COARSENESS FUZZY PARTITIONS APPLIED TO TEXTURE IMAGE RETRIEVAL

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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 di erent coarseness categories. Data about the human perception of neness is collected by means of a pool and it is used to obtain a fuzzy partition adapted to the human perception of coarseness- neness. This fuzzy partition is applied to texture image retrieval.

Keywords: Coarseness, neness, fuzzy partition, fuzzy texture, image features, texture features, image retrieval.

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 di cult to characterize due to its imprecision. For describing texture, humans use vague textural properties like *coarseness/ neness*, *orientation* or *regularity* [1, 2]. From all of them, the *coarseness/ neness* is the most common one, being usual to associate the presence of neness with the presence of texture. In this framework, a *ne* texture corresponds to small texture primitives (e.g. the image in gure 1(A)), whereas a *coarse* texture corresponds to bigger primitives (e.g. the image in gure 1(I)).

There are many measures in the literature that, given an image, capture the neness (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 ne 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 de ned 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 de ne 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 de ning 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 questions are not treated 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 di erent 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 well known 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.

Figure 1: Some examples of images with di erent degrees of neness

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 di erent coarseness categories. For this purpose, data about the human perception of neness is collected by means of a pool. 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- neness.

Moreover, we propose to apply the obtained fuzzy partition to texture image retrieval. The current image retrieval systems are based on features, such as color, texture or shape, which are automatically extracted from images. In this framework, a very important point to take into account is the imprecision in the feature descriptions, as well as the store and retrieval of that imprecise data. To deal with this vagueness, some interesting approaches introduce the use of fuzzy logic in the feature representation and in the retrieval process [9, 10]. These fuzzy approaches also allow to perform queries on the basis of linguistic terms, avoiding one of the drawbacks of the classical image retrieval systems, where the queries have to be de ned on the basis of images or sketches similar to the one we are searching for. This way, the proposed fuzzy partition will be used to describe images in terms of their texture coarseness and the queries will be performed by using linguistic labels.

The rest of the paper is organized as follows. In section 2 we present our methodology to obtain the fuzzy partition and its application to image retrieval. 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 neness measure. To face this problem, we propose to de ne a fuzzy partition on the domain of a given neness 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 de ne the partition on the domain of a given coarseness- neness 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 de ned 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 $K = 17$ measures shown in the rst 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 di erent degrees of neness. This analysis will be based on how the human perceives the neness-coarseness. To get information about human perception of neness, a set of images covering di erent degrees of neness will be gathered. These images will be used to collect, by means of a pool, human assessments about the perceived neness. From now on, let $\mathcal{I} = \{I_1, \ldots, I_N\}$ be the set of N images representing neness-coarseness examples, and let $\Gamma = \{v^1, \ldots, v^N\}$ be the set of perceived neness values associated to $\mathcal{I}$, with v^i being the value representing the degree of neness perceived by humans in the image $I_i \in \mathcal{I}$. We will use the texture image set and the way to obtain Γ described in [11].

Using the data about human perception, and the measure 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 neness degrees that each measure can discriminate (section 2.1). In addition, with the information given by the tests, we will de ne the fuzzy sets which will compound the partition (2.2).

Table 1: Result obtained by applying the algorithm proposed in [11]

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 [12]	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 [13]	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 [14]	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 [15]	4	{1,2-6,7-8,9}	-	0.153±0.0064	0.113±0.0093	0.099±0.0036	0.051±0.0041
DGD [16]	3	{1,2-8,9}	-	-	0.020±0.0010	0.038±0.0017	0.091±0.0070
FMPS [17]	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 [18]	3	{1,2-6,7-9}	-	-	0.1517±0.0425	0.2654±0.0466	0.4173±0.0497
SNE [19]	3	{1,2-8,9}	-	-	0.879±0.0182	0.775±0.0087	0.570±0.0232
SRE [20]	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	-	-	-	-	-	-

2.1 DISTINGUISHABILITY ANALYSIS OF THE FINENESS MEASURES

As it was expected, some measures have better ability to represent neness-coarseness than the others. To study the ability of each measure to discriminate different degrees of neness-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 shown in [11]. 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 Sche e, Bonferroni, Duncan, Tukey's least signi cant di erence, and Tukey's honestly signi cant di erence [21]), and nally the number of positive tests to accept distinguishability will be xed to $NT = 3$.

From now on, we shall note as $\Upsilon_k = C_1^k, C_2^k, \ldots, C_{N_k}^k$ the N_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. In this paper, we propose to compute $\bar{c}_r^k$ as the mean of the measure values in the class C_r^k.

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

[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

2.2 THE FUZZY PARTITIONS

In this section we will deal with the problem of de ning the membership function for each fuzzy set 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 de ning the 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 2.1. As it is known, in these tests con dence intervals around the representative value of each class are calculated (being accomplished 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 con dence interval.

The con dence interval CI_r^k for the class C_r^k is de ned as

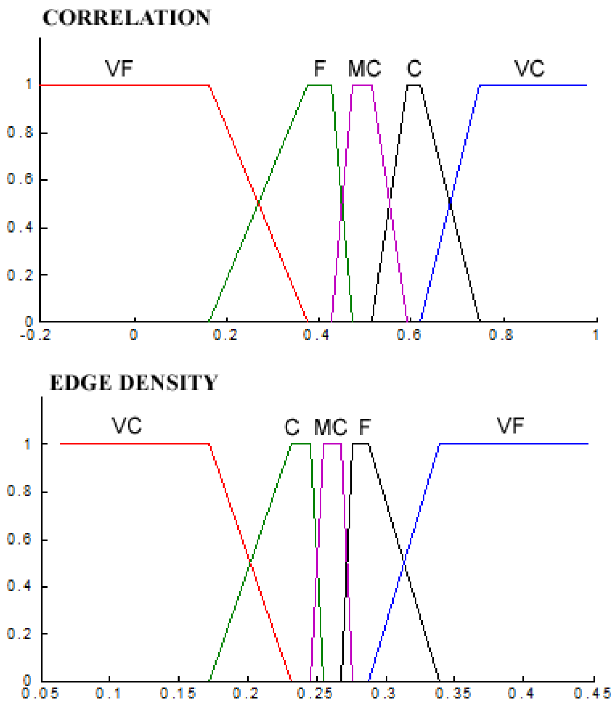

Figure 2: Fuzzy partitions for the measures Correlation and Edge Density. The linguistic labels are VC = very coarse, C = coarse, MC = medium coarse, F = ne, VF = very ne

$$CI_r^k = \bar{c}_r^k \pm 1.96 \frac{\bar{\sigma}_r^k}{\sqrt{||C_r^k||}} \quad (1)$$

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

$$KW_r^k = 3.92 \frac{\bar{\sigma}_r^k}{\sqrt{||C_r^k||}} \quad (2)$$

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 neness clases).

2.3 APPLICATION TO TEXTURE IMAGE RETRIEVAL

As it was pointed, we propose to apply the obtained fuzzy partition to texture image retrieval. This fuzzy partition will be used to describe the representative texture coarseness in an image. To do this, we will extract the dominant texture coarseness. Intuitively, a texture coarseness is dominant if it appears frequently in a given image, and it depends on the percentage of pixels where the texture coarseness appears. In order to calculate this percentage, for each pixel in the original image, a window centered on this pixel has been analyzed and its membership degree to each fuzzy set has been calculated. Thus, the percentage of pixels with texture coarseness C_r^k in the image under consideration will be

$$fr(C_r^k) = \frac{sc(C_r^k)}{NP} \quad (3)$$

where $sc(C_r^k)$ is the sigma-count histogram of the class C_r^k and NP is the number of pixels in the image.

Since frequent is an imprecise concept, dominance also is. It seems natural to model the idea of frequent apparition by means of a fuzzy set over the percentages, i.e., a fuzzy subset of the real interval [0, 1]. Hence, we de ne the fuzzy subset Dominant of texture coarseness as follows:

$$Dom(C_r^k) = \begin{cases} 0 & \text{if } fr(C_r^k) \leq u_1, \\ \frac{fr(C_r^k) \;\; u_1}{u_2 \;\; u_1} & \text{if } u_1 \leq fr(C_r^k) \leq u_2, \\ 1 & \text{if } fr(C_r^k) \geq u_2 \end{cases} \quad (4)$$

where u_1 and u_2 are two parameters such that $0 \leq u1 < u2 \leq 1$.

This way, we will describe images in terms of their dominant texture coarseness and the queries will be performed by using linguistic labels. The image retrieval process based on this dominant texture coarseness will be similar to the approach proposed in [22], based on dominant color descriptors.

3 RESULTS

In this section, the fuzzy partition de ned 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 di erent increasing degree of neness. Figure 3(B-F) shows the membership degree to the fuzzy sets "very coarse", "coarse", "medium coarse", " ne" and "very ne", 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

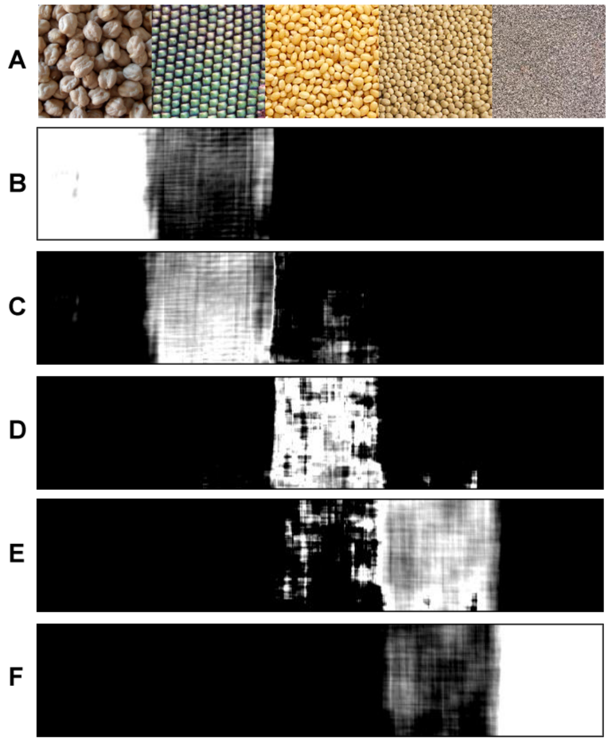

Figure 3: Results for a mosaic image. (A) Original image (B)(C)(D)(E)(F) Membership degree of each pixel to the sets ”very coarse”, ”coarse”, ”medium coarse”, ” ne” and ”very ne”, respectively (the darker the pixel, the lower the membership degree)

noticed that our model captures the evolution of the perception degrees of neness.

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 have 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)).

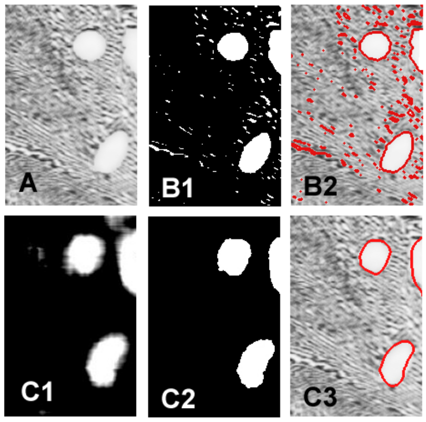

Figure 4: Example of pattern recognition (A) Original image (B1) Binary image obtained by thresholding the original one (B2) Region outlines of B1 superimposed on original image (C1) Membership degrees to the set ”very coarse” obtained with our model from the original image (C2) Binary image obtained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

Figure 5 presents an example of the application of the proposed fuzzy partition to image retrieval. We have used the dominant texture coarseness proposed in this paper as well as the dominant color descriptors shown in [22] in order to describe the images of a database containing about 700 color images. This example shows the results corresponding to the query *Dark orange color and very coarse texture*. It can be noticed that the images obtained match with the perception of very coarse textures.

4 CONCLUSIONS AND FUTURE WORKS

In this paper, a fuzzy partition for representing the neness/coarseness concept has been proposed. The number of fuzzy sets and the parameters of the membership functions have been de ned relating neness measures with the human perception of this texture property. Pools have been used for collecting data about the human perception of neness, and the capability of each measure to discriminate di erent coarseness degrees has been analyzed. The results given by our approach show a high level of connection with the human perception of neness/coarseness. As future work, the performance of the fuzzy partition will be analyzed in applications like textural classi cation or segmentation.

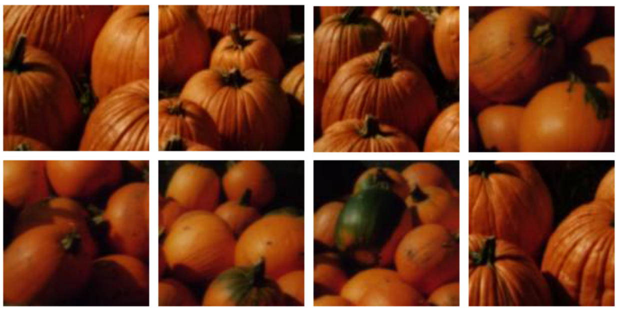

Figure 5: Example of the application to image retrieval. Results corresponding to the query *Dark orange color and very coarse texture*

References

[1] M. Amadasun and R. King. Textural features corresponding to textural properties. *IEEE Transactions on Systems, Man and Cybernetics*, 19(5):1264–1274, 1989.

[2] H. Tamura, S. Mori, and T. Yamawaki. Textural features corresponding to visual perception. *IEEE Transactions on Systems, Man and Cybernetics*, 8:460–473, 1978.

[3] R.M. Haralick. Statistical and structural approaches to texture. *Proceedings IEEE*, 67(5):786–804, 1979.

[4] M. Hanmandlu, V. K. Madasu, and S. Vasikarla. A fuzzy approach to texture segmentation. In *Proc. International Conference on Information Technology: Coding and Computing*, volume 1, pages 636–642, 2004.

[5] A. Barcelo, E. Montseny, and P. Sobrevilla. Fuzzy texture unit and fuzzy texture spectrum for texture characterization. *Fuzzy Sets and Systems*, 158:239–252, 2007.

[6] J. Chamorro-Martnez, E. Galn-Perales, J.M. Soto-Hidalgo, and B. Prados-Suarez. Using fuzzy sets for coarseness representation in texture images. In *Proceedings IFSA'07*, pages 783–792, 2007.

[7] S. Kulkarni and B. Verma. Fuzzy logic based texture queries for cbir. In *Proc. 5th Int. Conference on Computational Intelligence and Multimedia Applications*, pages 223–228, 2003.

[8] H.C. Lin, C.Y. Chiu, and S.N. Yang. Finding textures by textual descriptions, visual examples, and relevance feedbacks. *Pattern Recognition Letters*, 24(14):2255–2267, 2003.

[9] C.-C. Hsu, W.W. Chu, and R.K. Taira. A knowledge-based approach for retrieving images by content. *IEEE Transactions on Knowledge and Data Engineering*, 8:522–532, 1996.

[10] D. Sanchez, J. Chamorro-Martinez, and M.A. Vila. Modelling subjectivity in visual perception of orientation for image retrieval. *Information Processing and Management*, 39(2):251–266, 2003.

[11] J. Chamorro-Martnez, P. Martnez-Jimnez, and J.M. Soto-Hidalgo. De ning a fuzzy partition for coarseness modelling in texture images. *Proceedings IFSA'09*, 2009.

[12] J. Canny. A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6):679–698, 1986.

[13] N. Abbadeni, N. Ziou, and D.S. Wang. Autocovariance-based perceptual textural features corresponding to human visual perception. In *Proc. of 15th International Conference on Pattern Recognition*, volume 3, pages 901–904, 2000.

[14] S. Peleg, J. Naor, R. Hartley, and D. Avnir. Multiple resolution texture analysis and classi cation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, (4):518–523, 1984.

[15] J.S. Weszka, C.R. Dyer, and A. Rosenfeld. A comparative study of texture measures for terrain classi cation. *IEEE Transactions on Systems, Man and Cybernetics*, 6:269–285, 1976.

[16] S.I. Kim, K.C. Choi, and D.S. Lee. Texture classi cation using run difference matrix. In *Proc. of IEEE 1991 Ultrasonics Symposium*, volume 2, pages 1097–1100, December 1991.

[17] H. Yoshida, D.D. Casalino, B. Keserci, A. Coskun, O. Ozturk, and A. Savranlar. 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.

[18] S.D. Newsam and C. Kammath. 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*, April 2004.

[19] C. Sun and W.G. Wee. Neighboring gray level dependence matrix for texture classi cation. *Computer Vision, Graphics and Image Processing*, 23:341–352, 1983.

[20] M.M. Galloway. Texture analysis using gray level run lengths. *Computer Graphics and Image Processing*, 4:172–179, 1975.

[21] Y. Hochberg and A.C. Tamhane. *Multiple Comparison Procedures*. Wiley, 1987.

[22] J. Chamorro-Martnez, J.M. Medina, C. Barranco, E. Galn-Perales, and J.M. Soto-Hidalgo. Retrieving images in fuzzy object-relational databases using dominant color descriptors. *Fuzzy Sets and Systems*, 158(3):312–324, 2007.