An Adaptive Fuzzy Approach for Texture Modelling

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***Abstract*— In this paper, a method to adapt the fuzzy sets that models the "coarseness" texture property according to different coarse-fine perceptions is proposed. The membership functions associated to these fuzzy sets are obtained on the basis of the human assessments given by a pool, that represent the average coarse-fine perception degree. In the proposed method, the user's particular perception about coarseness-fineness and the changes in perception influenced by the image context have been taken into account to adapt the models. The membership functions are automatically adapted by means of a transformation of functions on the basis of the new coarse-fine perception.**

I. 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* [2], [18]. 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 (let us remark that "coarseness" and "fineness" are opposite but related textural concepts). 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 [8]. 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 no immediate way to decide whether there is a fine texture, a coarse texture or something intermediate (i.e. there is no textural interpretation).

The imprecision associated to these coarseness 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 [6], [8], [15], [18] 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) [16], [19], [14].

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Other interesting approaches emerge from the content-based image retrieval scope, where semantic data is managed by means of fuzzy sets [10], [11]. In these proposals, a mapping from low-level statistical features to high level textural concepts is performed by defining membership functions for each textural feature. However, given a feature, these membership functions are not obtained by considering the relationship between the computational feature and the human perception of texture, so the linguistic labels related to these membership functions do not necessarily match what a human would expect.

In previous works [5], we proposed to solve this problem by representing the concept of coarseness on the basis of fuzzy sets relating representative coarseness measures with the human perception of this property. These fuzzy sets represent the average perception about coarseness-fineness. The problem of this modelling is that a new user can have a different perception of coarseness-fineness and, moreover, it can change according to the image context. For example, the texture of the image in Figure 1(I) has been considered as coarse by users in [5], i.e. the fineness perception degree asigned to this texture is 0. Nevertheless, a new user can have a different fine-coarse perception and this texture may not be considered as coarse by him. An example where the coarse-fine perception changes according to the image context can be shown in Figure 3. The texture within the circular area is the same in (a) and (b), but in (a) it may be perceived as coarser than in (b) because of the surrounding texture[1].

In this paper we propose to solve these problems by adapting the fuzzy sets obtained in [5] (the non-adaptive modelling) according to new coarse-fine perceptions. This adaptation is performed by applying a transformation to the membership functions of these fuzzy sets. Specifically, a translation and an expansion (or compression) in the domain of the coarseness measure is applied. In order to obtain the parameters that define this transformation, some information representing the new perception is used. In the case of the adaptation to a new user's perception, a set of texture images and its corresponding perception degrees of fineness should be provided by the user to represent his particular perception. In the adaptation to the image context, it is natural to assume that the coarsest and the finest texture in the image will influence in the coarse-fine perception of the rest of textures. Thus, this information is used to adapt the fuzzy sets to the context of each image.

The rest of the paper is organized as follows. In section II we summarize the methodology to obtain the fuzzy sets proposed in [5], while in section III we introduce the

[1]This effect is more noticeable if the images are observed separately.

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

procedure employed to adapt the membership functions to new coarse-fine perceptions. Results are shown in section IV, and the main conclusions and future work are sumarized in section V.

II. Non-adaptive Coarseness Modelling

In this section we summarize the non-adaptive methodology proposed in [5]. In that work, we proposed to represent the concept of coarseness on the basis of fuzzy sets relating representative coarseness measures (our reference set) with the human perception of this property. These fuzzy sets represent the average perception about coarseness-fineness, but they don't take into account the different coarse-fine perception that a new user can have or the change in the perception due to the image context. For this reason, this modelling is noted as non-adaptive.

We proposed to define the membership function[2] of the non-adaptive fuzzy set $\mathcal{T}_k$ as

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

For this modelling, two questions were faced: (i) what reference set should be used for the fuzzy set, and (ii) how to obtain the related membership functions.

Concern to the reference set, we defined the fuzzy set on the domain of a given coarseness-fineness measure. From now on, we will note $\mathcal{P} = \{P_1, \dots, P_K\}$ the set of K measures analyzed in [5]. This set was formed by the $K = 17$ measures shown in the first column of table I. All of them were automatically computed from the texture image.

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

TABLE I
Fitting errors related to each measure and parameter values for the two measures with least error

Measure	Error
Correlation [8]	0.1466
Amadasun [2]	0.1515
Abbadeni [1]	0.1880
Fractal dim. (FD) [13]	0.1891
Tamura [18]	0.1994
Edge density (ED) [4]	0.2044
DGD [9]	0.2120
Local Homogeneity [8]	0.2156
Short Run Emphasis [7]	0.2211
SNE [17]	0.2365
Weszka [20]	0.2383
Newsam [12]	WSD
Entropy [8]	WSD
Uniformity[8]	WSD
FMPS [21]	WSD
Variance[8]	NR
Contrast [8]	NR

Parameters for Correlation	
a_3	-1.83828
a_2	1.23377
a_1	-1.20788
a_0	1.03395
α	0.76851
β	0.02893

Parameters for Amadasun	
a_3	-0.00006
a_2	0.00556
a_1	-0.17053
a_0	1.57472
α	16.5285
β	3.82800

With regard to the membership function, we proposed to obtain it by learning a relationship between the fineness measures and the human perception of fineness. For this purpose, two questions were faced: firstly, how to obtain the data about the "human perception of fineness" and, secondly, how to fit these data with the fineness measures in order to obtain the membership function.

To get information about human perception of fineness, a set of images covering different degrees of fineness were gathered. This images were used to collect, by means of a pool, human assessments about the perceived fineness. From now on, let $\mathcal{I} = \{I_1, \dots, I_N\}$ be the set of N images representing fineness-coarseness examples, and let $\Gamma = \{v^1, \dots, v^N\}$ 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 description of the texture image set and the way to obtain Γ are detailed in [5].

To obtain the membership function $\mathcal{T}_k$ for a given measure $P_k \in \mathcal{P}$, a robust fitting method was applied in order to obtain suitable functions relating (i) the values of the measure calculated for each image with (ii) the degree of fineness perceived by humans. As it is pointed in [5], from now on, we will note as $m_k^{i,w}$ the result of applying the measure P_k to the w-th window of the image I_i. Thus, we proposed to estimate $\mathcal{T}_k$ by fitting a suitable curve to the multiset of points $\Psi_k = \{(m_k^{i,w}, v^i), i = 1, \dots, N; w = 1, \dots, W\}$, with N being the number of images and W the number of windows considered for each image. In [5], a set of $N = 80$ images was selected (Figure 1 shows some images extracted from the set $\mathcal{I}$) and for each image $W = 2000$ subimages of size 32×32 were considered (so 16000 points were used for the fitting).

To define $\mathcal{T}_k$, the following considerations was 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 achieved from a certain value

Regarding the above properties, we proposed to define $\mathcal{T}_k$ as a function of the form[3]

$$\mathcal{T}_k(x; a_n \dots a_0, \alpha, \beta) = \begin{cases} 0 & x < \alpha, \\ poly^n(x; a_n \dots a_0) & \alpha \le x \le \beta, \\ 1 & x > \beta \end{cases} \quad (2)$$

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

$$poly^n(x; a_n \dots a_0) = a_n x^n + \dots + a_1 x^1 + a_0 \quad (3)$$

In [5], the parameters $a_n \dots a_0$, α and β of the function $\mathcal{T}_k$ were calculated by carrying out a robust fitting on Ψ_k with the constraint to obtain a monotonic function. For the polynomial function, the cases of n=1,2,3 (i.e. linear, quadratic and cubic functions) were considered. In this modelling, the robust fitting based on M-estimators (a generalization of the least squares fitting) was used [3]. Table I shows for each measure $P_k \in \mathcal{P}$ the least fitting error obtained. Note that this value can be viewed as a goodness measure of the ability of the measure to represent the perception of fineness.

Table I has been sorted in increasing order of the errors. The parameter values of the two measures with the lowest error (Correlation and Amadasun) are also shown in Table I. It should be noticed that we haven't carried out the fitting with six of the measures. Four of them (marked with WSD) are rejected because their values are affected by the window size, ie., they are window size dependent. The other two (marked with NR) produce a diffuse cloud of points Ψ_k which implies that these measures are not providing a representative information about the perception of fineness.

III. Adaptation to Different Coarse-Fine Perceptions

As it was pointed out, the non-adaptive fuzzy set $\mathcal{T}_k$ shown in section II represents the average perception of coarseness-fineness. The problem of this modelling is that a new user can have a different perception of this property and, moreover, it can change according to the image context.

To face this problem, a solution would be to ask the new user for his particular coarseness perception of each of the images in the set $\mathcal{I}$ (introduced in section II). This information would be used as fitting data, instead of the assessments obtained in [5]. Thus, the models that represent the new user's perception would be obtained by applying the robust fitting method shown in the non-adaptive modelling (summarized in section II) to this data. Nevertheless, this solution is not practical in an interactive system, because it has to be trained for each user.

In this section, we propose a different solution to avoid repeating this process for each new user. In the proposed method, the membership function $\mathcal{T}_k$ will be automatically adapted according to the new coarse-fine perception. From now on, and extending our notation in [5], we will note $\tilde{\mathcal{T}}_k$ the adapted membership function for the measure P_k (obtained by adapting $\mathcal{T}_k$).

A. Adaptation to user's coarse-fine perception

In order to adapt the membership function to a particular user's perception about coarseness-fineness, a set of texture images and its corresponding perception degree of fineness should be provided by the user. Let $\mathcal{R} = \{R^1, \dots, R^Z\}$ be the set of $Z \ge 1$ texture images given by the user to represent his particular perception, let $\mathcal{V} = \{v^1, \dots, v^Z\}$ be the perception degrees of fineness associate to $\mathcal{R}$, and let $\mathcal{M} = \{m_k^1, \dots, m_k^Z\}$ be the values for the measure $P_k \in \mathcal{P}$ applied to each image $R^i \in \mathcal{R}$. According to this notation, let $\Omega_k = \{(m_k^i, v^i), m_k^i \in \mathcal{M}; v^i \in \mathcal{V}; m_k^i < m_k^{i+1}\}_{i=1,\dots,Z}$ be the set of pairs of values *measure/perception degree* ordered by the measure value.

We propose to obtain $\tilde{\mathcal{T}}_k$ by means of a transformation that adapts the membership function $\mathcal{T}_k$ to the new criteria Ω_k. This transformation is performed by translating and expanding (or compressing) $\mathcal{T}_k$ in the domain of the measure. Thus, we propose to define $\tilde{\mathcal{T}}_k$ as a function

$$\tilde{\mathcal{T}}_k : \mathbb{R} \to [0,1] \quad (4)$$

of the form

$$\tilde{\mathcal{T}}_k(x; \Omega_k) = \begin{cases} \mathcal{T}_k(\mathbf{A}_{m_k^1 m_k^2}^{\bar{m}_k^1 \bar{m}_k^2}(x)) & x < m_k^1, \\ \mathcal{T}_k(\mathbf{A}_{m_k^i m_k^{i+1}}^{\bar{m}_k^i \bar{m}_k^{i+1}}(x)) & m_k^i \le x \le m_k^{i+1}, \\ \mathcal{T}_k(\mathbf{A}_{m_k^{Z-1} m_k^Z}^{\bar{m}_k^{Z-1} \bar{m}_k^Z}(x)) & x > m_k^Z \end{cases} \quad (5)$$

with $\bar{m}_k^i = \mathcal{T}_k^{-1}(v^i)\ \forall i$ being the value of the measure where $\mathcal{T}_k$ takes the value v^i, with $(m_k^i, v^i) \in \tilde{\Omega}_k$, and where $\mathbf{A}_{a'b'}^{ab}(x)$ is defined as the horizontal translation and expansion function of

$$\mathbf{A}_{a'b'}^{ab}(x) = \frac{x - a'}{b' - a'}(b - a) + a \quad (6)$$

It can be seen that the values of $\tilde{\mathcal{T}}_k$ in each interval $[m_k^i, m_k^{i+1}]$ will be obtained by translating and expanding (or compressing) the interval $[\bar{m}_k^i, \bar{m}_k^{i+1}]$, i.e. the interval delimited by the values where $\mathcal{T}_k$ achieves v^i and v^{i+1}. The values of $\tilde{\mathcal{T}}_k$ for $x < m_k^1$ and $x > m_k^Z$ will be obained from the values of $\mathcal{T}_k$ for $x < \bar{v}_k^1$ and $x > \bar{v}_k^Z$ with the same transformations as in the intervals $[m_k^1, m_k^2]$ and $[m_k^{Z-1}, m_k^Z]$, respectively. It should be noticed that the values where $\tilde{\mathcal{T}}_k$ achieves 0 and 1, noted as $\tilde{\alpha}$ and $\tilde{\beta}$, will be obtained (if they are not defined in Ω_k) as

$$\begin{aligned} \tilde{\alpha} &= \mathbf{A}_{\bar{m}_k^1 \bar{m}_k^2}^{m_k^1 m_k^2}(\alpha) \\ \tilde{\beta} &= \mathbf{A}_{\bar{m}_k^{Z-1} \bar{m}_k^Z}^{m_k^{Z-1} m_k^Z}(\beta) \end{aligned} \quad (7)$$

where α and β are the values defined in (2).

It should be noticed that (5) is valid only for $Z > 1$. In the particular case of $Z = 1$ only a translation is performed

$$\tilde{\mathcal{T}}_k(x) = \mathcal{T}_k(x + \bar{m}_k^1 - m_k^1) \quad (8)$$

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

B. Adaptation to image context

Natural images will usually show several textures with different perception degrees of coarseness. It is natural to assume that the coarsest and the finest texture in the image will influence in the coarse-fine perception of the rest of textures, i.e. it can depend on the context.

In this section, we propose to adapt the membership function $\mathcal{T}_k$ to the image context in order to obtain the adapted model $\tilde{\mathcal{T}}_k$. In our proposal, the coarsest and the finest texture in the image will impose the minimum and the maximum perception degrees of fineness in the model, i.e. the values where the function $\tilde{\mathcal{T}}_k$ achieves the membership degrees 0 and 1. Thus, we will estimate the values of the measure P_k for the coarsest and the finest texture in the image, and the values $\tilde{\alpha}$ and $\tilde{\beta}$ for the adapted model will be imposed by them. The adaptation will be performed by transforming (translating and expanding/compressing) $\mathcal{T}_k$ in order to obtain the fuzzy set $\tilde{\mathcal{T}}_k$ that accomplishes these values.

In order to obtain $\tilde{\alpha}$ and $\tilde{\beta}$, the value of the measure P_k has been calculated for each pixel in the original image (a centered window of size 32×32 has been used). Let $\mathcal{M} = \{m_k^i,\ m_k^i \leq m_k^{i+1}\}_{i=1,\ldots,N}$ be the ordered set of the values obtained by applying the measure P_k to the N pixels of the image. We propose to define $\tilde{\alpha}$ and $\tilde{\beta}$ as the 20^{th} percentile and the 80^{th} percentile in $\tilde{\mathcal{M}}$, i.e. $\tilde{\alpha} = m_k^{round(0.2N+0.5)}$ and $\tilde{\beta} = m_k^{round(0.8N+0.5)}$, with $round(x)$ being the function that returns the nearest integer to x. These values are used to define the set $\Omega_k = \{(\tilde{\alpha}, 0), (\tilde{\beta}, 1)\}$, and the adapted membership function $\tilde{\mathcal{T}}_k$ is obtained by applying the transformation shown in section III-A on the basis of this set.

IV. Results

In this section, the membership function $\mathcal{T}_k$ with least fitting error (obtained for the measure Correlation and defined by the parameter values shown in Table I) will be adapted to different coarse-fine perceptions. The obtained membership function $\tilde{\mathcal{T}}_k$ will be applied in order to analyze the performance of this model according to a particular coarse-fine perception.

Let's consider Figure 2(a) corresponding to a natural image where several textures with different perception degrees of fineness are shown. Figure 2(b) shows a mapping from the original image to its fineness values using the initial non-adaptive model $\mathcal{T}_k$ for the measure Correlation. For each pixel in the original image, a centered window of size 32×32 has been analyzed and its fineness has been calculated. Thus, Figure 2(b) represents the degree in which the human perceives the texture, with a white grey level meaning maximum perception of fineness, and a black one meaning no perception of fineness (i.e., maximum perception of coarseness). It can be noticed that three different degrees of fineness are shown: a coarse texture (pixels with black grey level) corresponding to the big stones, a fine texture (pixels with white grey level) corresponding to the grass, and

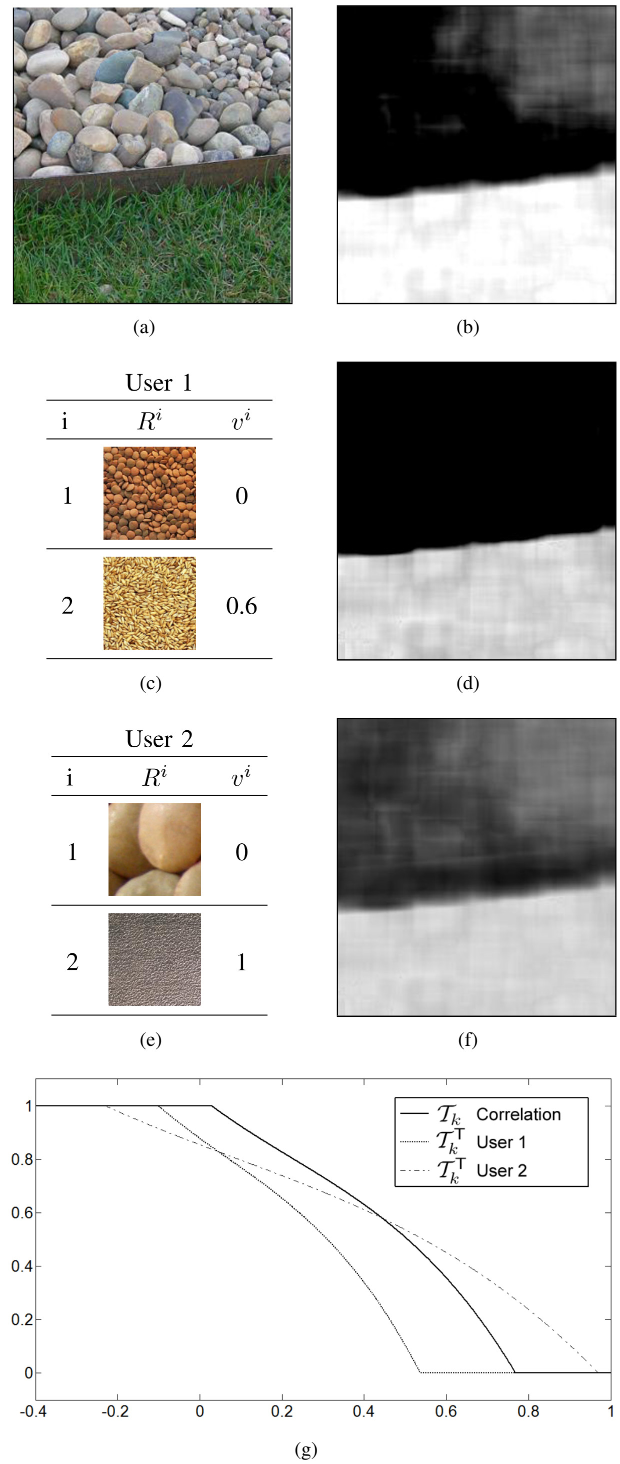

Fig. 2. Results for a natural image. (a) Original image (b) Mapping from the original image to its fineness values using the initial model $\mathcal{T}_k$ for the measure Correlation (c)(e) Samples representing the particular coarse-fine perception of two different users (d)(f) Mapping using the adapted model $\tilde{\mathcal{T}}_k$ for each user's perception and (g) Membership functions for the original and the adapted models.

a intermediate coarseness texture (pixels with an intermediate grey level) corresponding to gravel.

Figure 2(c) shows two texture images given by the *user 1* to represent his particular coarse-fine perception, and the perception degrees of fineness given by this user. It can be seen that the image R^1, that has an intermediate fineness perception according to the initial model (a fineness membership degree around 0.5), is now perceived as a coarse texture by this user ($v^1 = 0$). The perception degree of fineness given by the user to the image R^2 ($v^2 = 0.6$) is also smaller than the fineness membership degree obtained with the initial model. The adapted membership function $\tilde{\mathcal{T}}_k$ obtained on the basis of this information, together with the initial model $\mathcal{T}_k$, is shown in Figure 2(g). Comparing both functions, it should be noticed that, according to the particular perception of the *user 1*, all the textures will be considered coarser than those obtained when $\mathcal{T}_k$ is applied. Figure 2(d) shows a mapping from the natural image in Figure 2(a) using $\tilde{\mathcal{T}}_k$. It can be seen that in this case the gravel is also considered as a coarse texture, and the grass is not considered as fine as in Figure 2(b).

Figure 2(e) shows the samples given by a second user in order to represent his particular coarse-fine perception. According to this user, a coarse texture corresponds to very big texture primitives, whereas a fine texture corresponds to very small texture primitives. This implies that the adapted membership function $\tilde{\mathcal{T}}_k$ is obtained by expanding $\mathcal{T}_k$ in the domain of the measure, as it is shown in Figure 2(g). The mapping from the original image to its fineness values using $\tilde{\mathcal{T}}_k$ is shown in Figure 2(f).

Figure 3 presents an example where the model $\mathcal{T}_k$ for the measure Correlation has been adapted to the image context. Figures 3(a) and 3(b) show two texture images, with the same texture within the circular area and different textures in the surrounding area. Nevertheless, the texture within the circular area in Figure 3(a) may be perceived coarser than in Figure 3(b) because of the surrounding texture, that is very fine in the first image and very coarse in the second one. This effect is more noticeable if the images are observed separately. The mappings from the original images to their fineness values using the model $\mathcal{T}_k$ are shown in figures 3(c) and 3(d), respectively. This model doesn't take into account the changes in the coarse-fine perception due to the image context. Thus, the circular area has the same grey level in both images. Figures 3(e) and 3(f) show the mappings to the fineness values using the model $\tilde{\mathcal{T}}_k$, obtained by adapting $\mathcal{T}_k$ to the coarser and the finer texture in each image. It can be noticed that in this case the texture within the circular area is considered as coarse in Figure 3(e) (black grey level) and as fine in Figure 3(f) (white grey level), which matches to the human coarse-fine perception influenced by the image context.

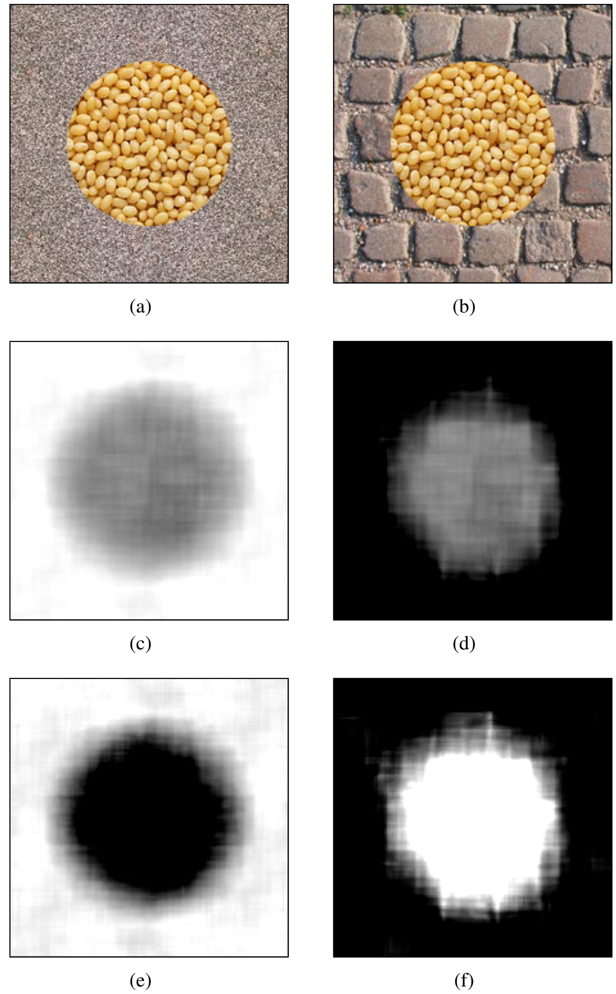

Fig. 3. Results for adaptation to the image context. (a)(b) Original images (c)(d) Mapping from the original image to its fineness values using the initial model $\mathcal{T}_k$ for the measure Correlation (e)(f) Mapping using the model adapted to the image context $\tilde{\mathcal{T}}_k$.

V. Conclusions and Future Works

In this paper, a method to adapt the fuzzy sets that models the fineness-coarseness concept (obtained in previous works) according to different coarse-fine perceptions have been proposed. The membership functions associated to these fuzzy sets have been automatically adapted by means of a transformation of functions on the basis of new coarse-fine perceptions. In the proposed method, the user's particular perception about coarseness-fineness and the changes in perception influenced by the image context have been taken into account to adapt the models. The obtained membership functions have been applied in order to analyze the performance of these models according to the particular coarse-fine perception, obtaining satisfactory results. As future work, a method to adapt bidimensional fuzzy sets will be performed.

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