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Application of Color Image Segmentation to Estrus Detection

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Abstract : Automatic segmentation and classification of color images is a problem of great practical interest in different areas. This paper presents an algorithm for this purpose which is divided in three steps. Firstly, the regions of interest are isolated from the rest of the image based on threshold functions defined in the *YUV* and *YIQ* color spaces, producing a set of connected components. Then, a set of features is computed to enable a quantitative evaluation of the segmented objects. Finally, the image is classified by means of a decision rule based on the analysis of the differences between the computed measures and a set of ideally segmented images, according to experts' assessment. The algorithm was applied to a decision support tool for estrus detection in cattle. This approach constitutes a valuable alternative to improve this process, as it may replace the visual observation by the automatic analysis of pictures taken to cows in controlled environments. Experimental results show that the segmentations obtained with this method are highly satisfactory and they allow a precise classification of the images with low computational complexity.

Keywords : Image segmentation, Thresholding, Feature extraction, Classification.

1. Introduction

In many image processing applications the goal is to extract information from the image data, which generally requires the identification of the objects of interest. Although the problem of segmenting a scene into parts can be properly resolved by the human visual system, performing the task automatically using computational algorithms is not so straightforward, even in simple cases.

In the field of image processing and computer vision, segmentation refers to the low level operation of partitioning an image into its constituent objects that should be meaningful according to each particular application. Frequently, this constitutes a major issue in the automation of feature extraction and it also determines the eventual success or failure of subsequent higher level processes such as classification, analysis and visualization (e.g., Gushchin et al., 2004; Vénere et al., 2001).

Numerous segmentation techniques have been proposed in the literature (Lucchese and Mitra, 2001). Thresholding is one of the simpler and more commonly used methods (Sezgin and Sankur, 2004). It is based on the statistical classification of the image gray levels, assuming that all pixels whose intensities lie within a certain range belong to the same object. On the other hand, boundary based approaches search for the limits of the image components, by detecting gray level discontinuities (Baxes, 1994). These algorithms work well on datasets with good contrast between different regions, but they encounter difficulties with noisy images. To overcome this drawback, different procedures for noise reduction have been proposed (e.g., Fujimatsu et al., 2005). Region-based methods (Adams and Bischof, 1994) are based on the determination of homogeneous areas inside the image, by merging those pixels that satisfy certain connectivity and similarity criteria. Finally, there are several methods that combine two or more of the previous approaches, like snakes or neural networks (Pham et al., 2000). However, most of these techniques are computationally intensive and therefore inconvenient for applications in real time.

The above mentioned methods were generally concerned with gray images. Recently, there has been a growing interest in developing algorithms for colored images, mainly because they generally convey more information, which in turn facilitates the identification of objects (Skarbek and Koschan, 1994). Among them, some "ad hoc" techniques were proposed, which use specific knowledge about the nature of color information. On the other hand, suitable extensions of the techniques used for gray-scale images can be explored. Most of the proposed algorithms can be directly applied to each component of the color space (*RGB*, *YIQ*, etc.), and then combine them to obtain the final result.

The application field of color segmentation is extremely wide, and interesting uses have emerged in diverse areas. In particular, estrus detection in dairy herds is a practical example of these applications. Estrus is a gradual process with a number of external symptoms, but the conclusive external sign indicating that cows are sexually receptive is that the animals are frequently mounted by their herd companions. Several factors contribute to failures in estrus diagnosis, but require the inability to recognize the signs of estrus is the most widespread problem that affects artificial insemination programs and consequently the reproductive efficiency. Different estrus detection aids have been proposed, such as implants, pedometers, pressure-sensitive detectors, and electronic aids. For example, pressure-sensitive mount detectors consist of sensors attached to each cow that are activated by the weight of another animal. Some of these alternatives are efficient but expensive devices, usually out of the budget of cattle breeders. Tail painting is another popular technique, which consists of painting a band, about 20 cm long, 5 cm wide, along the tail head of the animal from hooks to pins. When the cow is mounted, the paint is rubbed off or smudged. Therefore, the absence or deterioration of the lumbar painting can be used to determine estrus (Perry, 2004). This option is commonly used in large herds, and it appears to be as effective as the previous ones, while being less expensive. Currently, the detection is made by visual observation of trained operators since no automated devices exist for this purpose. Had real time segmentation of color images from artificial lumbar paintings been available, automatic estrus detection systems could be implemented, eliminating the operator dependence and reducing costs.

In this article, a computationally efficient algorithm for color image segmentation and classification is presented. The method have been applied to the segmentation of paintings from the lumbar area of cows, followed by the extraction and comparison of some image features in order to extract meaningful results. This tool provides a novel automatic decision support system that is able to determine in real time the estrus state of the animals, by means of the analysis of artificial lumbar painting. This improves estrus diagnosis leading to greater profits for dairy producers. The article is organized as follows. In Section 2, the segmentation algorithm based on thresholding of non-linear transformations of color spaces is discussed. The feature extraction and classification steps are described in Section 3. In Section 4, the performance of the method is comprehensively analyzed using different picture ensembles. Finally, Section 5 presents the general conclusions of the work.

2. Color Image Segmentation

In spite of the availability of other segmentation options, thresholding is among the most popular techniques for segmenting images due to its low computational complexity and good performance. Thresholding often provides a simple and suitable approach to discriminate the objects from the background using the image histogram. Provided that the ranges of intensities are well differentiated, this can be effectively done by choosing an appropriate threshold value in the valley between the two dominant modes. The problem is more complicated when the distributions are overlapped and the valley is not easy to define (Haralick and Shapiro, 1987).

In its simpler form, each pixel of an image *f(i, j)* is compared with a threshold *T*, and then it is classified to obtain a binary image *I(i, j)* defined as:

$$I(i,j) = \begin{cases} 1 & \text{if } f(i,j) > T \\ 0 & \text{if } f(i,j) \leq T \end{cases} \tag{1}$$

that is, pixels labeled 1 correspond to objects, whereas pixels labeled 0 correspond to the background.

Being thresholding a technique easy to apply to gray-level images, some complications appear in the case of color images. Color is commonly represented by a triple string of red, green and blue (*R, G, B*) scalar components in an orthogonal space, or some transformation of them. Detecting clusters of points in this space involve the analysis of peaks and valleys of three different histograms or choosing a proper threshold in a three-dimensional histogram, which may require high computational cost (Cheng et al., 2001). Furthermore, the *RGB* space is appropriate for color display, but it is not convenient for many image processing tasks because the high correlation among its components. The *YIQ* space, on the other hand, considers the human visual system's greater sensibility to changes in luminance (*Y*) than in color information (*I* and *Q*). These components are decoupled, so they can be independently processed. The *YUV* space is a version slightly different from *YIQ* but with the same advantages (Gonzalez and Woods, 1992).

Although the proposed algorithm can be applied to different areas with few modifications, the present study is focused on images with artificially painted areas of color red, yellow, green or blue (according to the colors used by veterinaries in different cycles of estrus) over backgrounds of color brown, black and white (corresponding to the possible bovine leathers). The main objective is to automatically separate the painting regions from the background for later evaluation (Fig. 1). Initially, the chrominance variables (*u, v* in the *YUV* space and *i, q* in the *YIQ* space) were analyzed for all the potential colors of painting and leather, trying to find a suitable threshold. However, neither in *YUV* nor in *YIQ* there is a range of values that can be used to effectively discriminate between objects and background. For this reason, several color functions of the chrominance variables were studied in order to identify a proper scalar field that ensures high segmentation performance.

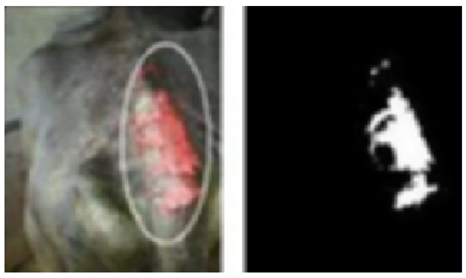
(a) (b)

Fig. 1. Segmentation of a typical image: band of painting along the tail head of a cow (a), object of interest isolated from the background (b).

In order to assess the segmentation results of the different color functions, a set of 1000 synthetic images resembling noise free scenarios was generated. This analysis allowed us to evaluate the performance of the functions that achieve an accurate distinction between the different colors used for the paintings and the colors associated with leather. As an example, Fig. 2 shows four histograms corresponding to the function $\sqrt{u^2+v^2}$, revealing a clear isolation between the two groups.

After having processed the images with the different proposed functions, a subset of them was chosen according to their performance. The selected functions were: $k\max(|u|,|v|)$ and $\sqrt{u^2+v^2}$, in the *YUV* space, and $k_1\max(|i|,|q|)+k_2\min(|i|,|q|)$ and $\sqrt{i^2+q^2}$, in the *YIQ* space, as they allow the segmentation of around 97 % of the test pictures, for the four painting colors and a quite wide range of values. The values of k, k_1 and k_2 were obtained by means of numerical tests. It was verified that $k = 11$ for the first case, and $k_1 = 10$, $k_2 = 2$ for the second one produce optimal segmentations at the fastest rate. This set of functions was used to be tested against experimental images, as will be explained in Section 4.

3. Post-Segmentation Processing

The binary image obtained in the segmentation step is processed by the application of erosion to eliminate possible spurious points that may appear during the thresholding step (Baxes, 1994). This morphological operation may slightly reduce the size of the objects, but in turn helps to reveal its basic shape, which is crucial in the classification step. After that, the remaining connected components are labeled in order to determine the regions of interest (Haralick and Shapiro, 1992). Then, these regions are evaluated by assessing their geometric characteristics and compare them with ideal measures (Fig. 3). The following subsections describe these steps.

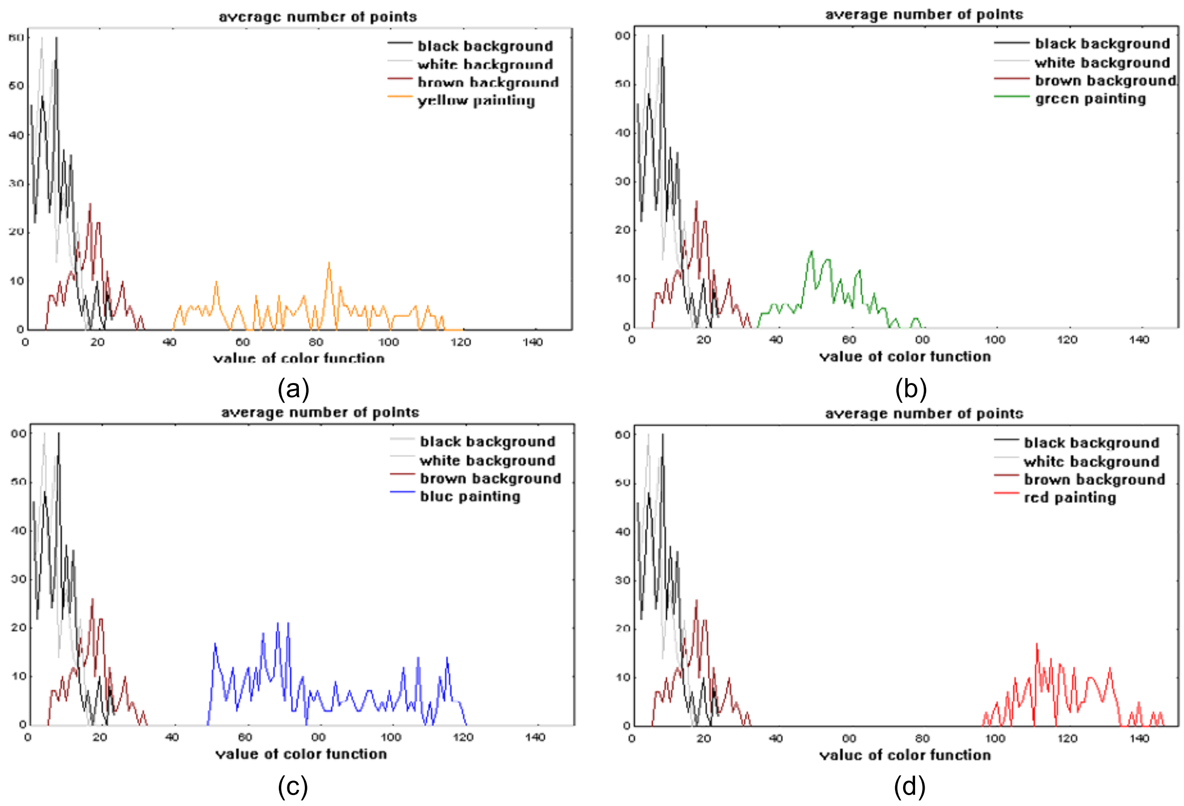

Fig. 2. Distributions of the values of $\sqrt{u^2+v^2}$ for the background colors (black, white and brown) and different paintings colors: yellow (a), green (b), blue (c) and red (d).

3.1 Feature Extraction

The regions detected by the segmentation process must be evaluated by their features and shape descriptors. Acquiring accurate measurements of the objects is a fundamental problem in image analysis, as such measures usually represent useful knowledge in which the subsequent classification can be based on (Baxes, 1994). In the present case, the segmented objects were characterized by the following metrics:

Area. The area is the zero order moment and it is calculated as the number of pixels inside the object including its border, that is:

$$A = \sum_x \sum_y I(x,y) \tag{2}$$

Dispersion. This metric indicates how scattered are the pixels of the object with respect to the centroid. Then, for those pixels with *I(x, y)* = 1:

$$D = \sqrt{\sum_x \sum_y \left(x-\bar{x}\right)^2 + \left(y-\bar{y}\right)^2} \tag{3}$$

where the centroid is given by the first order moments $\bar{x}$ and $\bar{y}$:

$$\bar{x} = \frac{\sum_x \sum_y x\ I(x,y)}{\sum_x \sum_y I(x,y)} \qquad \bar{y} = \frac{\sum_x \sum_y y\ I(x,y)}{\sum_x \sum_y I(x,y)} \tag{4}$$

Major axis length. The major axis of an object is defined as the longest line that can be drawn through the object. To calculate this measure, the distances between every combination of endpoints pixels (x_i, y_i) and (x_j, y_j) in the object boundary are calculated and the pair (x_{M1}, y_{M1}) and (x_{M2}, y_{M2}) with the maximal length is determined. Thus, the major axis length is the distance in pixels between the major axis endpoints (x_{M1}, y_{M1}), (x_{M2}, y_{M2}) and it represents the object length. It is calculated as:

$$L_M = \sqrt{(x_{M2} - x_{M1})^2 + (y_{M2} - y_{M1})^2} \tag{5}$$

Minor axis length. The minor axis is defined as the longest line that can be drawn perpendicularly to the major axis through the object. The minor axis endpoints (x_{m1}, y_{m1}) and (x_{m2}, y_{m2}) are found by calculating the pixel distance between every pair of border pixels (x_i, y_i) and (x_j, y_j) defining segments perpendicular to the major axis, and then determining the pair with the maximal length. Thus, the minor axis length is obtained as:

$$L_m = \sqrt{(x_{m2} - x_{m1})^2 + (y_{m2} - y_{m1})^2} \tag{6}$$

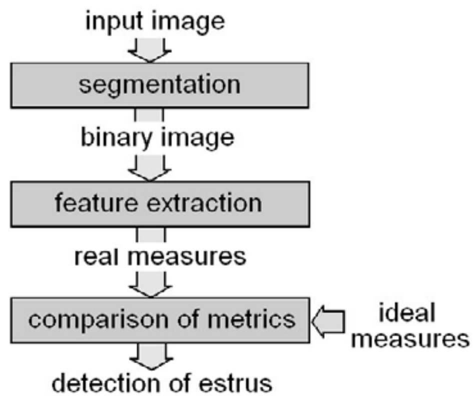

Fig. 3. Stages involved in the evaluation of functions.

3.2 Classification by Comparison of Measures

At this point of the evaluation process, the input image has been segmented into one or more objects and several measures have been computed for them, according to Eq. (2) to (6). These metrics are used in a third phase of classification to feed a decision rule that assess whether estrus is present or not.

A number of artificial intelligence algorithms can be used to assist the decision process. In the present approach a simple fuzzy logic rule was implemented for object classification. This rule is based on the analysis of the differences between the computed measures from a set of trial images, classified according to the evaluation of veterinary experts, and those obtained by the algorithm for each particular image (Fig. 4). The measures obtained from the first set were used as reference values to define confidence intervals for the geometrical features derived from the segmented region (A, D, L_M and L_m). Positive estrus requires that all the computed metrics for each picture fall within the respective confidence intervals. Based on experimental tests, painting losses smaller than 30 % represents non-estrus or doubtful cases, whereas more than 30 % indicates positive estruses. Therefore, the value used to discriminate positive and negative estrus cases was defined as 0.3 x, where x represents each one of the above descriptors. This criterion can be modified in the future after receiving the feedback of real applications.

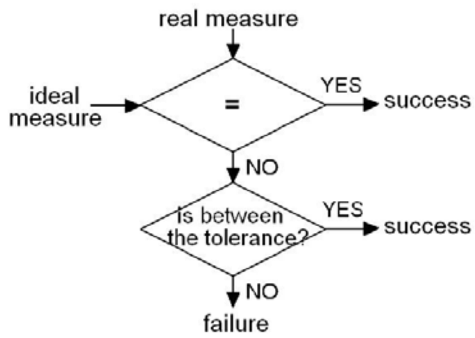

Fig. 4. Criteria of success.

4. Experimental Validation of the Threshold Functions

A comprehensive assessment was carried out over two ensembles of pictures corresponding to paintings on leather backgrounds. The first ensemble was taken in a light-controlled photographic laboratory, using real natural leather samples with painted bands of about 100 cm^2. The second ensemble was collected from real animals inside a shed of a cattle ranch (El Choique, Napaleofú, Argentina), in order to reproduce as close as possible the illumination conditions that are encountered in actual applications (Fig. 5). Table 1 shows the best estrus detection performances obtained with the present algorithm, as the number of matches with estrus states determined by clinical diagnosis. The second column shows the percentage of success of the selected color functions for the first ensemble, whereas the third column corresponds to the ensemble of real cows.

(a) (b)

Fig. 5. Color paintings on leather backgrounds: first ensemble (a), second ensemble (b).

Table 1. Best color functions performances.

Color function	% of success with laboratory pictures	% of success with in situ pictures
$\sqrt{u^2+v^2}$	96.28	94.59
$11\max(\lvert u\rvert,\lvert v\rvert)$	96.85	97.29
$\sqrt{i^2+q^2}$	97.71	97.29
$10\max(\lvert i\rvert,\lvert q\rvert)+2\min(\lvert i\rvert,\lvert q\rvert)$	97.14	94.59

Figure 6(a) shows the performance of the functions $11\max(\lvert u\rvert,\lvert v\rvert)$ and $\sqrt{i^2+q^2}$, which achieved the biggest success percentages in the classification when they were applied to pictures of the first ensemble. It can be seen that there is a wide range of threshold values for every function where the performance is good. For lower values the algorithm misses parts of the painting, whereas for higher values the background is not distinguished from the painted bands. The height of the curve (i.e., the maximum success percentages) indicates the segmentation power of the threshold function, whereas the width indicates its robustness (i.e., the wider the range the less sensitive the results are to color fluctuations). Figure 6(b) presents the behavior of the same functions for the second ensemble. In this case, the results seem to be less robust than the previous case. However, it should be noted this is due to the fact that the data set from real animals is smaller than in the controlled sample set.

Although visual observation is the commonly method used to determine estrus, its efficiency is only about 50 % in most dairy herds and it is generally agreed that 5 to 30 % of inseminations occur in cows that are not in estrus. The use of detection aids can improve this situation. For example, commercial systems based on pressure-sensing devices report accuracies about 95 %. The automatic system based on painting analysis presented in this work can provide an efficient alternative to detection of estrus, with accuracy near of 97 %, being cheaper and available to most of dairy producers.

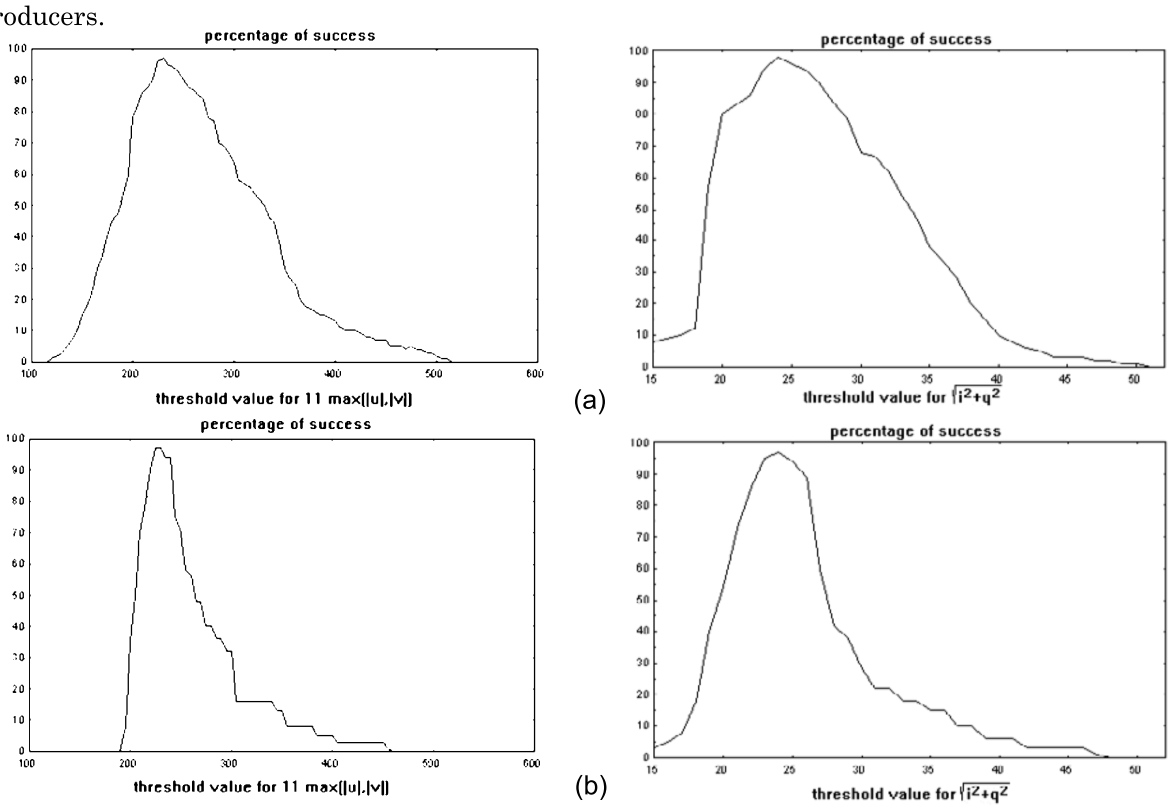

Fig. 6. Percentage of success reached by the functions: $11*\max(|u|,|v|)$ and $\sqrt{i^2+q^2}$ for the first ensemble of pictures –laboratory -(a) and for the set of pictures taken in-situ -(b).

5. Conclusion

A thresholding method for automatic segmentation of color images, based on non-linear transformations of the color coordinates *YUV* and *YIQ*, was presented. The method is simple, robust and showed excellent performance with low computational complexity. Furthermore, the threshold values and the reference values for classification are calculated only at the beginning of the system's operation. The segmentation technique does not need to set input parameters for every image, which avoids the disadvantages of user interaction.

The segmentation technique was applied to a decision support tool for estrus detection. This tool constitutes a valuable technological contribution to improve the effectiveness of this procedure, since still no automated devices were developed in this application domain. The segmentation results were characterized by geometrical metrics, which are valid parameters to determine the estrus state. The technique was tested successfully against ensembles of photographs taken in light controlled and field environments. It has been noticed that shadow effects, illumination changes, and noise may affect the segmentation performance. These will be investigated in the future.

References

Adams, R. and Bischof, L., Seeded region growing, IEEE Trans. Pattern Anal. Machine Intelligence, 16-6 (1994), 641-647.

Baxes, G., Digital Image Processing: Principles and Applications, (1994), John Wiley & Sons.
Cheng, H., Jiang, X., Sun, Y. and Wang, J., Color Image Segmentation: Advances and Prospects. Pattern Recogn., 34 (2001), 2259-2281.
Fujimatsu, N., Tamura, Y. and Fujii, K., Improvement of Noise Filtering and Image Registration Methods for the Pressure Sensitive Paint Experiments, Journal of Visualization, 8-3 (2005), 225-234.
Gonzalez, R. and Woods, R., Digital Image Processing, (1992), Addison-Wesley.
Gushchin, V., Kostomarov, A. and Matyushin, P., 3D Visualization of the Separated Fluid Flows, Journal of Visualization, 7-2 (2004), 143-150.
Haralick, R. and Shapiro, L., Computer and Robot Vision, (1992), Addison-Wesley Publishing Company.
Lucchese, L. and Mitra, S., Color Image Segmentation: A State-of-the-Art Survey, Image Processing, Vision, and Pattern Recognition, The Indian National Science Academy (INSA-A), 67-2 (2001), 207-221, New Delhi, India.
Perry, G., Detection of standing estrus in cattle, (2004), South Dakota State Univ., http://agbiopubs.sdstate.edu/articles/FS921B.pdf.
Pham, D., Xu, C. and Prince, J., A Survey of Current Methods in Medical Image Segmentation, Annual Review Biomedical Engineering, 2 (2000), 315-337.
Sezgin, M. and Sankur, B., Survey over image thresholding techniques and quantitative performance evaluation, Journal of Electronic Imaging, 13-1 (2004), 146-165.
Skarbek, W. and Koschan, A., Color Image Segmentation: A Survey. Technischer Bericht, Tech Univ. of Berlin, 94-32 (1994).
Vénere, M., Moreno, C., Clausse, A., Barbuzza R. and del Fresno, M., Tomographic System Based In Plasma Focus X-Rays, Nukleonika International Journal of Nuclear Research, 46-1 (2001), 93-94.

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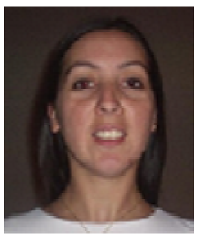

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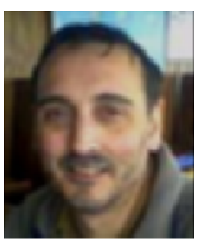

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