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A Fuzzy Approach for Texture Contrast Modelling

J. Chamorro-Martínez, P. Martínez-Jiménez, J.M. Soto-Hidalgo, and D. Sánchez

***Abstract*— In this paper, we propose to model the contrast of visual texture by means of a perceptual-based fuzzy approach. For this modelling, fuzzy sets defined on the domain of some of the most representative measures of the contrast property are employed. In order to obtain these fuzzy sets, a functional relationship between the computational values given by the measures and the human perception of contrast is learned. The goodness of each model is analyzed and tested with the human assessments, allowing us to identify the most suitable one to represent the contrast of visual texture. Finally, several experiments are performed in order to show the application of the proposed fuzzy model for pattern recognition.**

I. Introduction

TEXTURE is, together with color and shape, one of the most used features for image analysis and, in addition, one of the most difficult to characterize due to its imprecision. In fact, there is not an accurate definition for the concept of texture but some intuitive ideas, as local changes in the intensity patterns or as a set of basic items arranged in a certain way [1]. However, for humans, the most common way to describe texture is by using vague textural properties, like *contrast*, *coarseness* or *directionality* [2], [3], that give them an informal way to represent their perception about the texture.

Neurological experiments have shown that texture contrast has a strong influence on visual attention in natural images [4], and, moreover, it is closely related to the depth perception of the textured regions present in the image [5], [6]. In this sense, the *contrast* property is considered as one of the most important properties in texture analysis [7], [8], [9], playing a fundamental role in human visual interpretation [3]. By considering the importance of the texture contrast, in this paper we will focus our study on this perceptual property.

There are many measures in the literature that, given an image, capture the contrast presence in the sense that the greater the value given by the measure, the greater (lower) the presence of this property [10], [3], [1]. However, there is no perceptual relationship between the value given by these measures and the degree in which the humans perceive the texture. Thus, given a certain value calculated by applying a measure to an image, there is not an immediate way to decide whether there is a contrasted texture, a non-contrasted texture or something intermediate (i.e. there is not a textural interpretation).

The imprecision associated to these contrast measures suggests the use of representation models that incorporate the uncertainty. Nevertheless, the majority of the approaches that can be found in the literature are crisp proposals [11], [1], [12] which do not model any kind of imprecision. To face this problem, some proposals arise from the fuzzy set field, and more specifically from the content-based image retrieval area [13], [7], [14], [15], [16]. In these proposals, a mapping from low-level statistical features (the crisp measures described above) to high level textural concepts is performed by defining membership functions for each textural feature.

However, in all these fuzzy approaches the membership functions are adjusted manually or by using a fuzzy clustering, but without considering the relationship between the measure values and the human perception of the property. This implies that the obtained membership degrees do not necessarily match what a human would expect. In addition, all these fuzzy approaches do not propose a global modelling of the textural concept, but a fuzzy partition providing a set of linguistic terms associated to this concept. This type of solution is unsuitable for some classical tasks, like pattern recognition, because a single presence degree of the textural property cannot be obtained, but one membership degree for each linguistic term in the partition.

In this paper, we propose a perception-based fuzzy approach for texture contrast modelling in order to solve all these problems. In this approach, the contrast presence is modelled by means of a unique fuzzy set defined on the domain of a representative measure of this property. Thus, the obtained fuzzy set will directly represent the presence degree of the property, allowing its use in pattern recognition problems, as it will be shown in section V. In order to obtain the membership function, a functional relationship between the computational values given by the measures and the human perception of contrast is learned. This way, the presence degree given by the obtained fuzzy set will match what a human would expect.

The rest of the paper is organized as follows. In section II a general overview introducing our methodology is presented. After that, some elements of the model are describe in detail in the following sections; concretely, the way to obtain human assessments about contrast perception is faced in section III, while section IV describes the procedure employed to obtain the membership functions of the proposed fuzzy sets. In section V the results of applying the models are shown, and the main conclusions are summarized in section VI.

II. Fuzzy Modelling of Contrast: an Overview of the Proposal

In this paper we propose to model the contrast property of visual texture as a fuzzy set $\mathcal{T}_k$ defined on the domain of a representative contrast measure (our reference set). The

J. Chamorro-Martínez, P. Martínez-Jiménez and D. Sánchez are with the Department of Computer Science and Artificial Intelligence, University of Granada, Spain. email: {jesus,pedromartinez,daniel}@decsai.ugr.es
J.M. Soto-Hidalgo is with the Department of Computer Architecture, Electronics and Electronic Technology, University of Córdoba, Spain. email: jmsoto@uco.es

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(a) (b) (c) (d) (e)

Fig. 1. Some examples of texture images with different presence degrees of contrast.

membership function[1] of this fuzzy set will be defined as

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

For this modelling, two questions need to be faced: (i) what reference set should be used for the fuzzy set, and (ii) how to obtain the related membership function. Concerning to the reference set, we will define the fuzzy set on the domain of a given contrast measure. From now on, let $\mathcal{P} = \{P_1, \ldots, P_K\}$ be a set of contrast measures, with $P_k \in \mathcal{P}$ being the measure used to define $\mathcal{T}_k$. The measures analyzed in this paper are summarized in section II-A. All of them are automatically computed from the texture images.

With regard to the membership function, we propose to obtain it by using a perceptually-based approach that relates the contrast measures with the human perception of the property. For this purpose, two questions need to be faced: firstly, how to obtain the data about the "human perception" of contrast and, secondly, how to fit this data with the measures in order to obtain the membership function. To get information about the human perception of contrast, a set of images covering different presence degrees of this property has been gathered. These images are used to collect, by means of a poll, human assessments about the perceived contrast presence. From now on, let $\mathcal{I} = \{I_1, \ldots, I_N\}$ be the set of N images representing contrast examples, and let $\Gamma = \{v^1, \ldots, v^N\}$ be the set of contrast values associated to $\mathcal{I}$, with v^i being the value representing the degree of contrast perceived by humans in the image $I_i \in \mathcal{I}$. The description of the texture image set and the way to obtain Γ are detailed in section III.

To obtain the membership function $\mathcal{T}_k$ for a given measure $P_k \in \mathcal{P}$, a robust fitting method is employed in order to obtain suitable functions relating the values of the measure calculated for each image with the degree of contrast perceived by humans. This fitting method is described in section IV.

A. Contrast Measures

In this paper, we propose to use 4 of the most used contrast measures in the literature. Two of them try to estimate directly the contrast between texels by analyzing the pixels of the image. The first one is the measure defined by Tamura *et al.* in [3], which takes into account both the dynamic range of gray levels in the image and the kurtosis of their distribution. The second one is the contrast measure defined by Abbadeni in [17], which is based on the autocovariance function.

The other two measures are obtained by applying statistics over matrices that collect information about the relationships between the gray level of each pixel and their neighbours. The first one is the contrast statistic proposed by Haralick *et al.* in [1], which is obtained from GLCM matrices. The second one is the contrast measure proposed by Amadasun and King in [10], which takes into account both global statistics (as the dynamic range of gray levels in the image) and local statistics calculated from the Neighbourhood Gray-Tone Difference Matrix.

III. Assessment Collection

In this section, the way to obtain the set of values $\Gamma = \{v^1, \ldots, v^N\}$, that represents the presence degree of contrast perceived by humans in the images $I_i \in \mathcal{I}$, will be described. For this purpose, first the image set $\mathcal{I}$ will be selected (section III-A). After that, a poll for getting assessments about the perception of contrast will be designed (section III-B). Finally, for a given image, the assessments of the different subjects will be aggregated (section III-C).

A. The Texture Image Set

A set $\mathcal{I} = \{I_1, \ldots, I_N\}$ of $N = 80$ images representing examples of the contrast property has been selected. Figure 1 shows some images extracted from the set $\mathcal{I}$. Such set has been selected satisfying the following conditions:

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

Due to the third condition, each image can be viewed as "homogeneous" with respect to the presence degree of contrast, i.e., if we select two random windows (with a dimension which does not "break" the original texture primitives and structure), the perceived contrast presence will be similar for each window (and also with 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 (sub-images) with the same presence degree as the original one. This will be very useful for the fitting process, because we can have a larger number

[1] 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.

TABLE I

FITTING ERROR, TEST ERROR AND PARAMETERS OF THE MEMBERSHIP FUNCTION CORRESPONDING TO EACH CONTRAST MEASURE.

Contrast measure	Fitting error	Test error	a_3	a_2	a_1	a_0	α	β
Tamura [3]	0.0340	0.0649	1.6877	-3.9536	3.8763	-0.5728	0.1775	0.9620
Amadasun [10]	0.0780	0.1108	0.2803	-1.1488	1.8254	-0.3839	0.2462	2.1288
Abbadeni [17]	0.1003	0.1393	0.3977	-1.8684	2.9594	-1.0859	0.5172	2.6235
Haralick [1]	0.1157	0.1416	0.6232	-1.8714	2.0679	-0.4100	0.2502	1.8773

of fitting points without extending the number of images used in the poll.

B. The Poll

Given the image set $\mathcal{I}$, the next step is to obtain assessments about the perception of contrast from a set of subjects. From now on we shall note as $\Theta^i = [o_1^i, \ldots, o_L^i]$ the vector of assessments obtained from L subjects for the image I_i. To get Θ^i, subjects are asked to assign images to classes, so that each class has associated a perception degree of contrast.

In particular, five different classes have been considered in the poll. The five texture images shown in Figure 1 are the representative images for these classes. It should be noticed that these images are in decreasing order according to the presence degree of contrast. The first class (Figure 1(a)) represents the presence degree of 1, while the last one (Figure 1(e)) represents the presence degree of 0. The rest of classes represent presence degrees of contrast between 0 and 1, i.e. texture primitives with gradual variations in contrast between the previous ones.

In our approach, 20 subjects have participated in the 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 to which the image is assigned by the subject.

C. 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 contrast. To aggregate opinions we have used an OWA operator guided by a quantifier [18]. Concretely, the quantifier "the most" has been employed, which allows us to represent the opinion of the majority of the subjects. This quantifier is defined as

$$Q(r) = \begin{cases} 0 & \text{if } r < a, \\ \frac{r-a}{b-a} & \text{if } a \le r \le b, \\ 1 & \text{if } r > b \end{cases} \qquad (2)$$

$\forall r \in [0,1]$, with $a = 0.3$ and $b = 0.8$. Once the quantifier Q has been chosen, the weighting vector of the OWA operator can be obtained following Yager [18] 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 $v^i = w_1\hat{o}_1^i + w_2\hat{o}_2^i + ... + w_L\hat{o}_L^i$, where $[\hat{o}_1^i, \ldots, \hat{o}_L^i]$ is a vector obtained by ranking in nonincreasing order the values of the vector Θ^i.

IV. FITTING THE MEMBERSHIP FUNCTION

At this point, the aim is to obtain, for a given measure $P_k \in \mathcal{P}$, the corresponding membership function $\mathcal{T}_k$. In this paper, we propose to find a function that associates the values of the contrast measures with the human assessments about this property. As it was pointed out in section III-A, thanks to the "homogeneity" in the presence degree of contrast, each image $I_i \in \mathcal{I}$ can be seen as a set of sub-images with the same contrast degree v_i of the original one. From now on, we will denote by $\mathcal{I}_\mathcal{W} = \{I_{i,w}, i = 1, \ldots, N; w = 1, \ldots, W\}$ the set of sub-images extracted from $\mathcal{I}$, where $I_{i,w}$ is the w-th sub-image of I_i and W is the number of sub-images considered for each image; on the other hand we will denote by $m_k^{i,w}$ the result of applying the measure P_k to the sub-image $I_{i,w}$. According to this notation, let $\mathcal{I}_\mathcal{W}^{\text{fit}} \subset \mathcal{I}_\mathcal{W}$ and $\mathcal{I}_\mathcal{W}^{\text{test}} = \mathcal{I}_\mathcal{W} \backslash \mathcal{I}_\mathcal{W}^{\text{fit}}$ be two complementary subsets of $\mathcal{I}_\mathcal{W}$, that will be used for fitting the membership function and testing the obtained model, respectively.

Thus, in order to estimate the membership function that associates the measure values ($m_k^{i,w}$) and the human assessments of contrast (v^i), we propose to fit a suitable function of the form given in Eq. (1) to the subset of points:

$$\Psi_k^{\text{fit}} = \{(m_k^{i,w}, v^i); \forall I_{i,w} \in \mathcal{I}_\mathcal{W}^{\text{fit}}\} \qquad (3)$$

In this paper, for each image $I_i \in \mathcal{I}$, $W = 200$ sub-images of size 32×32 have been considered, so $\mathcal{I}_\mathcal{W}$ is formed by 16000 sub-images. We propose to randomly select 75% of them for the fitting, so that 12000 points are contained within Ψ_k^{fit}.

The measure values can be affected by some factors, like brightness, contrast or noise, which typically causes outliers in the fitting points. For this reason, in our approach the membership function is calculated by means of a robust fitting of the multiset Ψ_k^{fit}. In this modelling, the robust fitting based on M-estimators (a generalization of the least squares fitting) is used [19]. In addition, to define $\mathcal{T}_k$, the following considerations are taken into account:

- $\mathcal{T}_k$ should be a monotonic function.
- The values $\mathcal{T}_k(x) = 0$ and $\mathcal{T}_k(x) = 1$ should be reached.

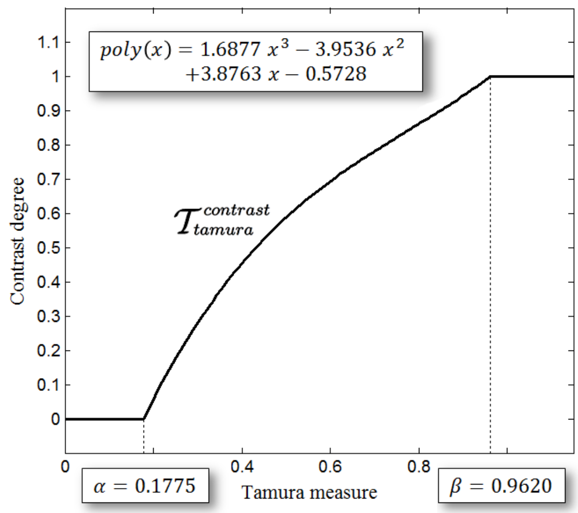

Fig. 2. Graphical representation of the model with the lowest error.

Regarding the above properties, we propose to define $\mathcal{T}_k$ as a function of the form[2]

$$\mathcal{T}_k(x; a_n \dots a_0, \alpha, \beta) = \begin{cases} 1 & x < \alpha, \\ poly(x; a_n \dots a_0) & \alpha \le x \le \beta, \\ 0 & x > \beta \end{cases} \tag{4}$$

with $poly(x; a_n \dots a_0)$ being a polynomial function

$$poly(x; a_n \dots a_0) = a_n x^n + \dots + a_1 x^1 + a_0 \tag{5}$$

In our proposal, the parameters $a_n, \dots, a_0$, α and β of the function $\mathcal{T}_k$ are calculated by carrying out a robust fitting on Ψ_k^{fit}, with the constraint to obtain a strictly monotonic function between α and β. For the polynomial function, the cases of $n = 1, 2, 3, 4$ (i.e. linear, quadratic, cubic and quartic functions) have been considered.

The second column of Table I shows for each measure $P_k \in \mathcal{P}$ the least fitting error obtained. Note that this value can be viewed as the goodness of each measure to represent the perception of contrast. Table I has been ranked in increasing order of these fitting errors. In all the cases, the least error has been obtained for a polynomial function of order $n = 3$ (the use of higher order functions does not provide better fits).

In addition, the test error for each measure has been calculated by using the subset of points Ψ_k^{test} and it is shown in the third column of Table I. In our approach, this error is calculated as the mean absolute difference between the values v_i and the degrees obtained by applying the function $\mathcal{T}_k$ to the values $m_k^{i,w}$, for all the points $(m_k^{i,w}, v^i) \in \Psi_k^{\text{test}}$, i.e.

[2] Note that this function is defined for measures that decrease according to the perception of contrast. For those that increase, the function needs to be changed appropriately, i.e. it takes the value 0 for $x < \beta$, it takes the value 1 for $x > \alpha$, and the polynomial function is computed for $\beta \le x \le \alpha$.

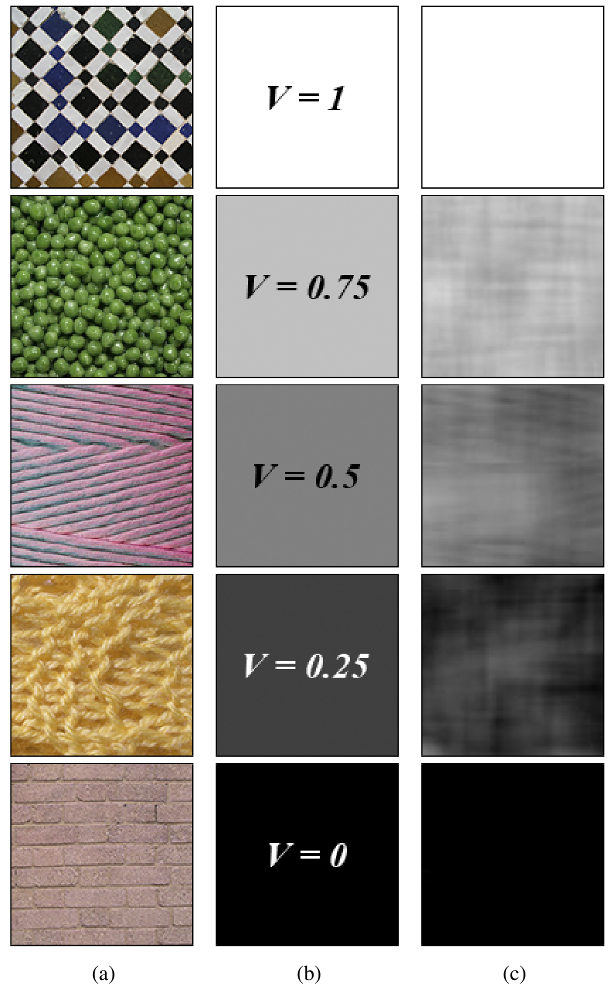

Fig. 3. Result for a collection of texture images (a), showing the human assessments about the presence degree of contrast (b), and the membership degrees obtained by applying the proposed contrast model (c).

$$E^{\text{test}} = \frac{\sum_{(m_k^{i,w}, v_i) \in \Psi_k^{\text{test}}} \left| \mathcal{T}_k(m_k^{i,w}) - v_i \right|}{card(\Psi_k^{\text{test}})} \tag{6}$$

with $card(\Psi_k^{\text{test}})$ being the cardinality of Ψ_k^{test}. The parameters of the membership function corresponding to each contrast measure are shown in the rest of the columns of Table I. In our experiments, the membership functions with the lowest error are obtained by using the measure of Tamura. The graphical representation of this model is show in Figure 2.

V. Results

In this section, the fuzzy sets proposed in this paper for texture contrast modelling will be applied to several examples in order to analyze their performance. In particular, the model with least fitting error and least test error (corresponding to the measure of Tamura according to Table I) will be used. For the first one, we have considered Figure 3(a), corresponding to a collection of texture images, each one with a different

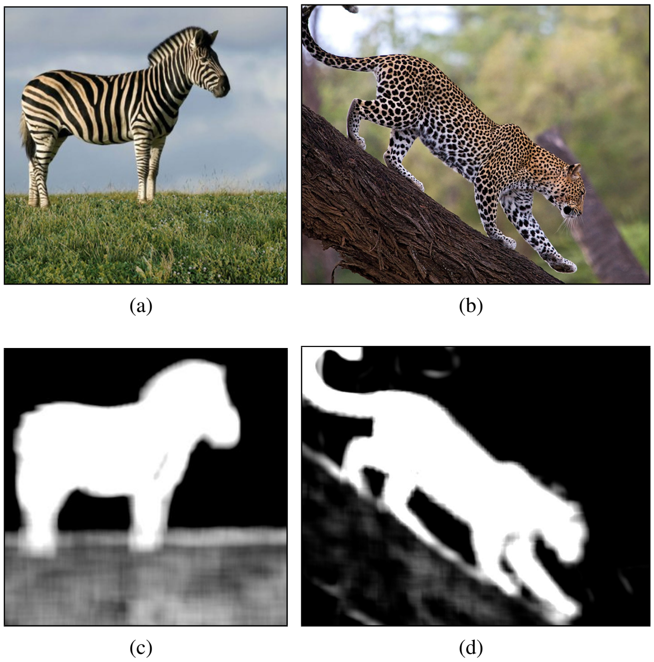

Fig. 4. Results for two natural images. (a)(b) Original images. (b) Mapping from the original images to their contrast values using the proposed model.

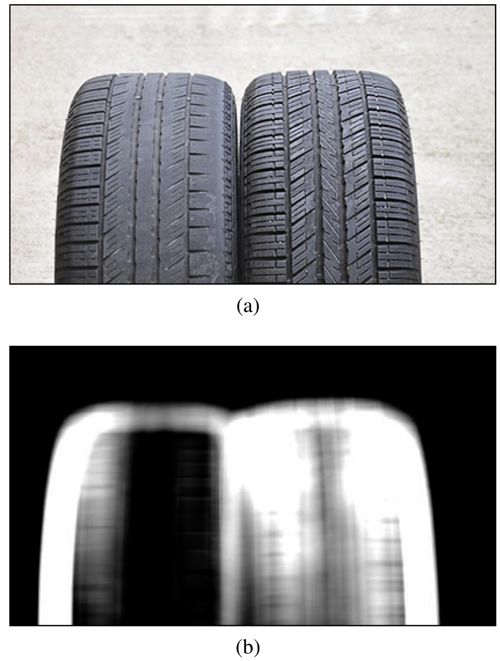

Fig. 5. Identification of defective patterns. (a) Original image. (b) Mapping from the original image to its contrast values using the proposed model.

decreasing perception degree of contrast. These images are part of the set used in the poll, so human assessments about contrast presence are available in order to compare them with the obtained results.

Figure 3(b) shows an ideal mapping from the original texture images to their contrast values, where all pixels corresponding to the same texture image have been mapped using the human assessment associated to that image. These assessments (between 0 and 1) have been mapped into a gray level from 0 to 255, so that a white pixel in the mapping indicates maximum perception of contrast, while a black one indicates no perception of this property.

Figure 3(b) shows a mapping from the original texture images to their contrast values obtained by applying the proposed model. For each pixel in the original images, a centered window of size 32×32 has been analyzed and its contrast membership degree has been calculated using the proposed model. This degree has been mapped into a gray level from 0 to 255. It can be noticed that the result obtained with our model matches what a human would expect, capturing the evolution of the perception degrees of contrast.

For the second experiment, we have considered Figures 4(a) and 4(b), corresponding to two natural images where several textures with different perception degrees of contrast are present. Figures 4(c) and 4(d) show a mapping from these natural images to their contrast values using the proposed model. It can be noticed that, as it was expected, three different degrees of contrast are shown in each mapping: a high contrasted texture (pixels in white), corresponding to the zebra in the first case and the leopard in the second one; a low contrasted texture (pixels in black), corresponding to the background of each image; and a half-contrasted texture (pixels with an intermediate gray level) corresponding to the grass and the branch, respectively. Therefore, we can say that the obtained mappings are directly interpretable by humans.

As it was commented in Section I, the contrast of a visual texture is related to the depth perception and the relief of the corresponding physical texture: textures with high relief in nature may appear with high contrast in the image (due to the illumination effect). Thus, similar physical textures with different relief, can be distinguished in an image by analyzing the contrast of the corresponding visual textures. Figure 5 shows an example where the proposed contrast model is used to identify defective patterns.

Lets consider the image shown in Figure 5(a), where we can see two tires with different wear levels. The tire on the right has deep grooves, while the one on the left has an irregular wear in the center and on one side. Figure 5(b) shows a mapping from this image to its contrast values using the proposed model. It can be noticed that the worn parts correspond to areas with low contrast degrees, so they can be identified if only the pixels with contrast degree lower than 0.1 are selected.

VI. Conclusions

In this paper, the contrast property of visual texture has been modelled by means of fuzzy sets defined on the domain of computational measures of this property. In order to define these models, parametric functions have been employed, where the corresponding parameters have been calculated by taking into account the relationship between the computational measures and the human perception of contrast. This way, the shape of the membership function has been adjusted to represent this relationship, and the obtained membership degrees match what a human would expect. We have concluded that the model obtained by using the measure of Tamura has the best ability to represent the perception of contrast. Moreover, the use of a unique fuzzy set to model the texture contrast as a whole has allowed its application to pattern recognition problems, as has been shown in the experiments of section V

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