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An automatic colour-based computer vision algorithm for tracking the position of piglets

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Abstract

Artificial vision is a powerful observation tool for research in the field of livestock production. So, based on the search and recognition of colour spots in images, a digital image processing system which permits the detection of the position of piglets in a farrowing pen, was developed. To this end, 24,000 images were captured over five takes (days), with a five-second interval between every other image. The nine piglets in a litter were marked on their backs and sides with different coloured spray paints each one, placed at a considerable distance on the RGB space. The programme requires the user to introduce the colour patterns to be found, and the output is an ASCII file with the positions (column X, line Y) for each of these marks within the image analysed. This information may be extremely useful for further applications in the study of animal behaviour and welfare parameters (huddling, activity, suckling, etc.). The software programme initially segments the image in the RGB colour space to separate the colour marks from the rest of the image, and then recognises the colour patterns, using another colour space [B/(R+G+B), (G-R), (B-G)] more suitable for this purpose. This additional colour space was obtained testing different colour combinations derived from R, G and B. The statistical evaluation of the programme's performance revealed an overall 72.5% in piglet detection, 89.1% of this total being correctly detected.

Additional key words: animal behaviour, image analysis, pattern recognition, piglets activity, segmentation.

Resumen

Sistema de visión artificial basado en el color, para el seguimiento de la posición de lechones

La visión artificial es una potente herramienta de observación al servicio de la investigación en el campo de la producción ganadera. En este sentido, se ha desarrollado un software de tratamiento digital de imagen, basado en la búsqueda y reconocimiento de manchas de color en la imagen, que permite la detección de la posición de los lechones en una corralina de maternidad. Para ello, se capturaron 24.000 imágenes en cinco tomas (días), con un intervalo de 5 segundos entre cada dos imágenes. Los nueve lechones presentes en estas camadas fueron pintados en el lomo y laterales con colores distintos y alejados entre sí en el espacio RGB. El programa precisa la introducción por el usuario de los patrones de color a buscar, devolviendo como salida un fichero ASCII con las posiciones (columna X, fila Y) de cada una de esas manchas en cada imagen analizada. Esta información podría ser de gran utilidad en posteriores aplicaciones para el estudio de parámetros de comportamiento y bienestar de los animales (hacinamiento, actividad, amamantamiento, etc.).El software realiza una segmentación previa de la imagen en el espacio RGB, para aislar las manchas de color del resto de la imagen, y posteriormente el reconocimiento de los patrones de color utilizando otro espacio de color [B/(R+G+B), (G-R), (B-G)] más adecuado para tal fin, obtenido a partir de pruebas con diferentes combinaciones de R, G y B. Se ha evaluado estadísticamente el funcionamiento del programa, obteniéndose un 72,5% de detecciones de los lechones, de las cuales, 89,1% fueron correctas.

Palabras clave adicionales: actividad, análisis de imagen, comportamiento animal, reconocimiento de patrones, segmentación.

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Introduction

The objective of this research is to develop and test an artificial vision system to be used as a tool in studies on piglet behaviours such as their location, suckling behaviour, suckling and social hierarchy, activities and the like.

Artificial vision techniques are used in many research areas for automation process purposes, or for biological data collection, as an alternative to manual collection, which according to Tillett (1991), is very costly and difficult to implement. DeShazer *et al.* (1988) thoroughly discussed many practical aspects of piglet well-being and behaviour which can be addressed through image analysis. For instance, posture, activity, and the group behaviour of animals (huddling, aggression, etc.) may be used as indicators to detect health or environmental problems. McFarlane and Schofield (1995) used a sequence of 200 images captured from video tape to develop an algorithm to segment and track 10 piglets in a pen. In other studies (Brandl and Jorgensen, 1996; Marchant *et al.*, 1999), these techniques have also been used to estimate the shape and weight of pigs and fish (Lines *et al.*, 2001). These techniques are useful to reproduce 3D models of the exterior shape of animals (Wu *et al.*, 2004), and to guide a robotic system towards specific points on the surface of the animal (Frost *et al.*, 2000).

Appropriate environmental control is essential to maintain the comfort, health and performance of livestock. Usually current climate control systems only offer the optimal air temperature considered suitable for the pigs, in accordance with values cited in the literature (Geers *et al.*, 1989). However, other key factors are considered by Boon (1981) and Geers *et al.* (1996) to be necessary for proper environmental control (air velocity, floor temperature, etc.). As Shao *et al.* (1996) concluded, if the control is not adjusted to the behaviour of the pigs, then health problems may continue to appear.

Research into climatic comfort techniques used in porcine accommodation has aimed to conduct automatic quantitative evaluations of the heat balance status of the animal by measuring a large number of parameters related to the pig's environment (*e.g.* changes in the CO_2 content of the air, temperatures and drafts) (Van der Stuyft *et al.*, 1989).

Castelein *et al.* (1997) used simple algorithms to track behaviour through several applications. These authors obtained a series of indexes (activity, huddling), which are quite useful for measuring the response of the pigs to their thermal environment. Studies by Wouters *et al.* (1990) and Shao *et al.* (1996) employed this same approach. Results obtained by Xin and Shao (2005) for environmental control based on the animals themselves, working in real time, are promising.

When dealing with live animals, which are in constant movement, other problems may hamper image segmentation, such as lighting, shadows, or overlapping. Marchant and Schofield (1993) described how snake-based algorithms (Kass *et al.*, 1988), which have a rudimentary knowledge of the probable boundary shape, can be used to segment pigs within the image. Tillet (1991) developed a model-based technique to locate pigs in images; this technique required previous knowledge of the shape and deformation of the animal. Tillet *et al.* (1997) also used this technique to track the movements of a pig in image sequences, modelling the bending and head nodding as well as the position and rotation.

There is a clear relationship between activity and welfare. In much research, through distinct objectives, movements and activities of animals have been observed and measured (Fraser, 1978; Olivo and Thompson, 1988; Schofield, 1993; Brandl, 1997). In these studies, a first possibility involves looking at the animals and noting their behaviour. Schofield (1993) and Brandl (1997) made video recordings for subsequent viewing and analysis. The programme developed by Schwarz *et al.* (2002) allows for an automatic in-depth tracking and analysis of animal behaviour.

Another approach involves reading these parameters directly from the behaviour of the pig itself, using the animal as a sensor for the control system. The control model may be based on an artificial vision system, the parameters of which (such as huddling, posture, activity, etc.) are the inputs for the environmental control system. Thus, methods to quantify the behaviour of the pigs must be designed. To this end, Shao and Xin (2008) developed a real-time computer vision system that continually assesses and controls the thermal comfort of group-housed pigs based on their resting patterns. This system detects animal movements and classifies animal

Abbreviations used: CCD (charge-coupled device), DE (detection error), PIC (peripheral component interconnect), RGB (red green blue).

thermal behaviours into cold, comfortable or warm/hot.

In this study, we propose a new system to establish for each moment of time (captured image), the position (coordinates) of the piglets in a farrowing pen. The system is based on colour information. Images in which each piglet is painted using a different colour are captured. The system first segments the images and then recognises the colour patterns.

With these positional data, several parameters for behaviour and welfare can be obtained: parameters relating to group behaviour (huddling), suckling as well as individual and group movement and activity. Therefore, a small interval between images was selected (5 seconds).

Material and methods

Experimental procedure

The data (images) were collected from a farrowing pen located on a porcine farm of sows, with natural ventilation and heating using infrared gas screens. The pens, 2.05 x 1.85 m, are made of concrete and dark grey grid of 1.5 m. To capture the images a Charge-Coupled Device (CCD) colour video camera was placed in a zenithal position at the centre of the pen, 2.6 m from the floor (Fig. 1). A zoom lens was used with 6 mm of focal

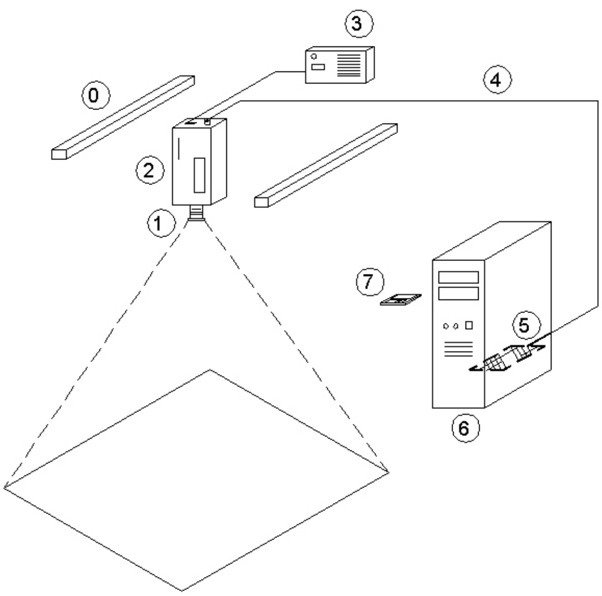

Figure 1. System for data capture. 0, lighting; 1, lens; 2, CCD camera; 3, feeder; 4, coaxial cable; 5, capture card; 6, PC ; 7, capture software.

distance and a lens aperture of 1.4. From this video signal, images were captured using a card connected to the Peripheral Component Interconnect (PCI) bus of a 486 PC at 100 MHz with 32 MB of RAM memory. Due to limitations in the speed of the hardware used (it requires about 4 s to capture an image), 1 image/5 s was selected as the capture-rate; however, this is considered sufficient to allow for further studies with these data. The images were stored on the local hard disk, and subsequently transferred to CD-Rom. Five sessions of data gathering were held throughout the lactation period (21 days). Thus, a total of 18,284 valid JPG Red Green Blue (RGB) 24-bit truecolor images, with 574 x 567 spatial resolution, were obtained. In order to assure homogeneous lighting conditions throughout the capture time, two fluorescent tubes of 36 W, 120 cm long, with a luminous flux of 2,100 lm, were placed above the zoom lens.

To fix the capture elements and illuminate the setting, a metallic support, adjustable in length and height, was designed and used.

Nine different colours of glossy spray paints were used to mark the backs and sides of the nine existing piglets in the pen. Initially, so that the image digital processing algorithms could efficiently discriminate the different marks, combinations of nine colours separated as much as possible from each other in RGB space were thought to be used. But in practice such combinations could not be obtained; colours had to be chosen from a limited range commercially available in spray. From this range, after rejecting a few colours which were very similar to those found in the background and on the sow herself, nine colours were finally chosen. The colours are commercially known as 3000, 2003, 1021, 6005, 6018, 5010 and 4006 of the Dupli-Color RAL series, and 5012 and R-V2 from Montana Colors. In this study, the colours are designated in the same order: 0 (red), 1 (orange), 2 (yellow), 3 (dark green), 4 (light green), 5 (dark blue), 6 (light blue), 7 (violet), 8 (mauve).

The programme searches each image of the captured sequence, and recognises the nine colour patterns previously introduced by the user. Then an ASCII file is produced with the coordinates of the nine colours (*i.e.* the nine piglets) in each analysed image.

Image analysis

This application was implemented in the Visual C++ 5.0 programming environment. The designed interface is user friendly and allows for a correct visualisation of the images, the detection process, the introduction of the colour patterns to be found and other parameters.

Subsequently, the images were processed (see the flow chart in Fig. 2) in accordance with the main phases of any image treatment application: pre-processing, segmentation, pattern recognition, and the interpretation of results.

Working with a considerable number of individuals (9) requires that any differences in colour be detected. In addition, the existence of irregular surfaces which, despite the uniform lighting, results in reflections and differences in tone within the same colour spot.

Statistical treatment (Jain *et al.*, 2000) was used for segmentation and pattern recognition. The difference between the phases is the colour space used.

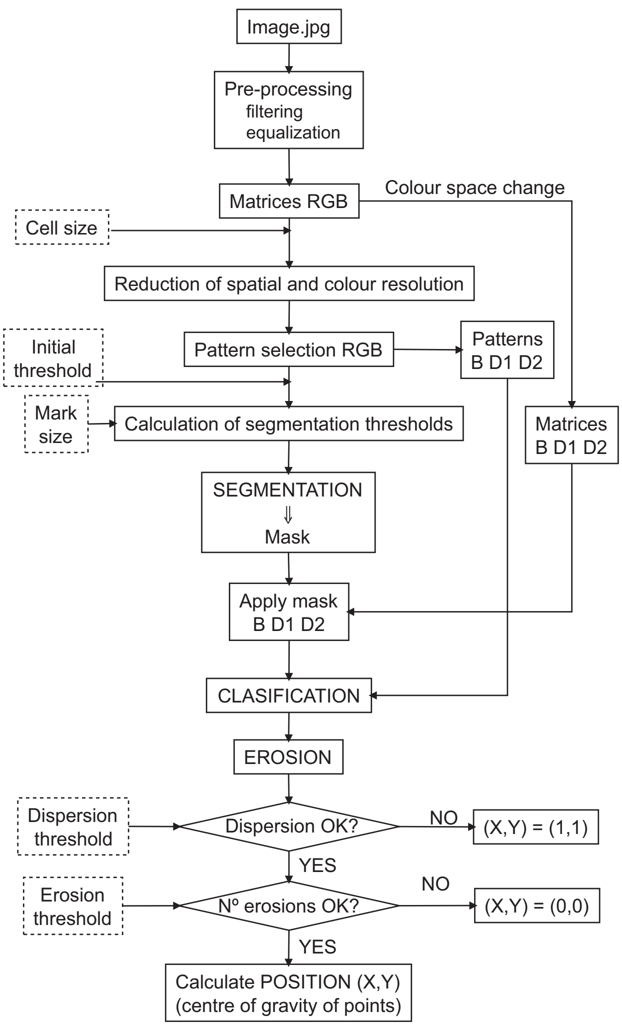

Figure 2. Flow chart of the software programme.

To develop the image analysis system, 100 previous images were captured and tested. In the following, the process stages are explained with one image being used as an example.

Pre-processing of the image

Prior to segmentation, and in order to reduce the changes in tonalities within a colour spot, a filter of granular noise was used, applying the 3x3 average filter three times to the image. Thus, a greater homogeneity in the tone of each colour spot was obtained.

Colour coordinate selection

The convenience of the colour space chosen for pattern recognition is justified next. Table 1 shows the mean values in the RGB space of the pattern (colours) used to mark the piglets. These values were recorded measuring over 50 images from previous tests.

To illustrate its distribution, these values are represented in Fig. 3A in 3D space (*), as well as its projections (o) on each of the 2D planes.

Although in principle it seems that points (*) are quite separate, considering that Fig. 3A represents a singular view in perspective, it is in fact difficult to distinguish the separation between points (*) in space; thus, a 2D representation was used. Accordingly, the projections of the points in the RG, RB and GB planes are shown. Observing the projections (o) on the RG plane, it appears that these two coordinates are sufficient to perform the analysis. The same applies to the RB plane, but not to the GB plane, where the points are too close-

Table 1. Mean RGB values of the nine colours used to paint the piglets

Colour	R	G	B
0 (red)	142	90	95
1 (orange)	176	137	80
2 (yellow)	183	168	87
3 (dark green)	92	130	121
4 (light green)	112	145	102
5 (dark blue)	63	88	113
6 (light blue)	76	129	168
7 (violet)	126	104	127
8 (mauve)	131	132	167

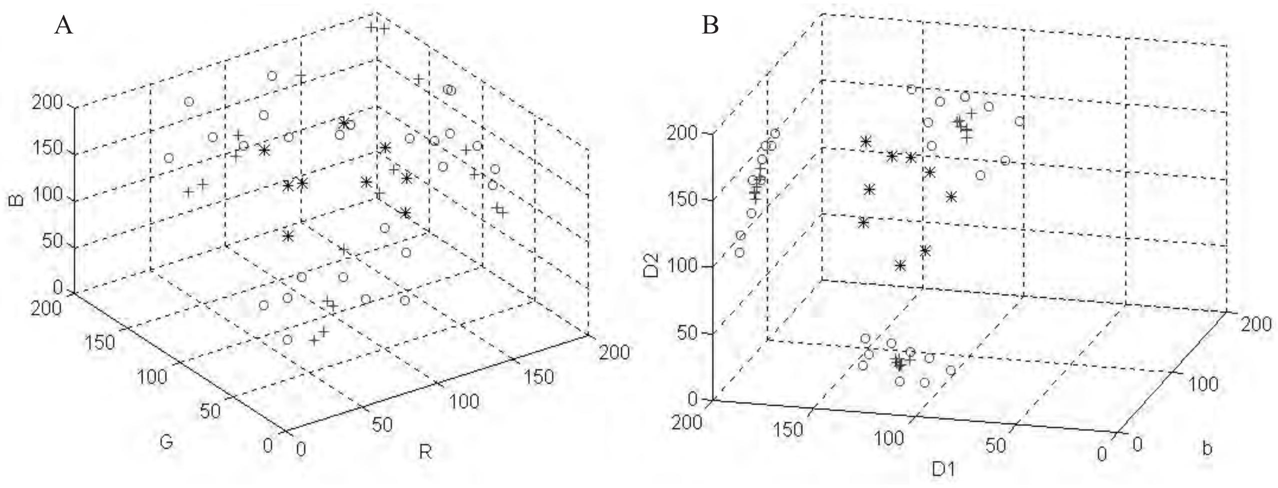

Figure 3. Representation in RGB space (A) and in bD1D2 space (B) of colour patterns (*) and their 2D projections (o), and projections of the colours appearing in the background of images (+).

ly located. Nevertheless, since the three coordinates are registered, and assuming that the use of three instead of two coordinates can only improve performance, all the information has been used (all three coordinates R, G and B) for the present work. However, this analysis is not as straight-forward as Fig. 3A illustrates, since in practice, the separation between points is not so clear. In this case (as shown in Fig. 4 where the background was eliminated using Adobe PhotoShop tools, leaving only the colour marks), the individual colour spots do not correspond to a single value (as in the case of Fig. 3A or Table 1). Instead, they show tone variations due to the irregular surface of the piglet and differences in illumination.

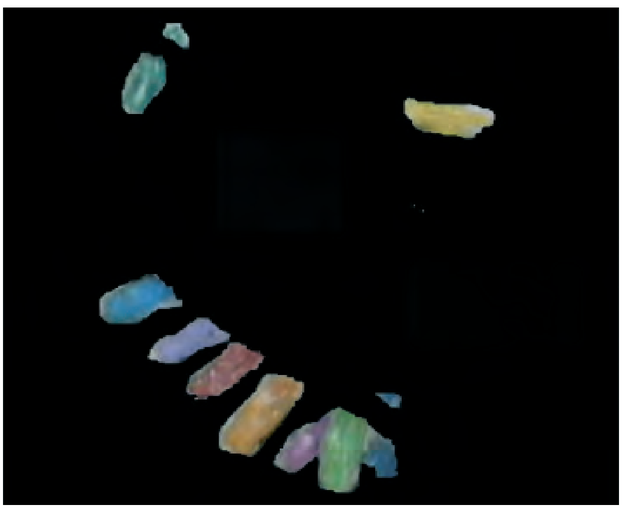

Figure 4. Image with colour spots only.

When representing on a plane components R and G of all the 574 x 567 pixels of the image in Fig. 4, Fig. 5A is obtained. Most of these points (corresponding to black pixels in Fig. 4) are superimposed on the coordinate 0,0 in Fig. 5A. The remaining points in Fig. 5A correspond to the nine colour spots in Fig. 4. Nine different colours were used in Fig. 5A to represent the points belonging to each colour spot in Fig. 4.

The nine patterns (values in Table 1) were also represented (♦). If each colour spot in Fig. 4 were uniform, Fig. 5A would only contain points superimposed on the nine symbols ♦. But as observed, the distribution that was, *a priori,* admissible since it accurately separated the colours (patterns) is no longer so, given the tone variations which are produced This is because a spot (in Fig. 4) is not made up (for all its points) by the pattern colour (Table 1), but rather it contains the aforementioned variation within these. Thus, an additional colour space was found, in which the colours (the painted marks from Fig. 4) can be placed at a greater distance from each other and are clustered around the patterns (♦).

Following Ohta *et al.* (1980), the colour distributions that provide different linear combinations of the RGB components were tested and evaluated. Those providing better results were (G-R) and (B-G). However, two colours (5 and 6) were not placed far enough apart. The component in which these colours resulted so far away was b [B / (R+G+B)]. When component b was included, the results for the remaining colours were not affected. In addition, as suggested by Gevers *et al.* (1998) as well as Schlüns and Koschan (1998), component b displays

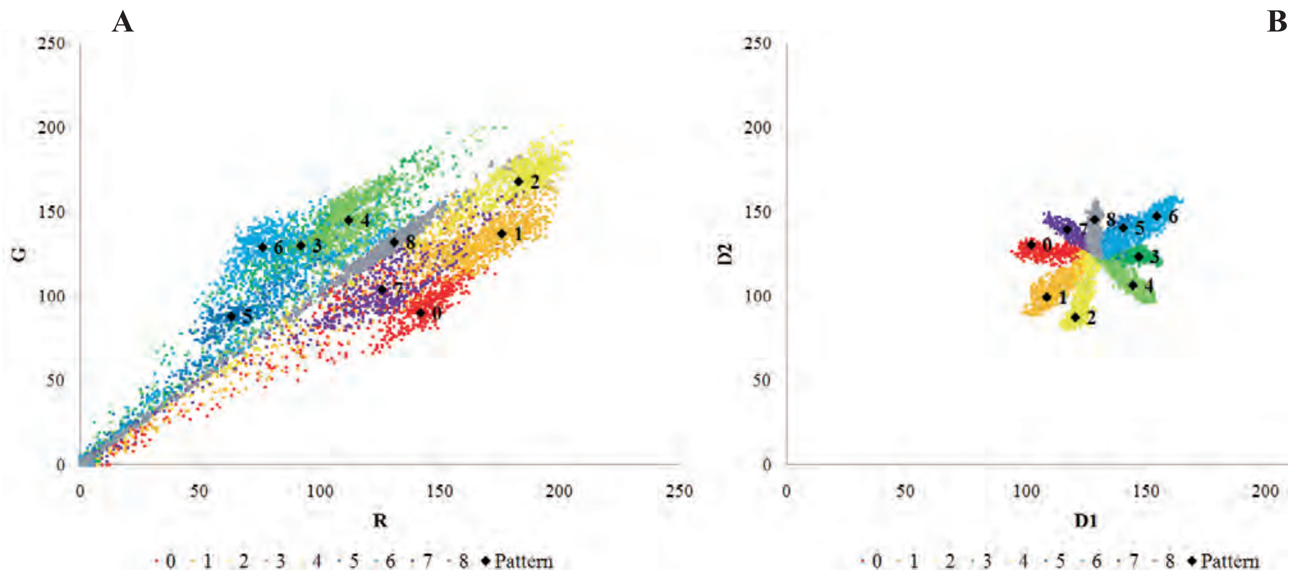

Figure 5. Distribution on the RG plane (A) and on the D1D2 plane (B) of the points of image shown in Fig. 4. The pattern values are represented (◆). Nine different colours were used (see Table 1) to represent the points corresponding to each one of the colour spots in Fig. 4.

very good behaviour in regard to changes in illumination.

Therefore, the space initially chosen was (G-R), (B-G), and B/(R+G+B), and its effectiveness in pattern recognition is confirmed next. To maintain the value rank within [0, 255] so that the 8 bits per component representation could be used in the programming, the definitive space was bD1D2, being $b = B / (R + G + B) * 255$, $D1 = (G - R) / 2 + 128$, $D2 = (B - G) / 2 + 128$.

In the same way as Fig. 3A was obtained, when patterns of Table 1 are transformed to bD1D2 space and represented in it, Fig. 3B is obtained. Both figures represent the same patterns in different colour spaces. Symbols in Fig. 3B are the same as those specified in Fig. 3A.

A regular distribution of the points can be observed in Fig. 3B. To better detect the spatial separation amongst them, it is useful to observe their projections in the 2D planes. Looking at plane D1D2, it can be seen that the points (o) are well separated; thus, the D1D2 space may be enough to recognise the different colours. The same applies to the bD1 space, although this is not possible for the bD2 combination, since the points are placed at very short distances. Nevertheless, for the same reason given for Fig. 3A, all the available information was used (all three coordinates bD1D2).

In Fig. 5B, the distribution within the D1D2 two-dimensional space of the colours in the real spots is represented (that is, the distribution of image shown in Fig. 4).

This distribution is quite suitable to differentiate the colours. However, when the colours that appear in the background of the image are added, there is some confusion, as noted in Fig. 3B, where, represented by crosses (+), the projections on the three planes of these background colours also appear. Although the distance to the patterns seems to be correct, there is, in fact, too much room for confusion, since, throughout the three planes, they are close together. Returning to the RGB space, if the projections (+) of the background colours in Fig. 3A are observed, it can be seen that these are more separated from the colour patterns in all the planes, and therefore, when the 3D distances are calculated, it should be easier to discriminate between background and patterns.

To sum up, the RGB space was chosen to carry out the **segmentation** and to eliminate the background, whereas for the **recognition** phase, the colour space bD1D2 was selected.

Segmentation

Segmentation aims is to discriminate the colour spots from the rest of the image. It uses labels to identify the regions with different colours (classes), which, a priori, correspond to the spots used to mark the piglets. The starting point is an image which is only a set of points in the RGB space, and n (in this case 9) patterns or classes, also in RGB, which are being sought. The probabilistic method (Jain *et al.*, 2000) used to segment the classes establishes decision boundaries between the patterns and assigns the input points (pixels) to one of the patterns (nine colours in Table 1). A maximum probability estimation is calculated to assign the label. The distance of each pixel for all the patterns is calculated, and the label of the closest pattern is assigned whenever the distance is below a certain threshold; otherwise, it is not assigned to any pattern.

Selection of the patterns in images. To make the application more flexible, the user must first select the patterns to be searched for within the images. This operation is conducted previously on one or more images, by double clicking on the spots under observation. The histograms of the three RGB components, with a colour resolution of 4 bits (16 colours per component), for a square area centred on the clicked point, and 7 pixels per side, are calculated. The RGB values corresponding to the maximum of these three histograms will be the pattern used in segmentation (the value to search in images).

Only 4 bits in pattern selection were used so that the histogram's matrix in this zone of 7x7, is comprised of 16x16x16 (4,096) elements (different possible colours). If 8 bits were used, a matrix with 16,777,216 elements would be obtained, and there would be no points with a value greater than 1 in the 49-elements (7x7) histogram, because exact colours would not be repeated.

The size of the kernel used (in this case 7) is a critical parameter. It should be, at its largest, around half the size of the smallest dimension of the spot subject to search (50 x 20 pixels, in this study).

Calculation of thresholds. Segmentation. We observed that histograms of any colour spot on a pig in the images, were distributed in a manner similar to the normal distribution (with the average value and typical deviation of the same colour spot). Hence, the Gaussian model was considered appropriate to represent the colour spots. When the RGB histogram of the image spots is projected on each axis (Fig. 6), a series of high and low values are observed. The colour regions subject to search will correspond to certain peaks in these projections. As a direct consequence and to model the colour distributions using the Gaussian model, it is necessary to establish the average values (m) and typical deviation (σ) of these colour patterns to be searched for within the images. These were obtained carrying out measurements in five randomly-chosen images. In Fig. 6, the histogram

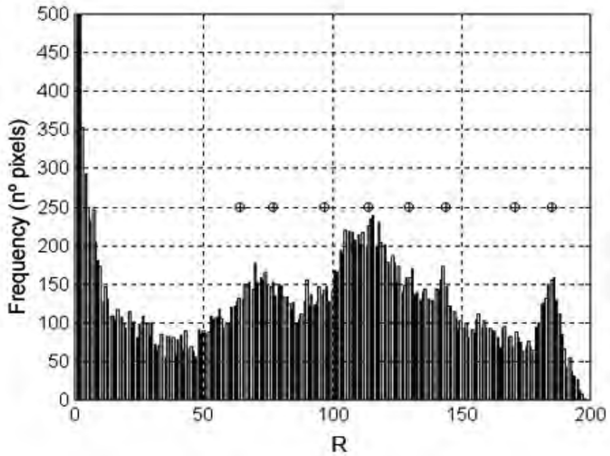

Figure 6. Histogram R of the colour spots in images. Mean values are represented by circles.

of component R of the colour spot is represented, as well as the mean values. These values are placed at the peaks of the histogram, the height of which depends on the existing number of pixels for each colour.

The values for the typical deviations vary from approximately 6 to 20. If a single threshold were fixed for all the spots (colours), the result would be far from optimal, since this intermediate threshold would provide too much tolerance for certain colours, and be inadequate for the correct detection of others. The most appropriate measure involves using a different threshold for each class or colour, obtained from the mean size N (in pixels) of the searched colour spots in the image. N will be one of the most crucial input parameters. These mean values were estimated measuring several images, ranging between 1000 and 1500 pixels (depending on the aging of the piglets).

To calculate the threshold for each colour (pattern), the following procedure was used: firstly, the distance of each pixel in the image from the pattern is calculated, and the threshold that allows the N points closest to the pattern to be determined is obtained. Starting from an initial threshold to save time (30), the number of points placed at a smaller distance is calculated. If this number is above N (size of the searched spot), the threshold is reduced and the number of points placed below this is recalculated. This process is repeated until a number of points below size N of the colour spot previously established, is obtained. This threshold will be used for that colour when the segmentation is carried out. Repeating this process, the threshold vector is obtained.

Segmentation mask obtaining and applying. Once the threshold is obtained for each colour, the distance of each point in the image from all the patterns is calculated. If the minimum distance is below the threshold that corresponds to a specific pattern, the point is assigned to it in the detection matrix, and is marked with a label indicating the pattern number (from 0 to 8). The points that are not assigned to any pattern will be assigned the number 255. Once all the points are analysed, a mask will be generated (Fig. 7), in which the input (i,j) is set at '1' if the point (i,j) has been associated with one of the patterns, regardless of which one. Later, in the identification stage, the correspondence between patterns and points will be determined.

This mask will be applied to the matrixes (images), eliminating the background points which could lead to confusion, prior to the recognition stage.

Pattern recognition and interpretation of results

Once the background is eliminated, the points which are candidates to be selected as part of the searched spots must be assigned to the closest pattern.

In this case, the colour space considered is bD1D2, and the probabilistic method is once again employed to assign each point to one particular class. Each point will be assigned to the closest pattern, as long as the distance is below the corresponding threshold.

Classification. The same thresholds obtained in the segmentation phase are used here, since the new colour space bD1D2 is a function of the previous space (RGB).

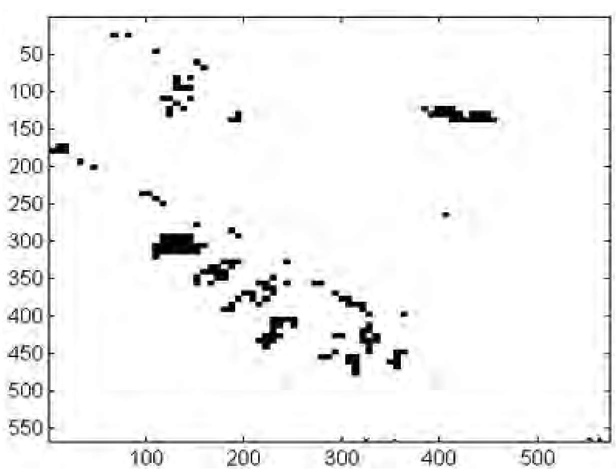

Figure 7. Segmentation mask. Image points identified as colour spots are represented in black.

Since the starting point is now an image with any problematic points eliminated, the tolerance will be increased to 1.5s in order to improve the results of the classification.

The output obtained is a matrix, *DetectionMatrix*, whose elements indicate the class to which the point has been assigned through the use of a label indicating the number of the assigned pattern (0, 1, 2, …, 8) or no pattern is assigned, label 255.

Erosion. Once the candidate points are assigned to the patterns, an erosion process is applied to every class included in the *DetectionMatrix*, thereby eliminating the external points within each zone, until reaching the point where one more erosion would result in the elimination of all the points. Thus, the smallest regions are eliminated, since they usually cause confusion between the patterns (or with background colours) during the segmentation and identification processes, and only the central points of the larger regions remain.

When the number of erosions applied to each class is calculated, a minimum size can be established so as to consider whether a spot has been detected. In this case, 3 is the minimum number of erosions, which indicates that the region must have a minimum diameter of 6 pixels. In the case that one individual has gone undetected (the number of erosions is lower than stipulated, and, therefore, the size of the spot is insufficient), it will be assigned the position (0,0).

Position assignment. Additionally, the dispersion of the points obtained following the erosion is calculated (Eq. [1]), and the result of the detection is rejected when it exceeds a specified threshold (25), which is indicated by assigning the position (1,1). The reason for choosing 25 is that, being the approximate dimensions of a spot of 50x20 pixels, in the case of a line of 50x1 pixels, the average distance would be 13, and in the worst situation (only detected at the two ends of that line) dispersion would be 25; that is, a greater dispersion indicates that an incorrect zone is being considered, which will alter the result giving an incorrect position, and this situation is ruled out by assigning the value (1,1). Thus, the possibility that an individual is marked at an erroneous zone is avoided (the centre of gravity of several dispersed points).

$$DevX = (1/N)\sum |X_i - X| \qquad DevY = (1/N)\sum |Y_i - Y| \qquad \mathrm{i = 1\ to\ N} \qquad [1]$$

Where (X, Y) are the coordinates of the centre of gravity for each colour; (X_i, Y_i) are the coordinates for each point (following erosion); N is the number of points.

If the result of erosion exceeds the minimum size, and provided it is not too disperse, the centre of gravity of the zone for each pattern is validated, and this position (*X,Y*) is assigned to the piglet.

Programme output data

When a set of images is processed, the programme returns a standard text file. The first column is the number of the image, in order of capture, and the two other columns indicate each analysed colour (assigned coordinates *X* and *Y*). The possible cases for these output coordinates, as well as their causes, are given in Table 2.

Statistical analysis

In order to study the consistency of the programme, a series of statistical models were developed. This validation is implemented from the positional data obtained when all the available images are analysed. First of all, the way in which the detection has worked is evaluated. Afterwards, the types of error in the programme performance are defined and estimated.

Colour detection analysis

A multinomial logistic regression model was introduced for the 164,556 (X,Y) observations obtained (18,284 images multiplied by the nine colours), considering the explicative variables as *dummy*. The model aims to detect the effects of the colour variable on the different probabilities of colour detection (*(0,0)* no detection, *(1,1)* high dispersion, *(>1,>1)* detection). The model applied was:

$$P(Z=j)=\frac{e^{u_j}}{1+\sum_{i=1}^{J-1}e^{u_i}}$$

$$P(Z=J)=1-\sum_{j=1}^{J-1}P(Z=j)$$

Where *Z*=colour detection; *j*=detection options: (0,0) = not detected, (1,1) = high dispersion, (>1,>1) = detection; u_j=linear function of the explicative variables.

This function is:

$$u_j=\beta_{Cj}+\beta_{0j}xC_0+\beta_{1j}xC_1+\beta_{2j}xC_2+\ldots+\beta_{8j}xC_8$$

Where β_{kj}=coefficients related to the explicative variables for the state Z=j; C_i=1 if the colour is i (0 in the opposite case). i = 0,...8.

To estimate all these parameters, a CATMOD procedure in SAS system (SAS, 2001) was used.

Table 2. The casuistry behind the values for coordinates obtained in the detection. Types of errors considered

	(X_i,Y_i)	**Code**	**Reason / Type of error**
Not detected	(0,0)	0	Piglet (colour) hidden Piglet present but not detected (detection ERROR) (Fig. 8)
High dispersion	(1,1)	1	High dispersion of image points candidates to the colour spot
Detected	(>1,>1)	2	Correctly detected (correct colour) Mistaken for another colour or part of the image (Confusion ERROR) (Fig. 9)

Methodology for error examination

Types of errors. As shown in Table 2, two types of errors in the performance of the programme were considered: *Detection error* (DE) (Fig. 8) occurs when a colour —piglet— is present and visible in the image, but has not been detected [so the assigned position is (0,0)]; and *Confusion error* (Fig. 9), when a colour has been detected, albeit erroneously, and has been mistaken for another colour (either for another piglet or for the background colours in the image) and the output position provided by the programme is, therefore, erroneous. In Fig. 8, a high dispersion case can also be seen: piglet 3 (dark green) is present in the image, but the programme assigns it position (1,1) because it has also been detected in other places, with high dispersion.

To examine these errors, and, consequently, to verify the adequate performance of the programme, it is necessary to observe the images and analyse the causes.

Taking into account the enormous amount of available images (18,284) each with 9 observations, that is, a total of 164,556 observations, the necessity of sampling

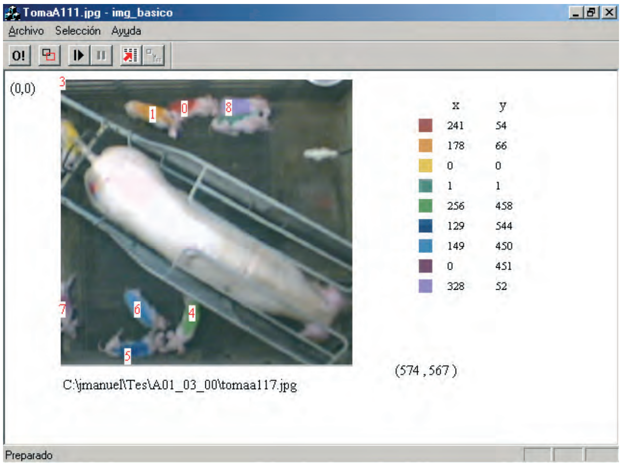

Figure 8. Detection error: colour 2 visible, but not detected (coordinates (0,0)).

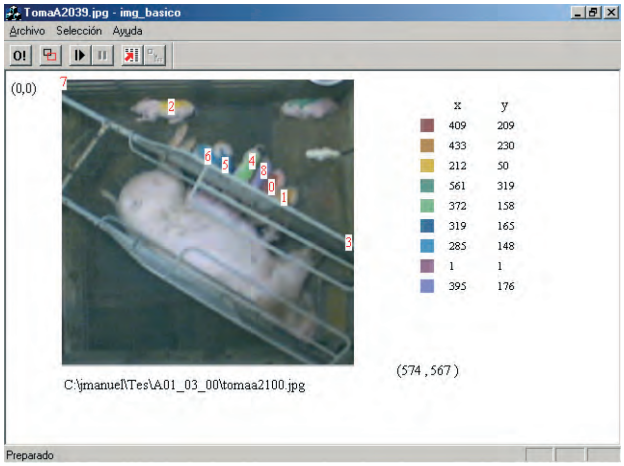

Figure 9. Confusion error: colour 3 has been mistaken (erroneous coordinates).

in order to carry out the appropriate verifications is deduced. Two types of samplings were carried out: i) stratified periodical sampling, to verify the detection errors; and ii) consecutive periodical sampling, to assess the confusion errors.

Detection errors. The expression of the confidence interval for the ratio, allows us to calculate a sample size for a stratified periodical sampling, to estimate and limit the DE.

Analysis of confusions between colours. In the processing of an image, we considered that colour i (or piglet i) was mistaken for j when for the colour i the programme provides the output coordinates (X_i, Y_i), which correspond to the space occupied by the colour j (j being equal to 0, 1, …, 8, or any other colour existing in the background of the image).

The study was developed in three phases. Observing a sample (25%) of the processed images, two dimensions tables (one table for each take, plus one global table) were elaborated with the values of total confusions among colours, and other layouts of a similar structure with the proportion of confusions.

To verify if certain colours were mistaken more often than others, a chi-square test was carried out on the values of total confusions for each colour.

Results

Five coordinates text files were obtained, one for each set of data recording, and then grouped into a single file with 18,284 rows (images).

Colour detection analysis

The multinomial logistic regression model obtained is shown in Table 3.

Since we are dealing with a saturated model, the adjustment is perfect between the values predicted by it and the observed values (given in Table 4). The overall percentage of detection (>1,>1) was 72.5%.

The reference colour (piglet) is 0, and from this, the behaviour of the other colours can be deduced, considering the prediction of the probability of obtaining a value for P(Z=j).

For the prediction of *(0,0)*, all the coefficients are significant in relation to the referral colour. Therefore, all the colours behave differently from 0 in one sense or another (a greater or smaller probability), according to their sign. To predict *(1,1)* (high dispersion), all the coefficients are also significant in relation to the referral piglet.

The programme searched for nine colour spots in each image; 72.5% of these searches were successful [*colour detected*, coordinates (>1,>1)]. In the remainder cases (27.5%), there was *no detection***:** 7.6% of times it is because the colour sought was found (and thus confused) also in other parts of the image (floor, or wall, or another colour), returning the value (1,1) to indicate such dispersion, and 19.9% of the times, this search does not find the colour sought [coordinates (0,0)], because either the colour was not present in the image, or because a programme error (called DE) occurred (colour is present but not detected) (see Table 2).

There is a relationship between the distribution of values (0,0) and (>1,>1) for colours: the higher the

Table 3. The multinomial logistic regression model obtained

Response	J	Colour detection
1	0	(0,0)
2	1	(1,1)
3	2	(>1,>1)

Analysis of maximum likelihood estimators

Parameter	Function number	Coefficient	Standard error	Chi-square	Pr>ChiSq
Const	1	-2.122	0.0247	75.24	<0.0001
	2	-2.614	0.0309	785.38	<0.0001
C1	1	0.3837	0.0325	139.64	<0.0001
	2	-0.6262	0.0522	144.13	<0.0001
C2	1	1.333	0.0294	2053.91	<0.0001
	2	-3.565	0.199	323.94	<0.0001
C3	1	-0.6932	0.0443	244.73	<0.0001
	2	1.532	0.0355	1864.03	<0.0001
C4	1	1.023	0.0302	1149.42	<0.0001
	2	-0.4917	0.0521	89.04	<0.0001
C5	1	0.4921	0.0322	233.38	<0.0001
	2	0.1491	0.0430	12.01	<0.0001
C6	1	2.279	0.0288	6248.87	<0.0001
	2	-1.673	0.0989	286.49	<0.0001
C7	1	0.5158	0.0326	251.00	<0.0001
	2	0.8651	0.0383	511.15	<0.0001
C8	1	0.3065	0.0335	83.51	<0.0001
	2	0.7592	0.0386	386.89	<0.0001

value (0,0), the lower the detection (>1,>1). This is expected since (0,0) is the leading cause of non-detection, as with colours 6 and 2. Colour 3 is a departure from this behaviour; therein, the main cause of not-detection is (1,1), since it is mistaken for other colours in the scene, and so a high dispersion is obtained when calculating the coordinates.

Table 4. Proportions predicted by the multinomial logistic regression model

Colour	J=0 (0,0)	J=1 (1,1)	J=2 (>1,>1)
0	0.1004	0.0614	0.8382
1	0.1447	0.0322	0.8231
2	0.3119	0.0014	0.6867
3	0.0428	0.2422	0.715
4	0.2419	0.0325	0.7256
5	0.153	0.0663	0.7807
6	0.5359	0.0063	0.4578
7	0.146	0.1265	0.7275
8	0.1234	0.1186	0.758

Methodology for error examination

Detection error

The proportion p of DE was determined in the population of cases in which the programme produced the result (0,0) (not detected). The size of this population is 32,706 times. Since the behaviour of the DE is unknown, and in order to scan all the instants (images), a periodical and stratified sampling was chosen. To this end, it was, first of all, necessary to divide the population of images into nine subpopulations (L_0, L_1,..., L_8), where L_i is the subpopulation of images where i cases of non-detection (0,0) were produced. The estimation of this proportion p will be, considering an infinite population:

$$p \pm z_c \,(p\,(1-p)\,/\,M)^{1/2} \qquad [2]$$

Where p = proportion of DE; M = size of the sample observed, expressed by number of “non-detections” (not number of images); and z_c =1.96.

After an initial estimation (examining images of subpopulations L_6 and L_7, in which there are several cases of (0,0), a preliminary value for p equal to 0.0664 was observed. After admitting an error in the estimation of ± 0.02, a sample size M=595 is obtained by Eq. [2]. Once these 595 samples are divided through stratification into nine subpopulations, the nine sample sizes M_i are obtained for each subpopulation, in addition to the number of images (M_i/i) that need to be considered within each subpopulation L_i.

After this stratified sampling of images to observe 595 cases of non-detection (0,0), Eq. [2] gives as a result for the proportion of DE p = 0.11881 ± 0.026. As defined in Table 2, the result reveals that the DE is a small proportion of the cases in which no detection was produced. In other words, when the programme returns the value (0,0) this is mainly due to the fact that the colour is not present in the image, because the piglet is either hidden or lying on the side painted with the colour.

Analysis of colour confusions

The results for Table 5 indicate that 89.1% of the detections were correct (the overall percentage of confusion being 10.9%). The chi-square test showed different colour confusion behaviours (Chi square 2096.79; DF 8, P-value <0.01).

In short, considering all the possibilities, Table 6 shows the general distribution of the different situations in Table 2.

From the combined analysis of detections and confusions, it can be deduced that colour 6 is only slightly detectable (46% of images, Table 4). However, when it is detected, it is correctly detected (96.8% of the detections are correct, Table 5). Colour 2 behaves similarly; it is detected 69% of the time, and almost always correctly (99.8%).

Colour 3 is also a "slightly detectable" colour, as previously mentioned. However, in this case, the cause is (1,1). In the confusions analysis, this colour is one of the most misread (16.8% of the time that it is detected) mainly due to "other things" (pen walls, soil). It is obvious that since it is a colour which can quite often be mistaken for others, the frequency of (1,1) is quite high: the programme "detects" several pixels in the image as belonging to this colour 3, and, since they are separate from each other, this colour is assigned the value (1,1) in such cases.

It must be pointed out that the colours with the poorest behaviour with regard to detection (6 and 2) are those least mistaken for other colours.

Discussion

A system was developed to record and analyse images to facilitate the monitoring of piglets. The piglets (colour marks) are identified by the programme at an overall percentage of 72.5%, with 89.1% of these detections being correct. This means that with every search the programme finds a colour spot and classifies it correctly, with a success rate of 64.6% (0.72 x 0.891).

Table 5. The proportion (%) of colour confusion errors. Column "other" indicates confusion with other parts of the image. For example: colour 4 was detected in 3,456 visually explored images, yet it was mistaken for colour 2 1.5% of the time. Np = population size

Colour	0	1	2	3	4	5	6	7	8	Other	Total Conf	Np	Sample
0	0.00	0.91	0.33	0.00	0.00	0.00	0.00	0.05	0.00	5.76	7.05	15,326	3,956
1	0.03	0.00	10.80	0.00	0.00	0.00	0.00	0.03	0.00	0.21	11.06	15,049	3,860
2	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	12,555	3,390
3	0.00	0.00	0.00	0.00	0.55	0.15	0.29	0.00	0.00	15.81	16.79	13,053	3,448
4	0.00	0.00	1.50	0.00	0.00	0.00	0.03	0.00	0.00	2.84	4.37	13,267	3,456
5	0.00	0.00	0.00	0.00	0.00	0.00	26.63	0.00	0.00	1.36	27.99	14,274	3,815
6	0.00	0.00	0.00	0.00	0.00	2.63	0.00	0.00	0.04	0.56	3.23	8,371	2,506
7	2.04	0.03	0.00	0.00	0.00	0.00	0.03	0.00	0.40	6.76	9.26	13,302	3,478
8	0.00	0.00	0.00	0.00	0.00	1.07	0.90	0.03	0.00	12.83	14.82	13,858	3,562
Global values											10.93	119,055	31,471

Table 6. Detailed percentage distribution of the different situations in Table 2

	Output coordinates	Code		Reason / Type of error	
Not detected	(0,0)	0	19.9%	Piglet (colour) hidden	17.59%
				Piglet present but not detected (detection ERROR) (Fig. 8)	2.36%
High dispersion	(1,1)	1	7.6%	High dispersion of image points candidates to be colour spot	7.6%
Detected	(>1,>1)	2	72.5%	Correctly detected (correct colour)	64.6%
				Mistaken for another colour or part of the image (Confusion ERROR) (Fig. 9)	7.96%

This percentage of correct classification of the piglets can be considered an acceptable starting point for assessing this method in more detail, using more powerful equipment and a standardized environment. One must also consider that not all the remaining classifications correspond to errors; only 7.9% is attributed to colour confusion, and for the other 27.5%, no colour was detected. The latter percentage is distributed amongst colours more or less regularly; hence, the study of animal behaviour would not be biased.

Taking into account this margin of error, and with future improvements, it can be considered a beneficial tool for the study of multiple facets of the animal behaviour and welfare and the actual design of livestock accommodation itself.

Unlike the published studies that focus on other important aspects or goals, such as McFarlane and Schofield (1995) or Shao and Xin (2008) the novelty of our research is the development of a system which allows for the identification of individual piglets in the group. Since most animal behavioural studies require individual identification, our innovation is promising since animals need not be directly observed nor do previous recordings need to be made (Brandl, 1997; Villagra *et al.*, 2007) and thus considerable savings in time are possible.

Illumination becomes more critical factor as the number of individuals being searched for increases, since this implies the need for lower margins of tolerance (at the thresholds). The shiniest colours are more sensitive to changes in illumination, and are mistaken for darker shades of the same colour, as occurs between light and dark blue (5 and 6).

The results depend on the success of the pattern selection. It is important to test the patterns in several images of the sequence before their final validation and launching the analysis process.

The probabilistic classification used for segmentation and recognition allows for satisfactory results, which could be improved when considering specific aspects for future study:

- The closer two colours are in the colour space used, the greater the confusion between them. Therefore, the colours must be as far apart as possible, and thus an exhaustive study into this matter should be conducted.
- The pre-existing colours within the scene must be avoided. Dark green (3) could be dismissed as a pattern, since it is too similar to the background of the pen.
- Elements which could lead to confusion should also be removed. The results would probably improve if the metallic bars were painted black.

Tests were carried out using the histograms as the basic tool for both processes (segmentation and recognition), as suggested both by Shafarenko *et al.* (1998) and Stillman *et al.* (1998). However, the required increase in the calculation capacity was not compensated by improved results, as indicated by Jain *et al.* (2000).

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