Customizing Fuzzy Partitions for Visual Texture Representation

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Abstract

Visual textures in images are usually described by humans using linguistic terms related to their perceptual properties, like "very coarse", "low directional", or "high contrasted". Thus, computational models with the ability of providing a perceptual texture characterization on the basis of these terms play a fundamental role in tasks where some interaction with subjects is needed. In this sense, fuzzy partitions defined on the domain of computational measures of the corresponding property have been proposed in the literature. However, the main drawback of these proposals is that they do not take into account the subjectivity associated to the human perception. For example, the perception of a texture property may change depending on the user, and in addition, the image context may influence the global perception of the properties. In this paper, we propose to solve these problems by means of a methodology that automatically adapts any generic fuzzy partition modeling a texture property to the particular perception of

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a user or to the image context. In this method, the membership functions associated to the fuzzy sets are automatically adapted by means of a functional transformation on the basis of the new perception. For this purpose, the information given by the user or extracted from the textures present in the image are employed.

Keywords: image analysis, texture modelling, fuzzy partitions, linguistic labels, human perception, adaptive models

1. Introduction

Texture is one of the most used low level features for image analysis and computer vision. In fact, since all the objects in nature have texture (see the natural image in Figure 1(a)), its analysis plays a fundamental role in their recognition and classification [7, 13, 19]. An example of this importance can be appreciated in figures 1(b)-(e), where several images with the same shape and a similar color are shown, but that can be identified thanks to the analysis of their texture.

There are many techniques in the literature for texture analysis, and the use of one or another depends on the particular task in which it is applied. In this sense, for tasks where a textural description interpretable by humans is not needed, such as segmentation or texture classification, we can find a lot of techniques that try to model texture by means of feature vectors. These types of approaches are based on genetic programming [23, 25], dictionary learning [8, 31], kernel learning [6, 17], Gabor functions [12, 32] or Wavelets [11, 15], that are considered as the golden standard in the literature.

However, in tasks where some interaction with subjects is needed, techniques with the ability of providing a perceptual texture characterization interpretable by humans can be more useful. In these types of approaches, texture is modeled on the basis of some vague textural properties that are usually employed by humans, like *coarseness*, *directionality*, *contrast*, *line-likeness* or *regularity* [2, 9, 26]. These perceptual properties are imprecise by nature, in the sense that, except in extreme cases, we cannot set a precise threshold between textures that accomplish strictly a property and textures that do not. In this sense, it is natural for humans to give assessments about the presence degree of these perceptual properties. For example, regarding the properties of coarseness and contrast, we can reasonably say that the texture shown in Figure 2(a) is "very coarse" and "high contrasted", that the texture shown in Figure 2(b) is "coarse" and "medium contrasted", and that the texture shown in Figure 2(c) is "very fine" and "very low contrasted".

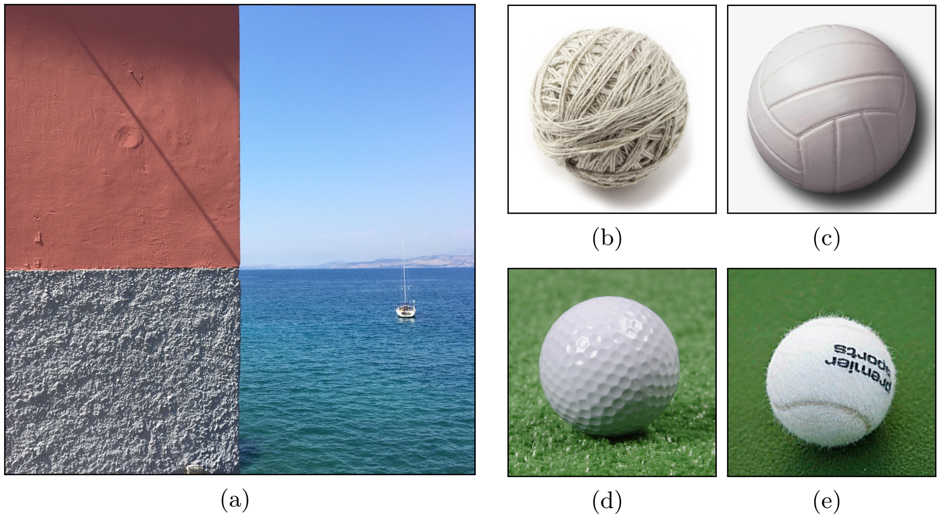


Figure 1: Importance of the analysis of texture. (a) All the objects in nature have texture. (b)-(e) Example of objects with the same shape and color, but different texture.

This way, focusing our attention on the perceptual texture characterization, the most interesting approaches arise from the fuzzy set field [1, 3, 14], as they are able to take into account the inherent uncertainty. In these proposals, a mapping from low-level statistical features (crisp computational measures of the corresponding property) to high level textural concepts is performed by defining membership functions for each textural feature. In particular, fuzzy partitions defined on the domain of computational measures are proposed in the literature, providing a set of linguistic labels that are related to the presence degree of the property [5, 20, 18, 24]. In these partitions, piecewise linear membership functions, such as triangular or trapezoidal functions, are usually employed. These fuzzy approaches can be very useful in classical tasks where a texture characterization using linguistic terms is needed, such as semantic description of images or content-based image retrieval using linguistic queries.

In the majority of these fuzzy techniques [1, 3, 14, 18, 24, 28, 29], the measures proposed by Tamura *et al.* in [26] are used as reference set, and the fuzzy partitions are generated through an unsupervised fuzzy clustering algorithm on the basis of the measure values obtained from an image database. In more recent approaches [5, 20], a distinguishability analysis based on the human perception of the texture properties are proposed to generate the fuzzy partitions. In this case, several computational measures

(a) (b) (c)

Figure 2: Examples showing the imprecision associated to the properties.

are used as reference set, analyzing their capability to discriminate between different categories of the corresponding property. In addition, the membership functions are adjusted by considering the relationship between the measure values and the average human perception of the property, obtaining fuzzy partition that are able to represent the presence of the texture properties according to this average perception.

However, all these fuzzy techniques have a main drawback that, to the best of our knowledge, has not been faced in the literature: these approaches do not take into account the subjectivity associated to the human perception. On the one hand, the perception of a texture property may change depending on the user or the application. For example, the concept of "very fine" may be different for a geologist, who analyzes satellite images, than for a medical expert, who study the textures present in x-ray or microscopic images. Moreover, even in the same field of application, two users may have different perceptions about the texture properties. For example, although we have considered that the texture shown in Figure 2(a) is very coarse, another user may consider that this texture is not so coarse.

On the other hand, the image context may affect the global perception of these properties, i.e. the perception of a texture may change depending on the presence of the surrounding ones. An example of this fact can be shown in Figure 3, where several textures with different fineness degrees are present. The images in figures 3(a) and 3(b) are very similar, but in the last one a new texture has been added. The presence of this texture, that is much coarser than the others, can inhibit the rest of textures, and they may be perceived as finer than in Figure 3(a). Considering the property of contrast, it can be noticed that the texture added in Figure 3(b) is much more contrasted than the others. Thus, the presence of the new texture can also influence the perception of this property, and the rest of textures may

(a) (b)

Figure 3: Example showing the influence of the image context in the perception of fineness and contrast properties. The presence of the very coarse and very contrasted texture in (b) can inhibit the rest of textures, and they may be perceived as finer and less contrasted than in (a).

be perceived as less contrasted than in Figure 3(a)[1].

In this paper we propose to face the problem related with the subjectivity of the human perception commented above. For this purpose, we propose a methodology that automatically adapts any generic fuzzy partition modeling a texture property to the particular perception of a user or to the image context. In this method, the membership functions associated to the fuzzy sets are automatically adapted by means of a functional transformation on the basis of the new perception. Since piecewise linear membership functions, such as triangular or trapezoidal functions, are usually employed in the fuzzy partitions, the proposed functional transformation consist basically in the adaptation of their parameters values. In order to take into account the particular perception of a new user, a set of texture images representing the particular profile of the user is employed in the transformation process. In the case of the adaptation to the image context, the information used in the transformation process is obtained by analyzing the textures present in the image.

The rest of the paper is organized as follows. In section 2 a general overview of our methodology, as well as the used notation, are presented. The technique proposed in this paper to obtain fuzzy partitions adapted

[1]Notice that this fact is more noticeable if the images are observed separately.

to the perception of different users or to the image context is described in sections 3 and 4, respectively. In section 5 some results obtained by applying these models are shown, and the main conclusions and future works are summarized in section 6.

2. Preliminaries and notations

As mentioned in the above section, the majority of the approaches in the literature that allow to obtain semantic descriptions of visual texture are based on fuzzy partitions defined on the domain of a given computational measure. In these approaches, piecewise linear membership functions, such as triangular or trapezoidal functions, are usually employed. From now on, let Π be a fuzzy partition modeling a texture property, and let $\mathcal{D}$ be the domain of the computational measure used as reference set. Let also N be the number of fuzzy sets in Π, let T_n be the n-th fuzzy set in the partition (with $n = 1, \ldots, N$) [2], and let $\mathcal{L} = \{l_1, \ldots, l_N\}$ be the set of linguistic terms modeled by Π.

The aim of this paper is to obtain, from a generic fuzzy partition Π, adaptive ones, allowing to represent the particular perception of a user or the influence of the image context. From now on, let $\tilde{\Pi}$ be the adapted fuzzy partition obtained from Π, and let $\tilde{T}_n$ be the n-th fuzzy set in $\tilde{\Pi}$.

In the proposed adaptation methodology, we assume $T_n(x), n = 1, \ldots, N$ to be piecewise linear functions, such as triangular or trapezoidal functions. That is,

$$T_n(x) = T(x, a_1^n, a_2^n, \ldots, a_k^n) \tag{1}$$

with k being the number of parameters of the piecewise function[3]. Considering this condition, we propose to obtain $\tilde{\Pi}$ from Π by transforming the parameters that define these membership functions according to the particular perception of the user or the image context, as we will explain in the following sections. This way, the adapted fuzzy partition $\tilde{\Pi}$ obtained with this methodology will satisfy the following properties:

[2] To simplify the notation, as it is usual in the scope of fuzzy sets, we will use the same notation T_n for the fuzzy set and for the membership function that defines it.

[3] Notice that in the case of triangular functions three parameters are used ($k = 3$), with a_1^n and a_3^n being the support limits, and with a_2^n being the kernel; while in the case of trapezoidal functions four parameters are employed ($k = 4$), with a_1^n and a_4^n being the support limits, and with a_2^n and a_3^n being the kernel limits.

- $\tilde{\Pi}$ will have the same reference set as Π (the domain $\mathcal{D}$ of the computational measure on which the partition is defined).

- $\tilde{\Pi}$ will have the same number N of fuzzy sets as Π (modeling the same linguistic labels $\mathcal{L} = \{l_1, \ldots, l_N\}$).

- $\tilde{\Pi}$ will have the same type of membership functions as Π, i.e. the type of $\tilde{T}_n(x)$ will be the same as $T_n(x)$ (triangular, trapezoidal, etc.), but with different parameter values $(\tilde{a}_1^n, \ldots, \tilde{a}_k^n)$.

3. Adaptation to user's profiles

Our aim is to obtain a fuzzy partition $\tilde{\Pi}$ representing the particular perception of a user about a texture property. In our adaptation approach, we propose to obtain $\tilde{\Pi}$ by adapting a certain generic fuzzy partition Π on the basis of the information given by the user. Specifically, the user should provide a collection of texture images $\mathcal{R} = \{R_1, \ldots, R_Z\}$, each one with an associated linguistic label $l_i \in \mathcal{L}$ of the corresponding property, in order to represent his/her particular perception. Notice that the user can associate the same linguistic term to different images in $\mathcal{R}$. From now on, let $P \leq N$ be the number of different labels given by the user.

On the basis of $\mathcal{R}$, our approach proposes to obtain $\tilde{\Pi}$ from Π by means of what we call the *adaptation points*, which are defined as pairs $p_i = (m_i \in \mathcal{D}, l_i \in \mathcal{L})$ for $i = 1, \ldots, P$; these points associate each linguistic label l_i given by the user in $\mathcal{R}$ with a representative value m_i of the computational texture measure[4]. Let

$$\Omega = \{p_i, \quad p_i < p_{i+1}\}_{i=1,\ldots,P} \tag{2}$$

be the ordered set of adaptation points, where the inequality $<$ is defined as $p_i < p_j$ *iff* $m_i < m_j \ \forall i, j$. In addition, we also impose the constraint $l_i < l_j \ \forall i, j$ for measures that increase according to the presence of the property, and the constraint $l_i > l_j \ \forall i, j$ for those that decrease. Notice that the number of points in Ω is P (the number of different labels in $\mathcal{R}$), so we need a procedure to obtain Ω from $\mathcal{R}$.

In order to obtain these adaptation points, we propose to analyze the information given by the user by following the method detailed in Algorithm 1. The input of this algorithm are the collection of labeled texture images

[4]Notice that only one adaptation point is defined for each different linguistic label given by the user.

Algorithm 1 Calculation of the adaptation points

Input:

  $\mathcal{R} = \{R_1, \ldots, R_Z\}$: the collection of labeled texture images

Let:

  $\mathcal{R}^{l_i}$: the subset of images in $\mathcal{R}$ with label l_i

  $m(R)$: the value of the computational measure applied to R

  $l_1 < l_2 < \ldots < l_P$: the semantically sorted linguistic labels in $\mathcal{R}$

Body:

  $m_1 = median\{m(X)\}_{X \in \mathcal{R}^{l_1}}$

  $p_1 = (m_1, l_1)$

  $\Omega = \{p_1\}$

  for each label $l_i, i = 2, \ldots, P$:

    $m_i = median\{m(X)\}_{X \in \mathcal{R}^{l_i}}$

    while $m_{i-1} \geq m_i$:

      Delete from $\mathcal{R}^{l_i}$ the image with lowest measure value

      if $card(\mathcal{R}^{l_i}) = 0$:

        //incoherent information in $\mathcal{R}$

        $\Omega = \emptyset$

        goto Output

      Recalculate $m_i = median\{m(X)\}_{X \in \mathcal{R}^{l_i}}$

    $p_i = (m_i, l_i)$

    $\Omega = \Omega + \{p_i\}$

Output: Ω

$\mathcal{R}$, and the output is the ordered set Ω. First of all, let us denote by $\mathcal{R}^{l_i}$ the subset of images in $\mathcal{R}$ with label l_i, and let us denote by $m(R)$ the value of the computational measure used as reference set applied to the image R. In addition, let $l_1 < l_2 < \ldots < l_P$ be the semantically sorted linguistic labels in $\mathcal{R}$, e.g. if we are modeling the contrast property the labels are sorted from the lowest contrast to the highest contrast[5].

In our algorithm, a representative value m_i of the computational measure is obtained for each linguistic label l_i. Since the user can provide several texture images associated to the same linguistic label, we propose to calculate this representative value as the median of the measure values obtained from

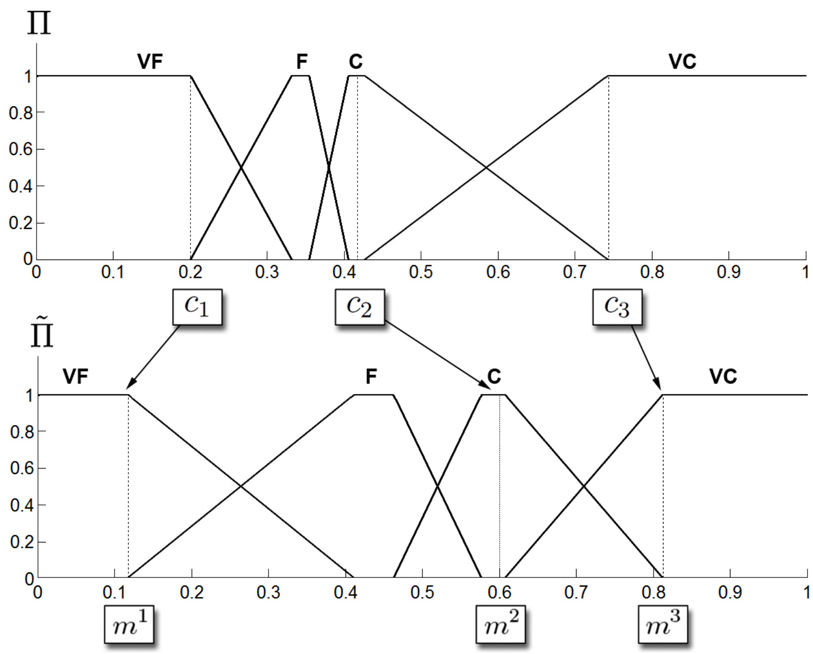
[5]This is only valid for measures that increase according to the presence of the property. For those that decrease, the labels should be sorted from the highest presence to the lowest presence of the property

the images in $\mathcal{R}^{l_i}$. Notice that, some of these images may generate abnormal computational values (due to their low quality, the effect of brightness, etc.), so the use of the median allows us to reduce the influence of these outliers. However, as has been commented above, the obtained representative values should maintain the same order as the linguistic labels, i.e. $m_1 < m_2 < \ldots < m_P$. In order to accomplish this constraint, each representative value m_i is compared with the previous one m_{i-1}. If $m_{i-1} < m_i$, the adaptation point $p_i = (m_i, l_i)$ is added to Ω. However, if $m_{i-1} \geq m_i$, an iterative process is applied. In this process, the image with lowest measure value in $\mathcal{R}^{l_i}$ is deleted, and m_i is recalculated. This iterative process continues until $m_{i-1} < m_i$. In this case, the adaptation point $p_i = (m_i, l_i)$ is added to Ω. However, if the subset of images $\mathcal{R}^{l_i}$ becomes empty during the iterative process, the adaptation will be not possible ($\Omega = \emptyset$), because incoherent information has been given by the user in $\mathcal{R}$ (the measure values for all the images with a linguistic label are lower than the representative value of the previous label).

Once Algorithm 1 has been applied, our aim is to obtain $\tilde{\Pi}$ by performing a suitable transformation of Π using the collection of adaptation points Ω. In our approach, the center of the kernel of the fuzzy set T_i associated to each linguistic label l_i in Ω, denoted by c_i in the following[6], will be translated to the corresponding measure value m_i. To do this, since $T_n(x)$ are piecewise linear functions, we propose to transform the parameters $a_j^n; n = 1, \ldots, N; j = 1, \ldots, k$ that define these membership functions in order to obtain the corresponding adapted parameters $\tilde{a}_j^n$. According to our adaptation method, the transformation applied to a_j^n will depend on the interval $[m_i, m_{i+1}]$ in which it is included. Thus, the adapted parameters $\tilde{a}_j^n; n = 1, \ldots, N; j = 1, \ldots, k$ can be calculated as follows

$$\tilde{a}_j^n = \begin{cases} \frac{m_2 - m_1}{c_2 - c_1}(a_j^n - c_1) + m_1 & a_j^n \leq c_1 \; or \; c_1 < a_j^n \leq c_2, \\ \vdots & \\ \frac{m_{i+1} - m_i}{c_{i+1} - c_i}(a_j^n - c_i) + m_i & c_i < a_j^n \leq c_{i+1}, \\ \vdots & \\ \frac{m_P - m_{P-1}}{c_P - c_{P-1}}(a_j^n - c_{P-1}) + m_{P-1} & c_{P-1} < a_j^n \leq c_P \; or \; a_j^n > c_P \end{cases} \tag{3}$$

[6]Notice that in the case of triangular membership functions the center of the kernel matches with the second parameter of the function, i.e. $c_i = a_2^i$, while in the case of trapezoidal functions it is calculated as the mean value between the second and third parameter, i.e. $c_i = (a_2^i + a_3^i)/2$.



(a)

	R_1	R_2	R_3	R_4	R_5
$m(R)$	0.6	0.56	0.12	0.43	1.06
label	"C"	"VC"	"VF"	"VC"	"VC"

(b)

Figure 4: Example of adaptation of the generic fuzzy partition Π (a-top) proposed in [21] to model the fineness property. The adapted partition $\tilde{\Pi}$ (a-bottom) is obtained by transforming Π according to the particular fineness perception of a new user (b).

It should be noticed that (3) is valid only for $P > 1$. In the particular case of $P = 1$ (only information about one label is provided by the user) the transformation applied to all the parameters is reduced to a translation

$$\tilde{a}_j^n = a_j^n + m_1 - c_1 \tag{4}$$

Figure 4 shows a real example that illustrates the proposed adaptation method: first, Algorithm 1 is applied in order to obtain the adaptation points; and then, they are used to calculate the adapted parameters $\tilde{a}_j^n$ according to equation (3). In this example, we have used the generic fuzzy partition Π proposed in [21] to model the fineness property (shown at the top of Figure 4(a)). The parameter values a_j^n that define the trapezoidal membership functions used in Π are listed in Table 1(a).

Let us suppose that a new user gives five texture images to represent his/her particular fineness perception ($\mathcal{R} = \{R_1, \ldots, R_5\}$). In addition, let us suppose that the values obtained by applying the fineness measure used as reference set for these images, as well as the linguistic labels given by the user, are the ones shown in Figure 4(b). Notice that three different labels are given by the user (*"C"* or *coarse*, *"VF"* or *very fine* and *"VC"* or *very coarse*), i.e. $P = 3$.

Our aim at this point is to obtain the ordered set Ω by applying Algorithm 1. Since the computational measure used as reference set in [21] decreases according to the presence of the property, the labels should be sorted from the highest fineness presence to the lowest fineness presence, i.e. $l_1 > l_2 > l_3$ with $l_1 =$ *"VF"*, $l_2 =$ *"C"* and $l_3 =$ *"VC"*. As we have commented above, a representative value m_i of the fineness measure should be obtained for each linguistic label. First, the value associated to the label $l_1 =$ *"VF"* is calculated as $m_1 = median\{0.12\} = 0.12$, and the adaptation point $p_1 =$ (0.12, *"VF"*) is added to Ω. In a similar way, we can calculate the value $m_2 = 0.6$, and, since $m_1 < m_2$, the adaptation point $p_2 =$ (0.6, *"C"*) is also added to Ω. Finally, the representative value for the label $l_3 =$ *"VC"* is calculated as $m_3 = median\{0.43, 0.56, 1.06\} = 0.56$. Since $m_2 > m_3$, the iterative process shown in Algorithm 1 should be applied. In this process, the image with lowest measure value from the ones with label *"VC"* is deleted, and m_3 is recalculated as[7] $m_3 = median\{0.56, 1.06\} = 0.81$. In this case $m_2 < m_3$, so the iterative process stops, and the point p_3 = (0.81, *"VC"*) is added to Ω. Thus, the output of Algorithm 1 is $\Omega = \{(0.12, \text{“}VF''), (0.6, \text{“}C''), (0.81, \text{“}VC'')\}$.

The first adaptation point (0.12, *"VF"*) imposes that the center of the kernel[8] of the fuzzy set $l_1 =$ *"VF"*, that is $c_1 = 0.2008$ in Π, should be translated to $m_1 = 0.12$ in $\tilde{\Pi}$. In a similar way, the center of the kernels corresponding to $l_2 =$ *"C"* and $l_3 =$ *"VC"*, that are $c_2 = 0.4165$ and $c_3 = 0.7430$ in Π respectively, should be set to $m_2 = 0.6$ and $m_3 = 0.81$ in the adapted partition $\tilde{\Pi}$. In this case, the adapted parameters $\tilde{a}_j^n$ can be

[7]Notice that if there is an even number of values, the median is calculated as the mean (average) of the middle pair of numbers.

[8]Notice that for the extreme fuzzy sets in the partition (the fuzzy sets associated to the labels *"VF"* and *"VC"* in this example) the kernel extends to ∞ and $-\infty$, respectively. Thus, we propose to set the center of the kernel as the value where the membership function reach the degree 1.

obtained by using (3) as:

$$\tilde{a}_j^n = \begin{cases} \frac{0.6-0.12}{0.4165-0.2008}(a_j^n - 0.2008) + 0.12 & a_j^n \leq 0.4165, \\ \frac{0.81-0.6}{0.7430-0.4165}(a_j^n - 0.4165) + 0.6 & a_j^n > 0.4165 \end{cases}$$

Table 1(b) shows the parameter values of the adapted fuzzy partition $\tilde{\Pi}$ (shown at the bottom of Figure 4(a)), which are calculated by applying the values a_j^n listed in Table 1(a).

Table 1: Parameter values $a_{n,j}$ corresponding to the generic partition Π (a), and adapted parameters $\tilde{a}_{n,j}$ obtained with the proposed method.

n	$a_{n,1}$	$a_{n,2}$	$a_{n,3}$	$a_{n,4}$
1	$-\infty$	$-\infty$	0.2008	0.3326
2	0.2008	0.3326	0.3551	0.4062
3	0.3551	0.4062	0.4267	0.7430
4	0.4267	0.7430	∞	∞

(a)

n	$\tilde{a}_{n,1}$	$\tilde{a}_{n,2}$	$\tilde{a}_{n,3}$	$\tilde{a}_{n,4}$
1	$-\infty$	$-\infty$	0.1200	0.4133
2	0.1200	0.4133	0.4633	0.5771
3	0.4633	0.5771	0.6066	0.8100
4	0.6066	0.8100	∞	∞

(b)

4. Adaptation to image context

It is widely known in psychology and neurophysiology fields that objects perceived by the human visual system compete with each other to selectively focus our attention. Consequently, some of these objects are inhibited by the presence of those that predominate in the visual cortex [4, 16, 30]. This inhibitory effect imply that the human perception of an object is strongly affected by its context (i.e. the object's surroundings) [10, 22, 27]. In this sense, the image context, understood as the set of surrounding visual elements of a given region or object, may influence the perception of the different image features. In the case of visual textures, this means that the perception of a texture may change depending on the presence of the surrounding ones. In particular, it is natural to assume that the textures with the maximum and the minimum presence of a property in the image may affect the perception of this property for the rest of textures. In addition, the inhibitory effect induced by the context seems to be stronger or weaker depending on these extreme textures. For example, in the case of the fineness property shown in Figure 3(b), the coarsest and the finest texture in the image may inhibit the rest of textures, and this inhibition is strong because there is a great difference in the fineness presence of these extreme textures.

In this section, we propose a methodology to automatically adapt a generic fuzzy partition Π to the image context. In our approach, we consider that the inhibitory effect induced by the image context will depend on the difference between the textures with the minimum and the maximum presence of the property in the image (e.g. the coarser and the finer texture in the case of fineness), in the sense that the greater this difference, the stronger the inhibition. If no inhibition is present in the image, the fuzzy partition do not need to be adapted (i.e. $\tilde{\Pi} = \Pi$).

The adaptation method proposed in this section is very similar to the technique shown in the previous one, but in this case the information used to adapt the generic partition Π is obtained by analyzing the textures present in the image. In particular, we propose to associate the extreme fuzzy sets in the partition (e.g. "very coarse" and "very fine" in the case of fineness) to the minimum and the maximum texture values in the image. However, this solution may not be appropriate for images where the difference between these extreme values is not very significant, as it may produce undesirable artifact. In order to solve this problem, we propose to introduce a correction factor that we call *inhibition factor*.

From now on, let m_{min} and m_{max} be the values obtained by applying the computational measure to the textures with the minimum and the maximum presence of the property in the image, respectively; let λ be the inhibition factor related to the image for the corresponding property; and let m^*_{min} and m^*_{max} be the values obtained by applying the inhibition factor λ to m_{min} and m_{max}, respectively. At this point, our first aim is to obtain the values m_{min} and m_{max} of the corresponding image. Secondly, these values will be used to estimate the inhibition factor λ. Finally, this inhibition factor will be used to calculate the adaptation values m^*_{min} and m^*_{max}. This way, the fuzzy partition $\tilde{\Pi}$ adapted to the image context can be obtained by applying the same transformation shown in the previous section on the basis of the set

$$\Omega = \{(m^*_{min}, l_1), (m^*_{max}, l_N)\} \tag{5}$$

with l_1 and l_N being the labels associated to the extreme fuzzy sets T_1 and T_N, respectively (e.g. "very coarse" and "very fine" in the case of fineness).

In order to obtain the textures with the minimum and the maximum presence of the property in the image, for each pixel in the original image, the value of the measure used for the reference set is calculated using a window centered at this pixel. Let $\mathcal{M} = \{m_i,\ m_i \leq m_{i+1}\}_{i=1,\ldots,W}$ be the ordered set of these values calculated from the W pixels in the image. It is natural to assume that the first and the last element in this set will correspond with the textures with the minimum and the maximum presence of the property[9], respectively, i.e. $m_{min} = m_1$ and $m_{max} = m_W$. However, in natural images it is usual to find isolated pixels in a texture with very low or very large measure values, which do not fit with the values of the rest of pixels in the texture. In order to avoid the influence of these outliers, we propose to choose the elements $z > 1$ and $z' < W$ in $\mathcal{M}$, i.e. $m_{min} = m_z$ and $m_{max} = m_{z'}$. In particular, the 20^{th} percentile and the 80^{th} percentile in $\mathcal{M}$ have been used, i.e. $z = round(0.2W + 0.5)$ and $z' = round(0.8W + 0.5)$, with $round(x)$ being the function that returns the nearest integer to x.

Once the values m_{min} and m_{max} are calculated, our aim is to estimate the inhibition factor λ present in the image. In this paper, we consider that λ will reach the highest degree ($\lambda = 1$) if the difference $|m_{max} - m_{min}|$ is *large enough*, and it will decrease as this difference is smaller. Thus, we propose to define the inhibition factor as a value between 0 and 1 of the form

$$\lambda = \begin{cases} \frac{|m_{max}-m_{min}|}{U} & |m_{max} - m_{min}| < U, \\ 1 & |m_{max} - m_{min}| \geq U \end{cases} \tag{6}$$

with U being the threshold value for considering that the difference between the textures with the maximum and the minimum presence of the property in the image is large enough. In our approach, we consider that the difference between textures corresponding to the extreme fuzzy sets T_1 and T_N in the generic fuzzy partition Π is large enough. In this paper, we propose to define this threshold as

$$U = |c_N - c_1| \tag{7}$$

with c_1 and c_N being the center of the kernel of the fuzzy sets T_1 and T_N in Π, respectively.

Finally, once the inhibition factor is estimated, the values m^*_{min} and m^*_{max} imposing the minimum and the maximum presence of the property in $\tilde{\Pi}$ are calculated. In our approach, if no inhibition is present in the image ($\lambda = 0$), m^*_{min} and m^*_{max} will coincide with the corresponding values of the generic fuzzy partition, i.e. $m^*_{min} = c_1$ and $m^*_{max} = c_N$. On the contrary, if the inhibition is strong ($\lambda = 1$), m^*_{min} and m^*_{max} will be imposed by the textures with the minimum and the maximum presence of the property in

[9] For measures that increase according to the perception of the property.

the image, i.e. $m^*_{min} = m_{min}$ and $m^*_{max} = m_{max}$. Thus, in general, we propose to calculate m^*_{min} and m^*_{max} as

$$m^*_{min} = c_1 + \lambda \cdot (m_{min} - c_1) \tag{8}$$

$$m^*_{max} = c_N + \lambda \cdot (m_{max} - c_N) \tag{9}$$

5. Results

In this section, the adaptation method proposed in this paper is applied to several experiments with natural images. In particular, we propose to adapt the generic fuzzy partitions Π defined in [21]. In the first three experiments (section 5.1), these generic partitions are adapted to the particular perception of different users, analyzing the ability of the adapted models to represent the corresponding profile. The last three experiments (section 5.2) show examples where the fuzzy partitions are adapted to the image context, analyzing their ability to represent the perception of the texture properties influenced by the context.

In order to analyze the ability of a fuzzy partition (adapted or not) to represent the perception of a texture property, we propose to obtain a mapping from the original image to the membership degree associated to the different fuzzy sets in the partition. To obtain this mapping, for each pixel in the original image, a centered window of size 32×32 is analyzed and its membership degree to each fuzzy set is calculated. This degree is mapped into a gray level from 0 to 255, with a white level meaning maximum degree, and a dark one meaning zero degree. This way, we can easily check whether the mapping agree with the perception of the property corresponding to the different textures present in the image.

5.1. Adaptation to user's profiles

For the first experiment, the image shown in Figure 5(a) has been used, where we can see a spherical colony of green cells, that is composed by several daughter colonies inside a main one. Figures 5(b)-(e) show a mapping from this image using the generic fuzzy partition Π proposed in [21] for the fineness property, as has been commented above. The labels associated to these images are "very fine", "fine", "coarse" and "very coarse", respectively.

As we can see, this mapping represents the fineness of the different textures present in the image according to the average human perception used in [21]: the region corresponding to the daughter colonies is considered as "very fine" (white levels in Figure 5(b) and dark levels in the rest), the main

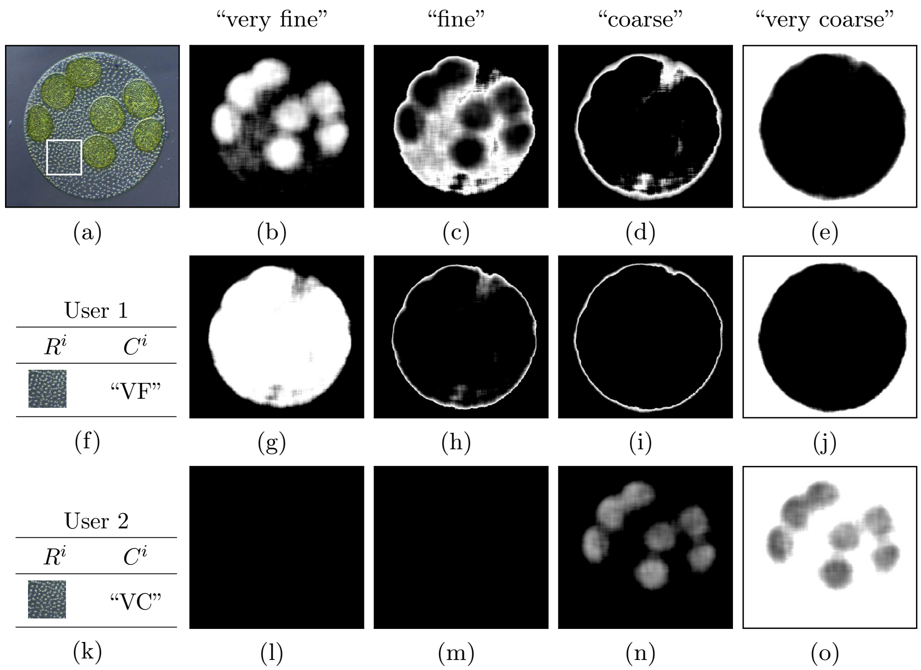


Figure 5: Results for the fineness property. (a) Original image. (b)-(e) Mapping from the original image obtained by applying the generic fuzzy partition Π for the fineness property. (f) Sample representing the particular fineness perception of the *user 1*. (g)-(j) Mapping from the original image obtained by applying the fuzzy partition adapted to the particular perception of the *user 1*. (k) Sample representing the particular fineness perception of the *user 2*. (l)-(o) Mapping from the original image obtained by applying the fuzzy partition adapted to the particular perception of the *user 2*.

colony is considered as a "fine" texture (white levels in Figure 5(c)), and the background is "very coarse" (white levels in Figure 5(e)). Note that, as can be seen in Figure 5(d), pixels in the border of two adjacent regions with different texture have high membership degrees to the intermediate fuzzy sets. This happens because the windows used for these pixels in the mapping process contain both textures, so the fineness measure gives an intermediate value.

Now suppose that we have two different users and we want to adapt the generic fuzzy partition to the particular fineness perception of each one. In this case, let us suppose that both users give only one sample image, selected by a white square in Figure 5(a), to represent their particular perception. Specifically, it contains the texture of the main colony, that, as it was commented above, is considered as “fine” according to Π. However, as it is shown in figures 5(f) and 5(k), the *user 1* considers that this texture is very fine (“VF”), while the *user 2* thinks that it is a very coarse texture (“VC”).

The method proposed in this paper is used to obtain the fuzzy partition $\tilde{\Pi}$ adapted to the particular perception of the *user 1*, and the corresponding mapping is shown in figures 5(g)-(j). As we can see in Figure 5(g), in this case the main colony is also considered as a “very fine” texture, together with the daughter colonies. This result matches the perception of the *user 1*, who considers that the texture of the main colony is very fine.

In a similar way, the fuzzy partition $\tilde{\Pi}$ adapted to the particular perception of the *user 2* is obtained, and the corresponding mapping is shown in figures 5(l)-(o). In this case, the main colony is considered as a “very coarse” texture (Figure 5(o)), together with the background, while the daughter colonies are considered as a “coarse” texture (Figure 5(n)). This matches the particular perception of the *user 2*, who considers that all textures are coarser than the average perception represented by the generic fuzzy partition.

For the second experiment, we have used the image shown in Figure 6(a). It can be noticed that in this case the textures present in the image, corresponding to the leopard skin, the branch and the background, have different perception degrees of contrast. In fact, these three textures can be differentiated in the mapping shown in figures 6(b)-(f), that has been obtained using the generic fuzzy partition proposed in [21] for the contrast property. The labels associated to this mapping are “very low contrasted”, “low contrasted”, “medium contrasted”, “high contrasted” and “very high contrasted”, respectively. In this mapping, we can see that, according to the average human perception, the texture of the leopard skin is considered as “very high contrasted” (Figure 6(f)), the region corresponding to the branch is considered as a “medium contrasted” texture (Figure 6(d)), and the background is “very low contrasted” (Figure 6(b)). As in the previous experiment, due to the windows used in the mapping process, pixels in the border of two adjacent regions with different texture have high membership degrees to the intermediate fuzzy sets (figures 6(c) and 6(e)).

Now let’s modify the non-adaptive model to the particular contrast perception of a user. Figure 6(g) shows six texture images given by this user to represent his/her particular perception, each one with an associated linguistic label. It can be noticed that the last texture in the first row, that is considered as “high contrasted” according to the non-adaptive model, is perceived as “medium contrasted” (“MC”) by this user. In addition, the

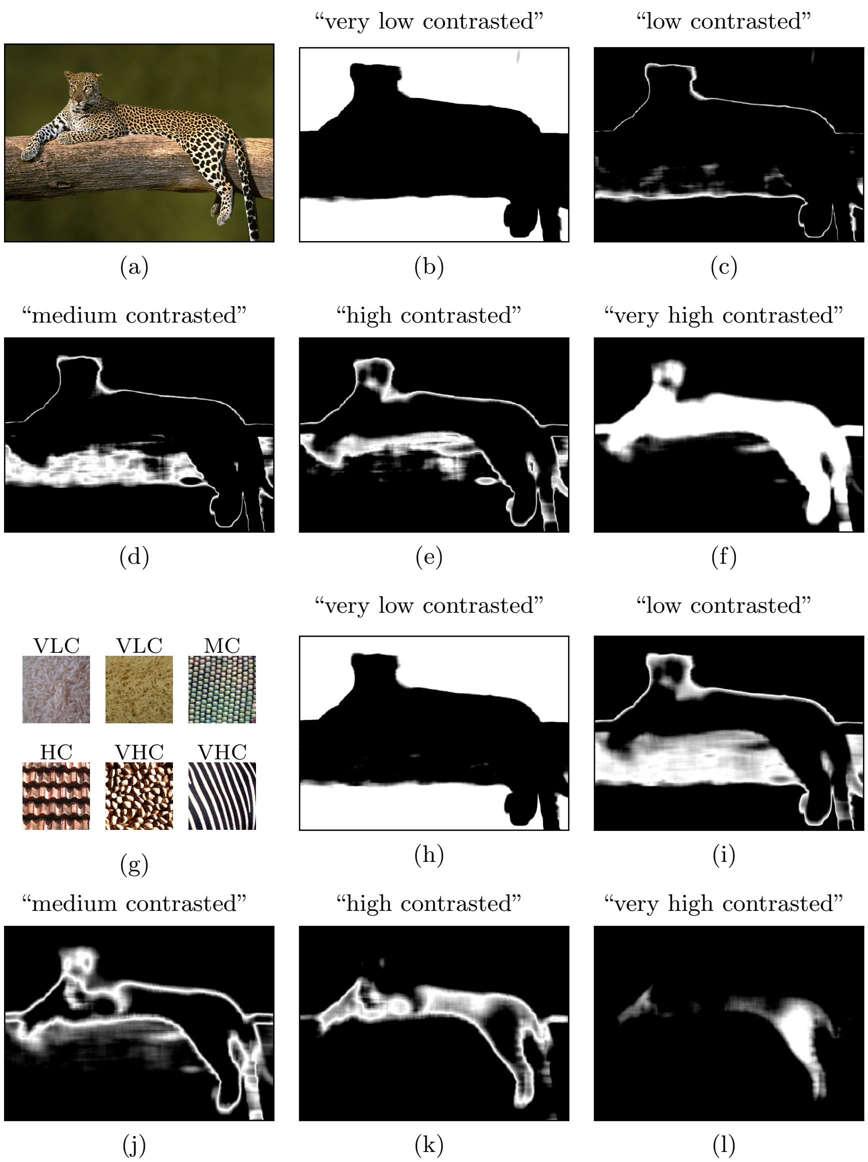


Figure 6: Results for the contrast property. (a) Original image. (b)-(f) Mapping from the original image obtained by applying the generic fuzzy partition for the contrast property. (g) Samples representing the particular contrast perception of a user. (h)-(l) Mapping from the original image obtained by applying the fuzzy partition adapted to the particular perception of the user.

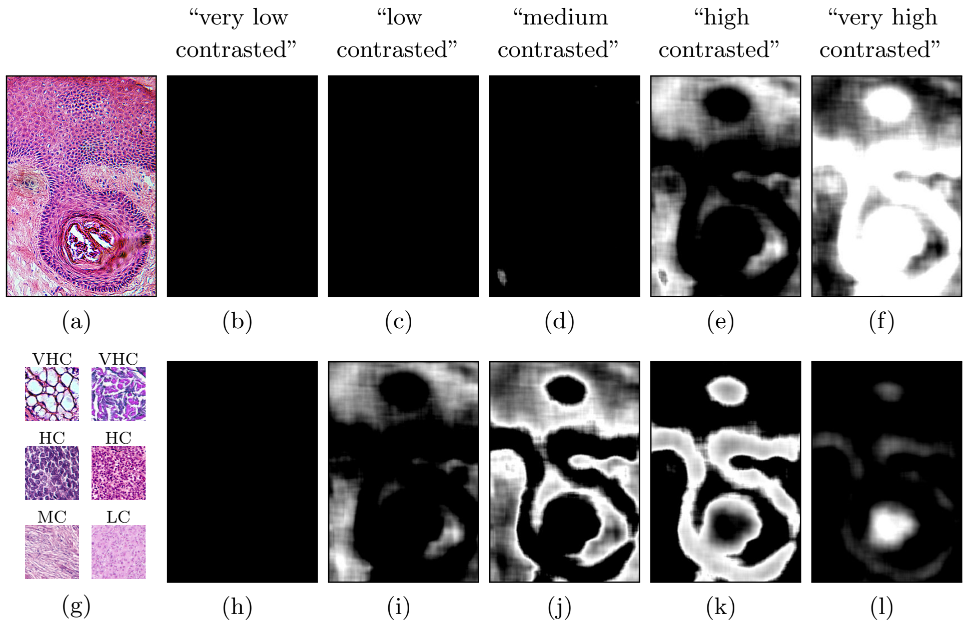


Figure 7: Results for the contrast property. (a) Original image. (b)-(f) Mapping from the original image obtained by applying the generic fuzzy partition for the contrast property. (g) Samples representing the particular contrast perception of a user. (h)-(l) Mapping from the original image obtained by applying the fuzzy partition adapted to the particular perception of the user.

first texture in the second row, that is considered as "very high contrasted" according to the non-adaptive model, is also perceived as less contrasted by the user. In fact, only extremely contrasted textures, as the last two ones, are considered as "very high contrasted" by this user. The fuzzy partition $\tilde{\Pi}$ adapted to the particular perception of the user is obtained using the method proposed in this paper, and the corresponding mapping is shown in figures 6(h)-(l). It can be seen that in this case all the leopard skin is not considered as a "very high contrasted" texture, but only the legs, where the skin is white and the spots are more salient. The rest of the body is now considered as a "high contrasted" texture, except the head, that is "medium contrasted". In addition, we can see that the branch is now considered as a "low contrasted" texture. Thus, the obtained mappings are in accordance with the contrast perception of the user. It should be noticed that our goal in this experiment is not to segment the whole leopard body, but to identify the different contrast degrees in textures.

In the third experiment, we show an example where the adaptation to user's profiles is applied in the field of medical images analysis. For this experiment, we considered Figure 7(a), corresponding to a microscopic image of a basal cell carcinoma. The basal layer is the innermost layer of the epidermis, and it is located just above the dermis. In this image we can see the basal layer (top) penetrating into the dermis (bottom) to surround a hair follicle (the rounded area with white regions). Since the tumor basal cells are darker than the normal cells, the neoplastic region has a more contrasted texture than the tumor-free tissue. As in the previous experiment, figures 7(b)-(f) show a mapping from this image using the generic fuzzy partition Π proposed in [21] for the contrast property. In this mapping, we can see that, according to the average human perception, the texture of the neoplastic basal cells is considered as "very high contrasted", as well as the hair follicle and part of the region corresponding to the tumor-free tissue (Figure 7(f)). Thus, the neoplastic region can not be clearly identified using the generic model.

Now suppose that a medical expert gives the texture images shown in Figure 7(g) to represent the contrast perception that should be used in this field of application. Figures 7(h)-(l) show the mapping obtained by using the adapted fuzzy partition $\tilde{\Pi}$. It can be seen that in this case only the hair follicle is considered as a "very high contrasted" texture (Figure 7(l)), while the region corresponding to the neoplastic basal cells is now considered as "high contrasted" (Figure 7(k)). In addition, the whole region of the tumor-free tissue is now considered as less contrasted than the neoplastic cells. Thus, results obtained with the adapted fuzzy partition are in accordance with the particular perception that should be used in this type of medical images according to the expert.

5.2. Adaptation to image context

In the fourth experiment, shown in figures 8 and 9, we propose to adapt the generic fuzzy partition Π for the fineness property to the image context. For the first part of this experiment, we have considered the image shown in Figure 8(a), where two textures with different fineness degrees are present. The mapping from this image obtained with the generic fuzzy partition is shown in figures 8(b)-(e). We can see that the region of the white beans is considered as a "very coarse" texture according to the average human perception, while the texture of the grains of pasta has intermediate membership degrees to the fuzzy sets "fine" and "very fine". The fuzzy partition $\tilde{\Pi}$ adapted to the image context is obtained using the method proposed in section 4. In this method, the coarsest and the finest texture in the image

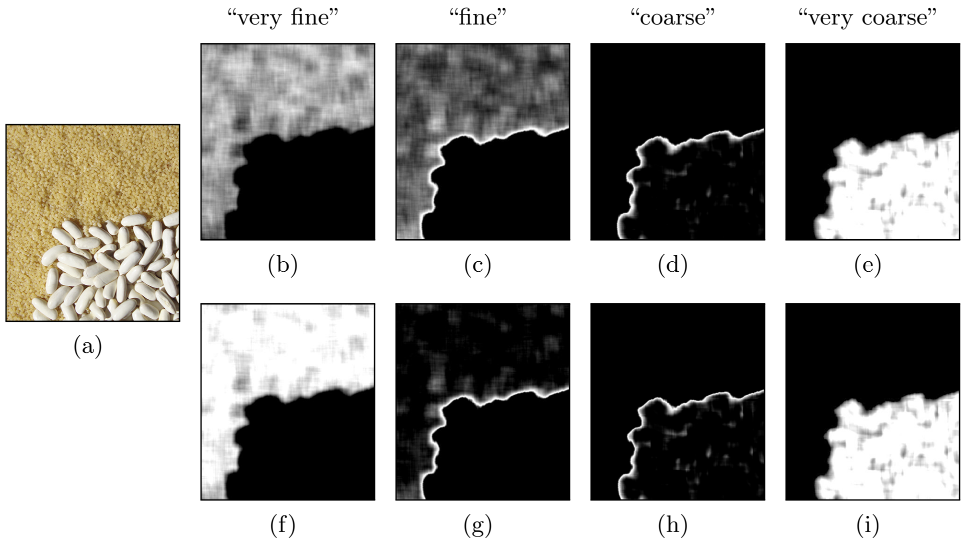


Figure 8: Adaptation to the image context. (a) Original image. (b)-(e) Mapping from the original image obtained by applying the generic fuzzy partition for the fineness property. (f)-(i) Mapping from the original image obtained by applying the fuzzy partition adapted to the image context.

(the texture of the beans and the grains of pasta, respectively) are used to estimate the inhibition present in the image, and this inhibition imposes the adaptation points. In this case, the mapping obtained with $\tilde{\Pi}$ (figures 8(f)-(i)) is very similar to the non-adapted mapping, as the inhibition factor related to this image is not very high (the only difference is that the texture of the grains of pasta is considered as finer than in the non-adapted mapping, due to the presence of the other texture, that is very coarse).

For the second part of this fourth experiment, we have considered the image shown in Figure 9(a), where a new texture has been added to Figure 8(a). The texture of the white beans is the same as in Figure 8(a), but in this case it may be perceived as finer by humans, because of the inhibition introduced by the new texture, that is much coarser[10]. The mapping from this image obtained with the generic fuzzy partition is shown in figures 9(b)-(e). We can see that the texture corresponding to the white beans, as well as the new texture, is still considered as very coarse, because we have

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

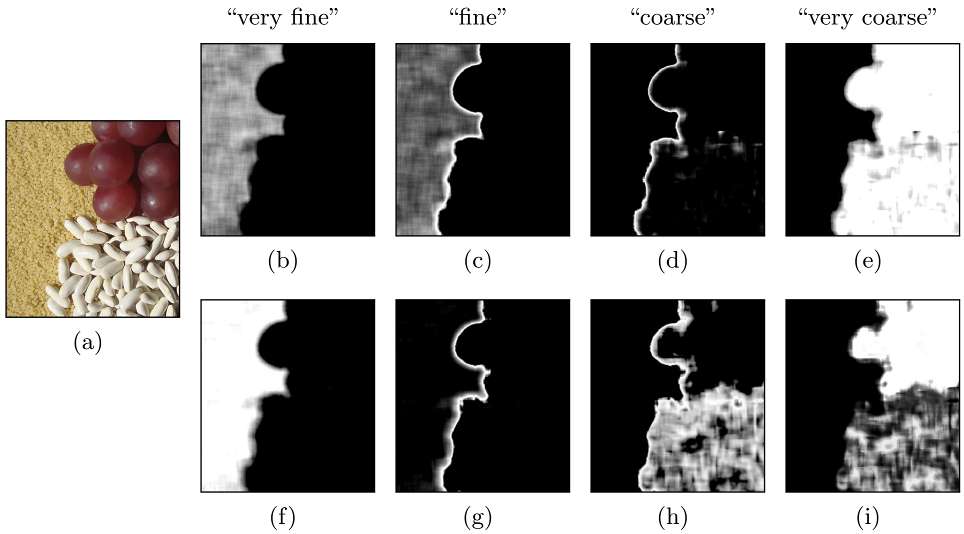


Figure 9: Adaptation to the image context. (a) Original image. (b)-(e) Mapping from the original image obtained by applying the generic fuzzy partition for the fineness property. (f)-(i) Mapping from the original image obtained by applying the fuzzy partition adapted to the image context.

not taken into account the changes in the fineness perception due to the image context. The mapping obtained with the fuzzy partition $\tilde{\Pi}$ adapted to the image context is shown in figures 9(f)-(i). In this case, only the new texture is considered as very coarse (Figure 9(i)), while the texture of the white beans has high membership degrees to the fuzzy set "coarse" (Figure 9(h)), which matches the human fineness perception influenced by the image context.

Figure 10 presents another example where the non-adaptive fineness model is adapted to the image context. For this experiment, first let's consider Figure 10(a), corresponding to a microscopic image of a corneal cell. Figures 10(b)-(e) show the mapping from this image obtained with the generic fuzzy partition. It can be noticed that the texture of the cell nucleus, that is much finer than the other textures in the image, is considered as "very fine" according to the non-adaptive model (Figure 10(b)). In addition, the rest of the corneal cell is considered as a "fine" texture (Figure 10(c)), while the region outside the cell is "very coarse" (Figure 10(e)). Now let's consider Figure 10(f), which is a zoom of a section of the image shown in Figure 10(a). The corresponding mapping using the non-adaptive model is

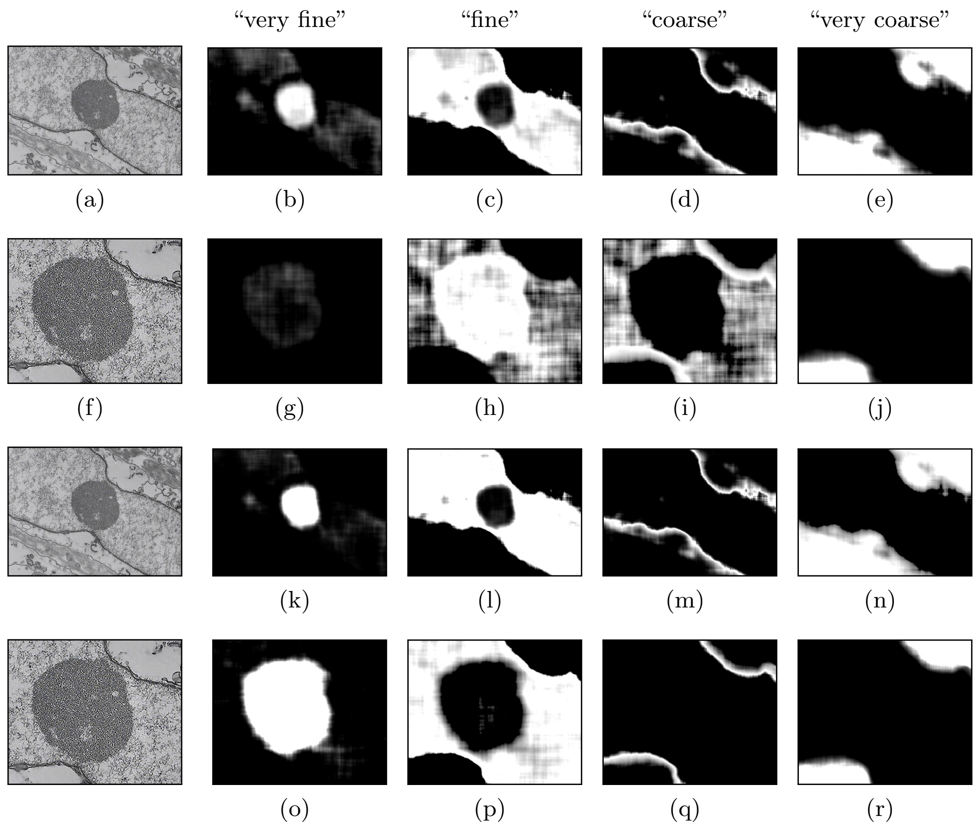


Figure 10: Adaptation to the image context for images with different zoom level. (a)(f) Original images. (b)-(e) and (g)-(j) Mappings obtained by applying the generic fuzzy partition for the fineness property to (a) and (f), respectively. (k)-(n) and (o)-(r) Mappings obtained by applying the fuzzy partition adapted to the image context to (a) and (f), respectively.

shown in figures 10(g)-(j). It can be noticed that, due to the absolute nature of the non-adaptive model, the obtained degrees depend on the zoom level of the image. In this case, the texture of the nucleus is considered as "fine" instead of "very fine", and the rest of the corneal cell has high membership degrees to the fuzzy set "coarse".

The adaptation to the image context proposed in this paper can be used to reduce the influence of the zoom level. In both original images (figures 10(a) and 10(f)) the difference between the finest and the coarsest textures in the image is "large enough" (greater than the threshold defined in equation

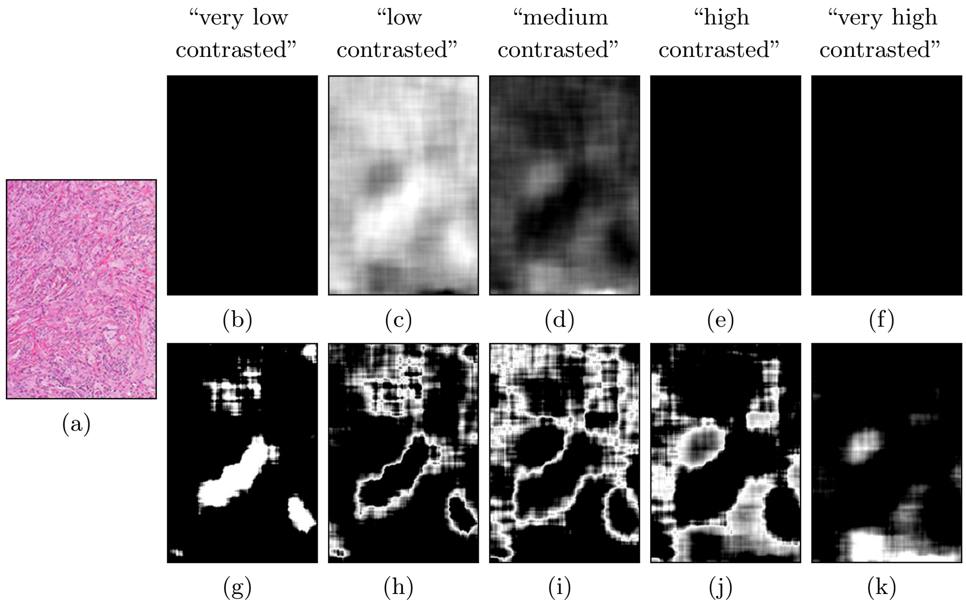


Figure 11: Adaptation to the image context with and without using the inhibition factor λ. (a) Original image. (b)-(f) Mapping from the original image obtained by applying the fuzzy partition adapted to the image context using the inhibition factor λ. (g)-(k) Mapping without using the inhibition factor λ.

(7)), i.e. the inhibition degree is strong ($\lambda = 1$). This imply that the fuzzy set corresponding to the label “very fine” in the adapted partition is directly imposed by the finest texture in the image (corresponding to the cell nucleus). Figures 10(k)-(n) and 10(o)-(r) show the mapping from 10(a) and 10(f) respectively using the corresponding adapted model. It can be seen that the region of the cell nucleus is now considered as “very fine” in both mappings (figures 10(k) and 10(o)), and the rest of the corneal cell is considered as a “fine” texture (figures 10(l) and 10(p)). Thus, the influence of the zoom level has been reduced, and the obtained results are in accordance with the change in the fineness perception due to the image context.

In the last experiment, shown in Figure 11, our aim is to highlight the importance of the inhibition factor λ in the adaptation to the image context. In the two previous experiments, the difference between the minimum and the maximum texture values in the image is large, which implies that the extreme fuzzy sets in the adapted partition are directly imposed by these extreme values. However, for images where this difference is not very significant, a correction factor λ is needed, as has been shown in section 4. For this experiment, we have considered Figure 11(a), corresponding to a microscopic image of human skin tissue. In this case, only one texture is present in the image and the perceptual degree of contrast is almost homogeneous. Thus, the inhibition associated to this property is very weak ($\lambda \approx 0$), which implies that the fuzzy partition adapted to the image context is very similar to the non-adaptive model. Figures 11(b)-(f) show the mapping obtained by applying the adapted fuzzy partition for the contrast property. It can be noticed that the whole image is considered as a "low contrasted" texture, which is in accordance with the contrast perception of this image.

Now suppose that the inhibition factor λ is not taken into account in the adaptation process, i.e. the extreme fuzzy sets in the adapted partition are directly imposed by the least contrasted and the most contrasted textures in the image. Figures 11(g)-(k) show the mapping obtained by applying the adapted fuzzy partition without using the inhibition factor λ. It can be noticed that in this case results are not in accordance with the human perception, because the adapted model imposes the lowest and the highest contrast degree for textures that are really similar.

6. Conclusions and future works

In this paper, we have proposed a methodology to adapt any generic fuzzy partition modeling a texture property to the particular perception of different user and to the changes in perception influenced by the image context. Some experiments have been performed in order to analyze the ability of the adapted models obtained with the proposed methodology to represent different perceptions of the properties. In particular, in the experiments shown in section 5, the generic fuzzy partitions Π defined in [21] have been used, although the proposed adaptation method is valid for any other fuzzy partitions representing the presence degree of texture properties. In these experiments we have shown that, in the case of the adaptation to users' profiles, the perception degrees provided by the obtained models match what each particular user would expect. In addition, in the case of the adaptation to the image context, we have shown that the obtained models are able to represent the perception of the texture properties influenced by the context.

The proposed approach can be very useful in applications where a perceptual texture characterization is employed, and, in particular, in tasks that need some interaction with subjects, where the subjectivity of human's perception may be an important issue. For example, it can be applied in expert systems, where the information provided by the expert is related to the presence of the texture properties. In this case, the perception of a texture property may change depending on the field of application: the concept of "very fine" may be different for a geologist, who analyzes satellite images, than for a medical expert, who study the textures present in x-ray or microscopic images. Moreover, even in the same field of application, two experts may have different perceptions about the texture properties. Thus, using the adaptive multidimensional fuzzy approach proposed in this paper, the systems can be adapted to the particular perception of the corresponding expert. In addition, the proposed approach can be used for context-awareness in different applications, such as semantic description of images or segmentation, as has been shown in the experiments of section 5.2.

In this work, several lines of research have been left open. First, we are working on a solution that allows to adapt fuzzy partitions defined on the domain of more than one dimension. Second, we will take into account the possibility of inconsistencies in the images given by subjects to represent his particular perception. And finally, we will extend the proposed methodology to other image features that can be modeled by a fuzzy partition Π, such as fuzzy colors. In fact, the proposed adaptive technique can be generalized, and it can be applied to any other domain (not necessarily related to image analysis), as long as the linguistic labels can be semantically sorted. In this sense, our approach can be applied to any piecewise linear function (triangular, trapezoidal, etc.), or any other type of membership function if we can define a central point and two parameters determining a left limit and a right limit with respect to this central point.

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