Fuzzy Sets for Image Texture Modelling Based on Human Distinguishability of Coarseness*

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Abstract. In this paper, the "coarseness" texture property is modelled by means of fuzzy sets, relating representative coarseness measures (our reference set) with the human perception of this type of feature. In our study, a wide variety of measures are analyzed, and the coarseness human perception are collected from polls filled by subjects. The capability of each measure to discriminate different coarseness degrees is analyzed, taking into account this capability for defining the membership function.

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

1 Introduction

Texture is, together with color and shape, one of the most used feature for image analysis. It is usual for humans to describe visual textures according to some vague "textural concepts" like *coarseness/fineness*, *orientation* or *regularity* [1,2]. From all of them, the *coarseness/fineness* is the most popular one, being common to associate the presence of fineness with the presence of texture. In this sense, 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 (i.e. there is not a textural interpretation). In this sense, the majority of the approaches in the literature are crisp proposals where uncertainty is not properly taken into account.

To face this problem, fuzzy logic has been recently employed for representing the imprecision related to texture. However, in many of these approaches, fuzzy logic is usually applied just during the process, but the output do not habitually model the imprecision (being often a crisp one) [4]. Other interesting approaches

* This work has been partially supported by the Andalusian Government under the TIC1570 and TIC249.

V. Di Gesù, S.K. Pal, and A. Petrosino (Eds.): WILF 2009, LNAI 5571, pp. 229–236, 2009.

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

emerge from the content-based image retrieval scope, where semantic data is managed by means of fuzzy sets [5]. However, these fuzzy sets are not obtained by considering the relationship between the feature and the human perception of texture.

In our approach, we propose to model fineness by means of fuzzy sets relating representative coarseness measures (our reference set) with the human perception of this type of feature. For this purpose, pools are used for collecting data about the human perception of fineness. This data is used to analyze the capability of each measure to discriminate different coarseness degrees, and to define the membership function on the basis of this capability.

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

2 Fineness Modelling

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 model the fineness perception as a fuzzy set defined on the domain of a given measure[1]. Let $\mathcal{P} = \{P_1, \ldots, P_K\}$ be a set of measures of fineness and let $\mathcal{T}_k$ be a fuzzy set defined on the domain of $P_k \in \mathcal{P}$ representing the concept of "fineness". Thus, the membership function associated to $\mathcal{T}_k$ will be defined as[2]

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

where a value of 1 will mean fineness presence while a value of 0 will mean no fineness presence (i.e. coarseness presence).

[1] Let us remark that "coarseness" and "fineness" are opposite but related properties.

[2] To simplify the notation, as it is usual in the scope of fuzzy sets, we will use the same notation $\mathcal{T}_k$ for the fuzzy set and for the membership function that defines it.

Given a measure $P_k \in \mathcal{P}$, we propose to obtain $\mathcal{T}_k$ by finding a functional relationship between P_k and the perception degree of fineness. To do it, we will use a set $\mathcal{I} = \{I_1, \ldots, I_N\}$ of N images that fully represent the different degrees of fineness. Thus, for each image $I_i \in \mathcal{I}$, we will obtain (a) a human assessment of the fineness degree perceived, noted as v^i, which will be collected by means of a poll with human subjects (section 2.1), and (b) a value calculated applying the measure $P_k \in \mathcal{P}$ to the image I_i, noted as m_k^i (section 2.2). From the multiset $\Psi_k = \{(m_k^1, v^1), \ldots, (m_k^N, v^N)\}$, the function $\mathcal{T}_k$ will be estimated (section 2.3).

2.1 Assessment Collection

In this section, the way to obtain a vector $\Gamma = [v1, \ldots, v^N]$ of the assessments from the image set $\mathcal{I} = \{I_1, \ldots, I_N\}$ will be described.

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 $\mathcal{I}$. The selection was done to cover the different perception degrees of fineness with a representative number of images. Furthermore, the images have been chosen so that, as far as possible, just one perception degree of fineness is perceived.

The Poll. In order to obtain assessments about the perception of fineness, L subjects will be asked to assign images from $\mathcal{I}$ to classes, so that each class has associated a perception degree of fineness. In particular, $L = 20$ 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). As result, a vector of 20 assessments $\Theta^i = [o_1^i, \ldots, o_{20}^i]$ 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 $k \in \{1, \ldots, 9\}$ is the index of the class C_k to which the image is assigned by the subject.

Assessment Aggregation. For each image in $\mathcal{I}$, one assessment v^i that summarizes the Θ^i values is needed. To aggregate opinions, an OWA operator guided by a quantifier have been used. Concretely, the quantifier "the most" has been used, which allows to represent the opinion of the majority of the subjects [6].

2.2 Fineness Measures

In this paper, we propose to use the 17 measures shown in table 1 (that includes classical statistical measures well known in the literature, measures in the frequency domain, etc.). As it was expected, some of them have better ability to represent fineness than the others. Thus, to study the ability of each measure to discriminate different degrees of fineness (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 and iteratively joins clusters until a partition in which all classes are distinguishable is achieved. In our proposal, the initial partition will be formed

Algorithm 1. Obtaining the distinguishable clusters

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: $\widetilde{Part}_k = C_1, C_2, \ldots, C_{n-k}$

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 [7]), and finally the number of positive tests to accept distinguishability will be fixed to $NT = 3$.

From now on, we shall note as $\Upsilon_k = C_1^k, C_2^k, \ldots, C_{NC_k}^k$ the NC_k classes that can be discriminated by P_k. For each C_r^k, we will note as $\bar{c}_r^k$ the class representative value and as $\bar{v}_r^k$ the presence degree of fineness associated to C_r^k. In this paper, we propose to compute $\bar{c}_r^k$ as the mean of the measure values in the class C_r^k and $\bar{v}_r^k$ as the mean of the presence degrees of fineness associated to the classes grouped into C_r^k.

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 how the initial classes have been grouped. The columns from third to eighth show the representative values $\bar{c}_r^k$ and $\bar{v}_r^k$ associated to each cluster.

2.3 Obtaining the Membership Function

In this section we will deal with the problem of obtaining the membership function for the fuzzy set $\mathcal{T}_k$. In our proposal, the following properties will be considered in order to define this function:

Table 1. Clusters, representatives of each class and RMSE found by applying the estimated membership function

Measures	Classes	$(\bar{c}_5, \bar{v}_5)$	$(\bar{c}_4, \bar{v}_4)$	$(\bar{c}_3, \bar{v}_3)$	$(\bar{c}_2, \bar{v}_2)$	$(\bar{c}_1, \bar{v}_1)$	RMSE
Correlation [3]	{1,2-4,5-6,7-8,9}	(0.122,1)	(0.403,0.812)	(0.495,0.562)	(0.607,0.219)	(0.769,0)	0.278
Abbadeni [8]	{1,2-8,9}	-	-	(0.089,1)	(0.166,0.566)	(0.404,0)	0.287
Amadasun [1]	{1,2-6,7-8,9}	-	(5.621,1)	(8.945,0.812)	(11.63,0.391)	(26.94,0)	0.293
ED [9]	{1,2,3-5,6-8,9}	(0.348,1)	(0.282,0.719)	(0.261,0.344)	(0.238,0.125)	(0.165,0)	0.332
Tamura [2]	{1,2-6,7-8,9}	-	(1.540,1)	(1.864,0.812)	(2.125,0.242)	(3.045,0)	0.366
SRE [10]	{1,2-8,9}	-	-	(0.995,1)	(0.987,0.477)	(0.966,0)	0.370
LH [3]	{1,2-8,9}	-	-	(0.023,1)	(0.052,0.621)	(0.127,0)	0.390
FD [11]	{1,2,3-8,9}	-	(3.383,1)	(3.174,0.539)	(2.991,0.125)	(2.559,0)	0.393
DGD [12]	{1,2-8,9}	-	-	(0.020,1)	(0.038,0.621)	(0.091,0)	0.396
Weszka [13]	{1,2-6,7-8,9}	-	(0.153,1)	(0.113,0.812)	(0.099,0.258)	(0.051,0)	0.398
SNE [14]	{1,2-8,9}	-	-	(0.879,1)	(0.775,0.477)	(0.570,0)	0.401
Contrast [3]	{1,2-5,6-8,9}	-	(3312,1)	(2529,0.781)	(1863,0.234)	(790.8,0)	0.420
Newsam [15], Entropy [3], Uniformity[3], FMPS [16], Variance[3]: {1-9}							

- $\mathcal{T}_k$ should be a monotonic function
- $\mathcal{T}_k(\bar{c}_r^k) = \bar{v}_r^k \ \forall r = 1, \ldots, NC_k$, i.e., for the representative values $\bar{c}_r^k$ of each class $C_r^k \in \Upsilon_k$, the membership function $\mathcal{T}_k$ should return the mean assessment given by the subjects to that class.
- The values $\mathcal{T}_k(x) = 0$ and $\mathcal{T}_k(x) = 1$ should be achieved from a certain value

To take into account the above considerations, in this paper we propose to define $\mathcal{T}_k$ as a function that associates the values given by a certain measure with the assessments given by the human subjects[3], i.e.:

$$\mathcal{T}_k(x) = \begin{cases} 0 & x \le x_1 \\ f^1(x) & x \in (x_1, x_2] \\ f^2(x) & x \in (x_2, x_3] \\ \vdots & \vdots \\ 1 & x > x_{NC_k} \end{cases} \tag{2}$$

with $f^r(x)$ being a line defined as $f^r(x) = a_1^r x + a_0^r$.

To define the knots x_r of equation 2, the representatives of the classes C_r^k, with $r = 1, \ldots, NC_k$, will be used (recall that these classes were obtained considering the ability of the measure P_k to discriminate the perception of fineness following the algorithm 1). Thus, we propose to define $x_r = \bar{c}_r^k$, with $r = 1, \ldots, NC_k$, and with $\bar{c}_r^k$ being the centroid of C_r^k. Note that the way the function is defined allows to ensure that, for the representative values $\bar{c}_r^k$ of each class, the membership function returns the mean assessment given by the subjects to that class (i.e., $\mathcal{T}_k(\bar{c}_r^k) = \bar{v}_r^k$ according with the second constraint). From this point of view,

[3] Note that this function is defined for measures that increases according to the perception of fineness. For those that decreases, the function needs to be changed appropriately.

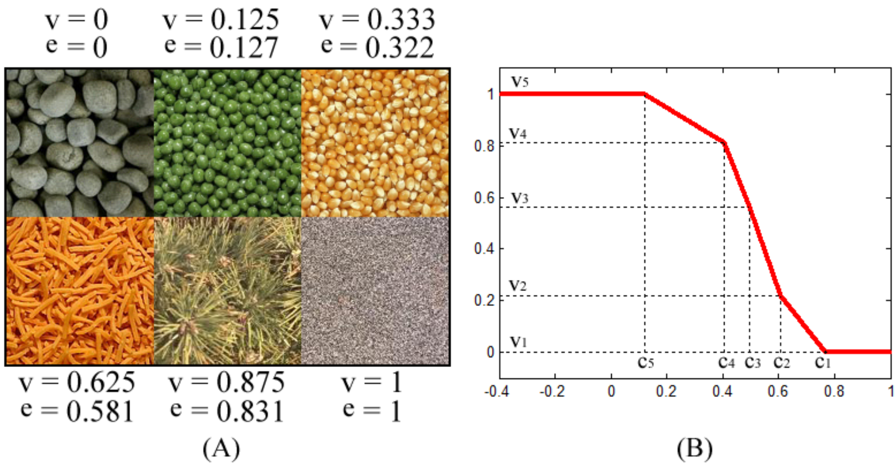

Fig. 2. Results for a mosaic image. (A) Original mosaic image with the assessment values given by users -v- and the value estimated with our model -e- (B)Membership function associated to the proposed fuzzy set.

$f^r(x)$ may be considered as a function that represents the transition between the classes C_r^k and C_{r+1}^k.

The function $f^r(x)$ will be obtained as the line defined between the points $(\bar{c}_r^k, \bar{v}_r^k)$ and $(\bar{c}_{r+1}^k, \bar{v}_{r+1}^k)$, with $\bar{v}_r^k$ being the fineness degree of presence related to the cluster C_r^k. Thus, the parameters a_1^r and a_0^r of $f^r(x)$ are computed as $a_1^r = \frac{\bar{v}_{r+1}^k - \bar{v}_r^k}{\bar{c}_{r+1}^k - \bar{c}_r^k}$ and $a_0^r = \bar{v}_r^k - \bar{c}_r^k a_1^r$, respectively.

The above approach has been used to define the membership functions $\mathcal{T}_k$ associated to the 17 measures studied in this paper. These functions have been applied to each image $I_i \in \mathcal{I}$ and the obtained value has been compared with the one assessed by human subjects. Table 1 shows the RMSE obtained for the different fuzzy sets considered in this paper (it has been sorted according to the RMSE value).

3 Results

In this section, the membership function $\mathcal{T}_k$ with least fitting error (obtained for the measures Correlation and defined by the parameter values shown in Table 1) will be applied in order to analyze the performance of the proposed model. Let's consider Figure 2(A) corresponding to a mosaic made by several images, each one with a different increasing perception degree of fineness. The perception degree of fineness for each subimage has been calculated using the proposed model and the numerical results are shown in Figure 2(A): v is the value of the human assessment and e is the computed degree. It can be noticed that our model

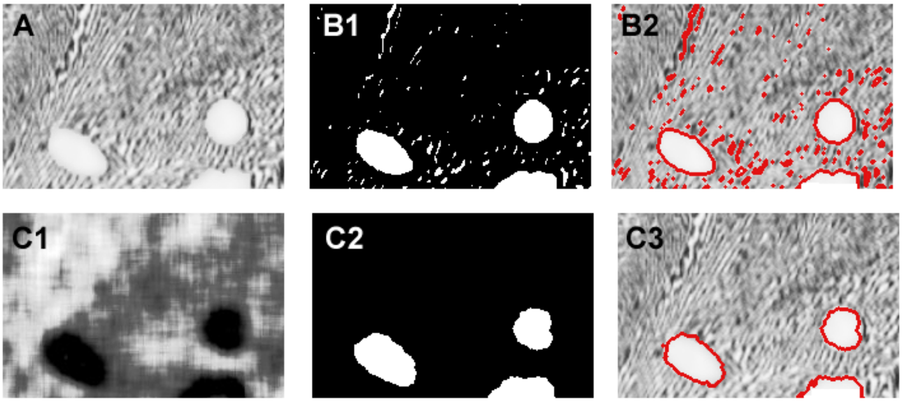

Fig. 3. Pattern recognition (A) Original image (B1) Binary image obtained by thresholding the original one (B2) Region outlines of B1 superimposed on original image (C1) Fineness membership degrees obtained with our model from the original image (C2) Binary image obtained by thresholding C1 (C3) Region outlines of C2 superimposed on original image

captures the evolution of the perception degrees of fineness. Figure 2(B) shows the membership function associated to the fuzzy set used in this experiment.

Figure 3 presents an example where the proposed fuzzy set has been employed for pattern recognition. In this case, the Figure shows a microscopy image (Figure 3(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 3(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 3(C1) shows a mapping from the original image to its "fineness" membership degree. In this case, we use a window of size 20×20. Thus, Figure 3(C1) represents the degree in which the human perceives the texture and it can be noticed that uniform regions correspond to areas with low degrees of fineness (i.e., high coarseness), so if only the pixels with fineness degree lower than 0.1 are selected (which it is equivalent to a coarseness degree upper than 0.9), the uniform light regions emerge with ease (Figure 3(C2,C3)).

4 Conclusions and Future Works

In this paper, fuzzy sets for representing the fineness/coarseness concept have been proposed. The memberships 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 assessments given by subjects. As future work, the performance of the fineness functions will be analyzed in applications like textural classification or segmentation.

References

1. Amadasun, M., King, R.: Textural features corresponding to textural properties. IEEE Transactions on Systems, Man and Cybernetics 19(5), 1264–1274 (1989)
2. Tamura, H., Mori, S., Yamawaki, T.: Textural features corresponding to visual perception. IEEE Transactions on Systems, Man and Cybernetics 8, 460–473 (1978)
3. Haralick, R.: Statistical and structural approaches to texture. Proceedings IEEE 67(5), 786–804 (1979)
4. Wang, C., Wang, H., Mei, Q.: Texture segmentation based on an adaptively fuzzy clustering neural network. In: Proc. of 2004 International Conference on Machine Learning and Cybernetics, vol. 2, pp. 1173–1176 (2004)
5. Lin, H., Chiu, C., Yang, S.: Finding textures by textual descriptions, visual examples, and relevance feedbacks. Pattern Recognition Letters 24(14), 2255–2267 (2003)
6. Yager, R.: On ordered weighted averaging aggregation operators in multicriteria decisionmaking. IEEE Transactions on Systems, Man and Cybernetics 18(1), 183–190 (1988)
7. Hochberg, Y., Tamhane, A.: Multiple Comparison Procedures. Wiley, Chichester (1987)
8. Abbadeni, N., Ziou, N., Wang, D.: Autocovariance-based perceptual textural features corresponding to human visual perception. In: Proc. of 15th International Conference on Pattern Recognition., vol. 3, pp. 901–904 (2000)
9. Canny, J.: A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence 8(6), 679–698 (1986)
10. Galloway, M.: Texture analysis using gray level run lengths. Computer Graphics and Image Processing 4, 172–179 (1975)
11. Peleg, S., Naor, J., Hartley, R., Avnir, D.: Multiple resolution texture analysis and classification. IEEE Transactions on Pattern Analysis and Machine Intelligence (4), 518–523 (1984)
12. Kim, S., Choi, K., Lee, D.: Texture classification using run difference matrix. In: Proc. of IEEE 1991 Ultrasonics Symposium, vol. 2, pp. 1097–1100 (1991)
13. Weszka, J., Dyer, C., Rosenfeld, A.: A comparative study of texture measures for terrain classification. IEEE Transactions on Systems, Man and Cybernetics 6, 269–285 (1976)
14. Sun, C., Wee, W.: Neighboring gray level dependence matrix for texture classification. Computer Vision, Graphics and Image Processing 23, 341–352 (1983)
15. Newsam, S., Kammath, C.: Retrieval using texture features in high resolution multi-spectral satellite imagery. In: Data Mining and Knowledge Discovery: Theory, Tools, and Technology VI, SPIE Defense and Security (2004)
16. Yoshida, H., Casalino, D., Keserci, B., Coskun, A., Ozturk, O., Savranlar, A.: Wavelet-packet-based texture analysis for differentiation between benign and malignant liver tumours in ultrasound images. Physics in Medicine and Biology 48, 3735–3753 (2003)