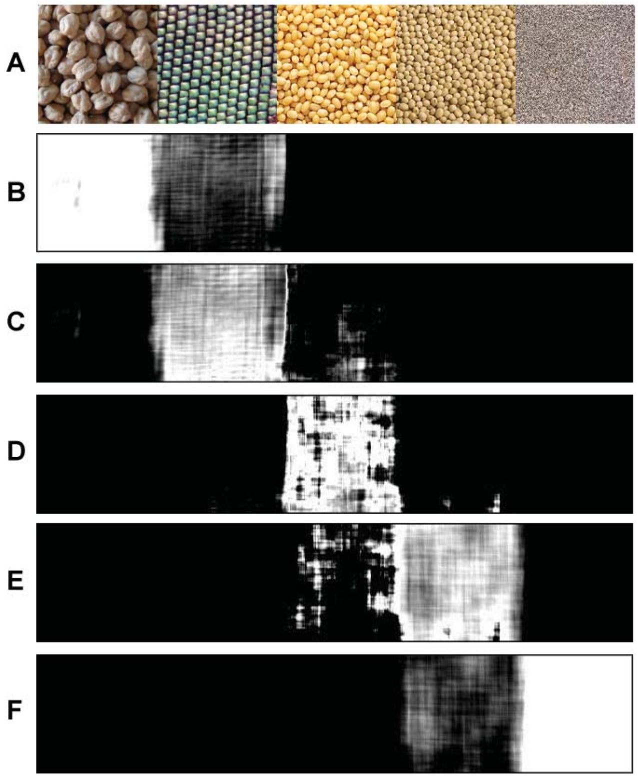

Figure 3: Results for a mosaic image. (A) Original image (B)(C)(D)(E)(F) Membership degree of each pixel to the sets ”very coarse”, ”coarse”, ”medium coarse”, ”fine” and ”very fine”, respectively (the darker the pixel, the lower the membership degree)

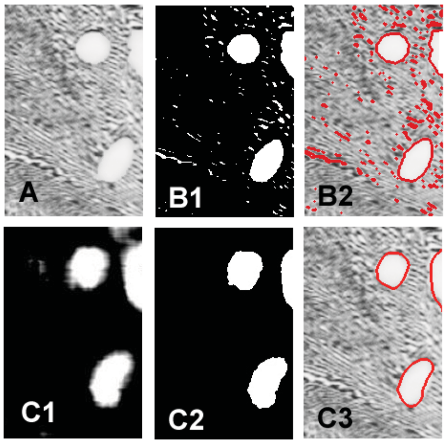

Figure 4: Example of pattern recognition (A) Original image (B1) Binary image obtained by thresholding the original one (B2) Region outlines of B1 superimposed on original image (C1) Membership degrees to the set ”very coarse” obtained with our model from the original image (C2) Binary image obtained by thresholding C1 (C3) Region outlines of C2 superimposed on original image

mance of the fuzzy partition will be analyzed in applications like textural classification or segmentation.

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