COLOR SEGMENTATION OF INK-CHARACTERS : APPLICATION TO MEAT TRACABEALITY CONTROL

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ABSTRACT

In this article, we study the color appearance of the ink printed on a background, according to both its concentration and the background color. We find some attributes, the *concentration quotients ratios*, that are more invariant to the ink concentration than simple color attributes. Our work deals with traceability of porcine products. We have to detect the animal identifier, printed with ink on the pork rind. Using the concentration quotients ratios, our segmentation technique succeeds for any quantity of ink and any hue of pork rind. This technique could be applied to segment any set of pixels, that are colorimetrically and spatially close, but nor necessary all connected.

1. INTRODUCTION

The common definition of color segmentation is the partition of an image in homogeneous areas of pixels, i.e. in sets of connected and colorimetrically close pixels. The literature counts a large number of segmentation techniques, which differ from one another by the topologic and colorimetric criteria on which they are based. Finally, no universal segmentation algorithm exists.

The structural approaches, such as the region growing [13] [11] [4] or the division-fusion [3] [8] [9] [7], and pyramidal methods [5] carry out the pixels distribution directly in the image, according to their colorimetric attributes. The area formation process considers at once the constraints of intra-area colorimetric homogeneity, the pixels connexity, and also takes into account the inter-area colorimetric differences. Nevertheless, the sequential nature of the region growing methods, or the inherent use of complex structures in division-fusion algorithms, often requires some heavy computational cost, compromising their use in real-time applications.

The classification methods [2] [1] [10] [12] is based on the assumption that colors of a region form either a group of points in the colorimetric space, or a mode in the color histogram. The different classes are extracted by partitionning the color representation space with multi-thresholding. In that case, the distribution of the pixels in the image is not taken into account, the segmentation being effective only if each cloud of points in the color space corresponds to a single area in the image.

Our work deals with porcine traceability control. We have to detect the identifier of the carcass, which consists of dark blue numerical characters, printed on the animal. The inhomogeneousness of the color of the pork rind and the variability of the quantity of ink printed are likely to complicate the segmentation task.

The method proposed in this article enables the segmentation of inked characters, whatever the quantity of ink and the background color are. It is based on an original definition of the segmentation since the region is viewed as a set of pixels which are spatially and colorimetrically close but are not necessarily all connected.

This article is structured as follows. In section 2, we study the relationship between color background, concentration of ink and ink appearance. Then, the segmentation algorithm is described in section 3. Lastly, some results concerning our application are shown in the section 4.

2. BACKGROUND COLOR AND INK APPEARANCE

The printed ink appears more or less translucent according to the quantity used. Thus, its color can highly depend on the background color ; therefore, ink segmentation can be improved as soon as it is adaptative to it.

The appearance of the ink printed on an object depends on its covering capacity and on the object color. Figure 1 (a) shows the color distribution of a brown ink printed with varying quantities on three differents backrounds (pink, blue and green). The color of the ink c_i, for $i \in \{RGB\}$ printed on the background is located on a segment $[c_b, c_e]$, c_b being the background color and c_e the ink color when no transparency effect is perceptible. By projection of the straight line on the subspaces (i, j) with $i, j \in \{RGB\}$, we obtain the following relationship :

$$c_i = a_{ij} c_j + b_{ij} \quad (1)$$

where a_{ij} et b_{ij} for $i, j \in \{RGB\}$, and $i \neq j$, are respectively the gradient of the line and the coordinate at the zero point of the straight line crossing the (O, C_j) axis :

$$a_{ij} = \frac{c_{b_i} - c_{e_i}}{c_{b_j} - c_{e_j}}, \; b_{ij} = \frac{c_{e_i} c_{b_j} - c_{e_j} c_{b_i}}{c_{b_j} - c_{e_j}}. \tag{2}$$

Let's consider the *concentration quotient* Q_{c_i} for $i \in \{RGB\}$ respect to c_b :

$$Q_{c_i} = \frac{c_i - c_{b_i}}{c_{e_i} - c_{b_i}} \text{ with } c_{e_i} \neq c_{b_i} \tag{3}$$

It is easy to show that this quotient corresponds to the opacity of the ink [6]. It doesn't depend on the background color. We compute the ratios λ^{ij} of the concentration quotients :

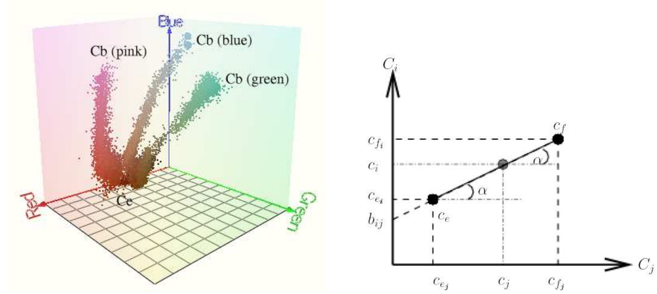
$$\lambda^{ij} = \frac{Q_{c_i}}{Q_{c_j}} \text{ with } Q_{c_j} \neq 0 \tag{4}$$

For a given background, these ratios are approximately invariant to concentration of ink, because these values depend little on the position of the color c_i on the segment $[c_b, c_e]$. Indeed, by computing the tangent of the angle α (figure 1 (b)) formed by the intersection of the line (c_b, c_e) and the axis (O, C_i), it is easy to prove the constancy of λ^{ij}. Theorically, $\lambda^{ij} = 1$. In practice, $\lambda^{ij} \simeq 1$. The table 1 compares the variances of RGB components for the ink printed with various quantities, and the variances of the correspounding coefficients λ. Three different inks are used : a black, a brown and a red one. It shows that the coefficients λ are less sensitive to variations of ink quantities than the simple color attributes.

3. COLOR INK SEGMENTATION

The color of the ink c_e can be measured and then is supposed to be known. The background color c_b is determined by analysis of the color histogram. The background cluster forms a mode in the histogram. If it is the most important cluster, it is represented by the largest mode. In that case, the mode is generally approximated by a Gaussian and the average color μ of the background is determined by the position of the maximum of the histogram.

The algorithm includes three stages ; first, candidates pixels of the identifier are selected. Secondly, these pixels and their neighborhood contribute to a membership score according to the values of their concentration quotients ratios. The wrong candidates are eliminated by analysis of their neighborhood. Then, the selection of the identifier mask is achieved, it selects the whole series of characters as it will be shown later. We will illustrate each stage by an example associated to our application. The initial images are shown on figures 2 (a), 3 (a) and 4 (a).



(a) (b)

Fig. 1. Influence of the background color on the ink appearance ; (a) The same brown ink is printed on three different backgrounds colors ; (b) Location of the colors of the ink printed on a colored background.

Table 1. Variance of RGB components and coefficient λ, computed on several ink blurs, made with several colors of ink (black, brown and red) with various quantities of ink ($\times 10^{-3}$).

	black	brown	red
RGB	16	0.53	12
λ	1.1	0.48	0.054

3.1. Selection of the candidates pixels.

The color of the ink printed on a background is approximately located on a straight line, then its color components can be obtained by the criterion $\mathcal{C}_0$:

$$\begin{aligned} \mathcal{C}_0(x, y) = \; & \{1 \text{ if } \forall (i, j), i, j \in \{RGB\}, \\ & |c_i - (a_{ij} c_j + b_{ij})| < \Delta_{ij}, \\ & \text{else } 0\} \end{aligned} \tag{5}$$

Δ_{ij} being the maximum distance between the color and the straight line. Considering the ink has a given covering power, we can generally restrict Q_{c_i} to an interval of values. So the following criterion can be used :

$$\mathcal{C}_1(x, y) = \{1 \text{ if } \forall i \in \{RGB\}, Q_{c_i}(x, y) > S_1^i, \text{ else } 0\} \tag{6}$$

The parameters S_{1i} and Δ^{ij} are fixed by a learning step on an image data base. Let's call (x_s, y_s) a candidate pixel.

3.2. Neighborhood analysis.

We compute the membership score of each candidate pixel $\mathcal{P}(x_s, y_s)$, according to its neighborhood attributes. The nearer the color components of its neighbor, the higher the membership score of the pixel. All the pixels must have approximately the same coefficient λ^{ij} for $i \in \{RGB\}$. Thus, for each (x, y) in the vicinity V_s of pixel (x_s, y_s), the color homogeneity is given by the euclidian distance $d_\lambda(x, y)$ between the pixel (x_s, y_s) and its neighbor (x, y) :

$$\mathcal{C}_2(x, y) = \{1 \text{ if, } (x, y) \in V_s \text{ eand } d_\lambda(x, y) < S_2, \text{ sinon } 0\}. \quad (7)$$

Moreover, the neighbor pixels must verify the same constraints as the ink, so they must satisfy criteria $\mathcal{C}_0$ and $\mathcal{C}_1$. Nevertheless, the thresholds used in this stage are less stricts than the one used to carry out the candidates selection. We call these criteria $\mathcal{C}_0^{'}$ and $\mathcal{C}_1^{'}$.

The current pixels for which no neighbor meets any membership criterion are eliminated, their membership score is cancelled. The following algorithm is thus applied :

For each pixel $(x, y) \in V_s$:
If $(\mathcal{C}_0^{'}(x, y), \mathcal{C}_1^{'}(x, y), \mathcal{C}_2(x, y)) = (1, 1, 1)$ then :

$$\left\{ \begin{array}{lcl} \mathcal{P}(x_s, y_s) & = & \mathcal{P}(x_s, y_s) + 2 \\ \mathcal{P}(x, y) & = & \mathcal{P}(x, y) + 1 \end{array} \right. \quad (8)$$

If for all pixels $(x, y) \in V_s$:
$(\mathcal{C}_0^{'}(x, y), \mathcal{C}_1^{'}(x, y), \mathcal{C}_2(x, y)) = (0, 0, 0)$ then :

$$\left\{ \begin{array}{lcl} \mathcal{P}(x_s, y_s) & = & 0 \\ \mathcal{P}(x, y) & = & 0 \; \forall (x, y) \in V_s \end{array} \right. \quad (9)$$

The result is a grey level image $\mathcal{P}(x, y)$, of size $N_x \times N_y$ whose values correspond to the membership scores. Some results are shown on figure 2 (b), 3 (b) and 4 (b). If there is only one identifier to detect, we divide the image pixels $\mathcal{P}(x, y)$ by their euclidean distance to the inertia centre of $\mathcal{P}(x, y)$. Indeed, it reduces the noise in the image ; it further increases the membership scores of the largest group of pixels with high membership scores. Furthermore, it decreases the membership scores of isolated pixels.

3.3. Selection of the identifier mask.

At this stage, the pixels that have a high membership score, are not necessary connected. In order to put it right, the image $\mathcal{P}$ is divided in windows W_{ij}, of size $M_x \times M_y$, and each pixel in the window is replaced by the average of $\mathcal{P}$ computed on this window (see figures 2 (c), 3 (c) and 4 (c)). The choice of the window's size is not easy and depends on the image, and more precisely on the size of the space between characters in the identifier. It must be large enough to ensure the formation of a connected component of positive windows covering the whole series of characters.

Then we form an image μ_W, of size $U \times V$ with $U = N_x/M_x$ and $V = N_y/M_y$, whose values $\mu_W(i, j)$ correspond to the averages of $\mathcal{P}$ computed on the windows W_{ij} :

$$\mu_W(i, j) = \sum_{(x,y) \in W_{ij}} \mathcal{P}(x, y)/(M_x.M_y) \quad (10)$$

The pixel in μ_W for which the average of the membership score is maximum, is considered as a seed point to carry out a region growing process. The 8 neighbors of the seed point are first analysed. If they meet a given homogeneity criterion, they are agregated to the region and their 8 neighbors are analysed in their turn, and so on.

The homogeneity criterion $\mathcal{C}_3$ used to achieve the propagation is very simple since only the positivity of $P(x, y)$ is taken into account :

$$\mathcal{C}_3 = \{1 \text{ if } P(x, y) > 0, \text{ else } 0\} \quad (11)$$

If the maximum is lower than a given threshold, we consider there is no identifier in the image.

The selected pixels in μ_W are associated to the windows W in the initial image, each of them containing a part of the identifier (see figures 2 (d), 3 (d) and 4 (d)). These windows can be used as a mask, including the whole identifier. It can be used to achieve a final binarization.

4. APPLICATION TO TRACEABILITY CONTROL

A color vision system has been devised to detect the identifier of the carcass on fresh hams. A diffuse and uniforme lighting enables to obtain images of high quality without shades or highlights. We avoid time instability of the vision system by correcting each image by the RGB components of a grey patch placed in the images (see figure 2 (a) for example). In order to define the thresholds used in the algorithm, a learning step has been carried out by an expert on a first image data base and tested on a second image data base.

The algorithm have been tested on 200 images of defected hams (occurence of grease stains, hematoma, etc.. that can complicate the detection of the identifier). The figures 2, 3 and 4 show some results. The color of the pork rind and the ink concentrations are quite different in each case. The figure 2 (b), 3 (b) and 4 (b) result from the candidates selection. The selection of the mask is achieved with a window size of 24 $\times$ 24 (see figures 2 (c), 3 (c) and 4 (c)). After the region growing process, we obtain a connected component, which includes the whole identifer (see figures 2 (d), 3 (d) and 4 (d)).

It gives good results, whatever the defects on pork rind are, and whatever the quantity of ink or the color of pork rind are, with a success rate of 95,1 %. Moreover the occurence rate of any defect being 5%, the detection rate could reach 99,75 %.

5. CONCLUSION

The segmentation method presented in this article is especially well adapted to the ink segmentation, whatever important the translucent effects may be. Indeed, the identifier is detected by analysing the color appearance of ink according to its covering power and the background color. We

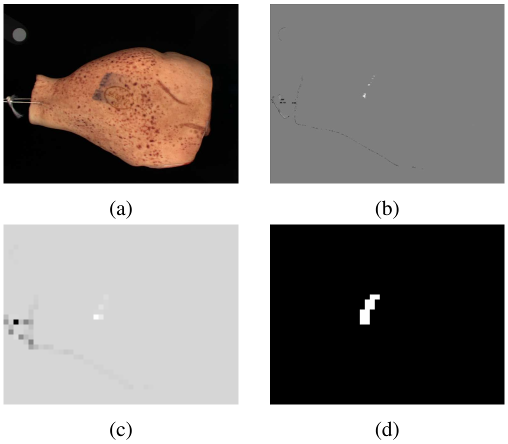


Fig. 2. (a) Initial image. (b) Candidate pixels detection. (c) Image of the local averages μ_W. (d) Connected component including the whole identifier.

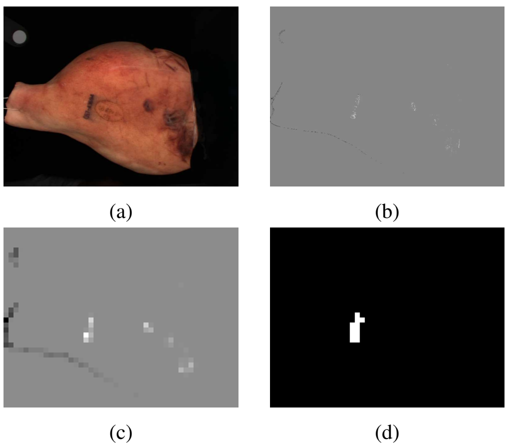


Fig. 3. (a) Initial image. (b) Candidate pixels detection. (c) Image of the local averages μ_W. (d) Connected component including the whole identifier.

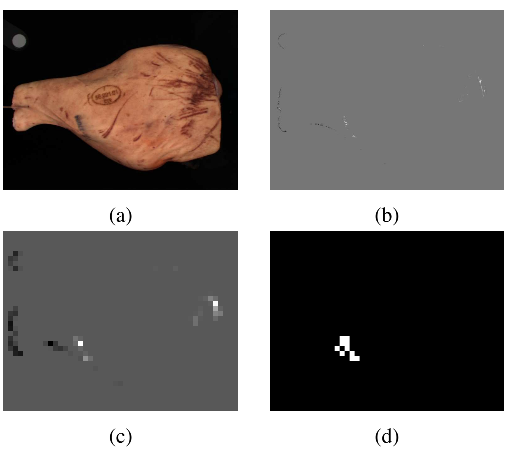


Fig. 4. (a) Initial image. (b) Candidate pixels detection. (c) Image of the local averages μ_W. (d) Connected component including the whole identifier.

have used some attributes that are less sensitive than RGB components to variations of ink concentration. Moreover, we can detect a set of pixels, which are colorimetrically and spatially close but not necessarly all connected. The application in traceability control has proved the efficiency of the method.

6. ACKNOWLEDGMENT

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