

Beef identification in industrial slaughterhouses using machine vision techniques

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Abstract

Accurate individual animal identification provides the producers with useful information to take management decisions about an individual animal or about the complete herd. This identification task is also important to ensure the integrity of the food chain. Consequently, many consumers are turning their attention to issues of quality in animal food production methods. This work describes an implemented solution for individual beef identification, taking in the time from cattle shipment arrival at the slaughterhouse until the animals are slaughtered and cut up. Our beef identification approach is image-based and the pursued goals are the correct automatic extraction and matching between some numeric information extracted from the beef ear-tag and the corresponding one from the Bovine Identification Document (BID). The achieved correct identification results by our method are near 90%, by considering the practical working conditions of slaughterhouses (*i.e.* problems with dirt and bad illumination conditions). Moreover, the presence of multiple machinery in industrial slaughterhouses make it difficult the use of Radio Frequency Identification (RFID) beef tags due to the high risks of interferences between RFID and the other technologies in the workplace. The solution presented is hardware/software since it includes a specialized hardware system that was also developed. Our approach considers the current EU legislation for beef traceability and it reduces the economic cost of individual beef identification with respect to RFID transponders. The system implemented has been in use satisfactorily for more than three years in one of the largest industrial slaughterhouses in Spain.

Additional key words: animal identification; traceability; ear-tag detection; automatic digit recognition; threshold-based segmentation; mathematical morphology; image processing.

Introduction

The identification and traceability of cattle in many advanced countries is an essential stage in handling animal safety policies, food production management and demands of consumers (Bowling *et al.*, 2008). Due to the relevance of the considered problem, at the beginning of the seventies of last century, several universities and research institutes have worked and developed the first electronic animal identification systems (Rossig, 1999; Schroeder & Tonsor, 2012). The Bovine

Spongiform Encephalopathy (BSE) crisis in 1996 brought about a reduction in beef consumption in Europe. A consequence of this was that the EU Commission decided to introduce the Beef Labelling Regulation 1760/2000, aiming to recover the confidence of consumers in beef products (EC, 2000). These norms lay out that it would be necessary to ensure the traceability of beef cattle, using proper labelling which would inform consumers about the origin of the product. Traceability is the “ability to maintain a credible custody of the animal identification or animal pro-

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Abbreviations used: ANPR (Automatic Number Plate Recognition); BID (Bovine Identification Document); CCD (Charge-Coupled Device); DPI (Dots Per Inch); ER (Error-Reject); EU (European Union); FAR (False Acceptance Rate); LRT (Likelihood Ratio Test); MSE (Mean Square Error); OCR (Optical Character Recognition); RFID (Radio Frequency Identification); UML (Unified Modeling Language).

ducts through all stages within the food chain” (McKean, 2001; Schroeder & Tonsor, 2012). According to Regulation 820/97 of the European Parliament (EC, 1997), bovine cattle traceability needs the following elements: (a) two individual ear-tags for identifying each animal, (b) an individual passport called the Bovine Identification Document (BID) containing the relevant information of each animal, (c) a register book for each holding (*i.e.* the farm) and (d) a computer database that at a national level registers all the animals’ movements, so as to identify them. This database must hold the following information for each head of cattle (Shanahan *et al.*, 2009): identification code (*i.e.* the ear-tag number), sex, breed, date of birth and herd of origin. Identifying and tracing bovine cattle is especially important for controlling the animals in the case of infectious diseases.

Individual animal identification can be made through different methods (Evans & Van Eenennaam, 2005). According to Marchant (2002), these methods can be classified as: mechanical, electronic and biometric ones. Typical mechanical methods include branding, tattoos, ear notching, and ear tags. The first three mentioned mechanical methods are considered insufficient for traceability purposes. Since all animals in a herd are branded identically this procedure is not useful to distinguish the animals. Moreover, it is not recognized internationally as a valid form of identification. The use of tattoos is restricted to small herds due to the time and work required. Finally, ear notching has limited use in large-scale identification programs. Mechanical ear tag-based methods include metal clips and plastic tags with bar codes. Metal ear clips are cheaper than plastic tags but their bad application can produce animal infections.

Electronic identification technologies for animal identification (Voulodimos *et al.*, 2010), usually based on radio frequency identification (RFID), rely on a device that contains a unique identification number associated with the animal, an activation reading device that initiates communication and interprets the code, and software which compiles and collates identification codes with other collected information (Marchant, 2002; Shanahan *et al.*, 2009). As external electronic tags (*i.e.* ear tags or neck chains) could to be lost, removed or damaged, the usage of internal devices (*i.e.* injectable or intra-ruminal transponders) has been adopted.

Accurate biometric identification methods used for animal identification include: iris scanning, retinal

images and DNA analysis. The first two modalities result intrusive for the animals. Iris scanning involves an acquisition of the iris pattern based on images or on a video-sequence. Retinal imaging is based on the uniqueness of the vascular pattern in the retina vessels (Allen *et al.*, 2008). DNA technologies can also be applied to identify the meat products derived from each specific animal (Dalvit *et al.*, 2007). In general, these biometric modalities when applied to animal identification can produce high identification rates, but they present the problem of their high cost compared to other approaches.

Due to their reduced cost and also because of being less intrusive for the animals, machine vision-based solutions have been applied to cattle identification in farms (Ahrendt *et al.*, 2011). These solutions present as advantages: (a) accurate cattle recognition results in real production conditions (in particular, they reduce the number of identification errors while the animals are in the slaughterhouses); (b) there is no need of incorporating any additional elements in the body of the animals that are to be slaughtered (*i.e.* electronic transponders), so it is better adapted to the traditional way the animals are handled in slaughters; (c) moreover, there is no need to modify the legal framework for beef traceability in slaughterhouses, since the proposed solution is based on the current EU legislation.

This work describes an imaging-based framework for the identification of each individual beef cow at the slaughterhouse. It is common for large slaughterhouses to butcher more than 400 animals per day. The development of an automatic system for beef identification must adapt to the conditions in slaughterhouses and should also become cost-effective. Shipments of beef livestock are transported to the slaughterhouse into trucks that can transport between 15 and 20 animals. Then, the beefs are placed into holding pens before they are slaughtered. The animals move individually along some corridors until they arrive at the abattoir room. After that, each animal is slaughtered and hung before the quartering commences. At this stage, one must ensure that each beef is properly identified by means of their both ear-tags and its BID. The proposed solution requires the automatic identification and matching of some numerical information contained in the animal ear tag with the one included in the BID of the same animal. After that, identification labels are generated for each piece resulting from the butchering of the beef. Before the proposed system was installed, the respective processes were done ma-

nually by a human operator who occasionally produced some annotation errors.

Spain, and produces about 20,000 t of beef meat and 65,000 t of pig meat per year.

Material and methods

In this section, we first describe an overview of the processes involved in the beef identification solution presented. Next, we detail the hardware/software components in the Computer Vision system proposed for the considered problem.

Two types of tests were performed to validate our proposal: laboratory and slaughterhouse tests. Supervised tests in the laboratory consisted in simulating the implemented system using image samples provided by the slaughterhouse (*i.e.* outside the production line). Slaughterhouse tests were carried out in practical working conditions and they considered the whole implemented system which has been in use for more than three years in the slaughterhouse of Fribin (<http://www.fribin.com/en>), situated in Binéfar (Huesca, Spain). This company, with more than 400 employees, has one of the largest industrial slaughterhouses in

Proposed solution for beef identification in slaughterhouses

Our proposed solution requires the following processes that are represented in the Unified Modeling Language (UML) Activity Diagram (Fowler & Scott, 2003) of Fig. 1: (a) Optical Character Recognition (OCR) reading of the BID and storing it in a database, (b) detection and analysis of some numerical information contained in the beef ear-tag and (c) matching of both of the respective pieces of extracted information for each animal.

Bovine Identification Document (BID) processing using an OCR system

Suppl. Fig 1 (pdf online) shows the structure proposed by the Spanish government for BID documents. A

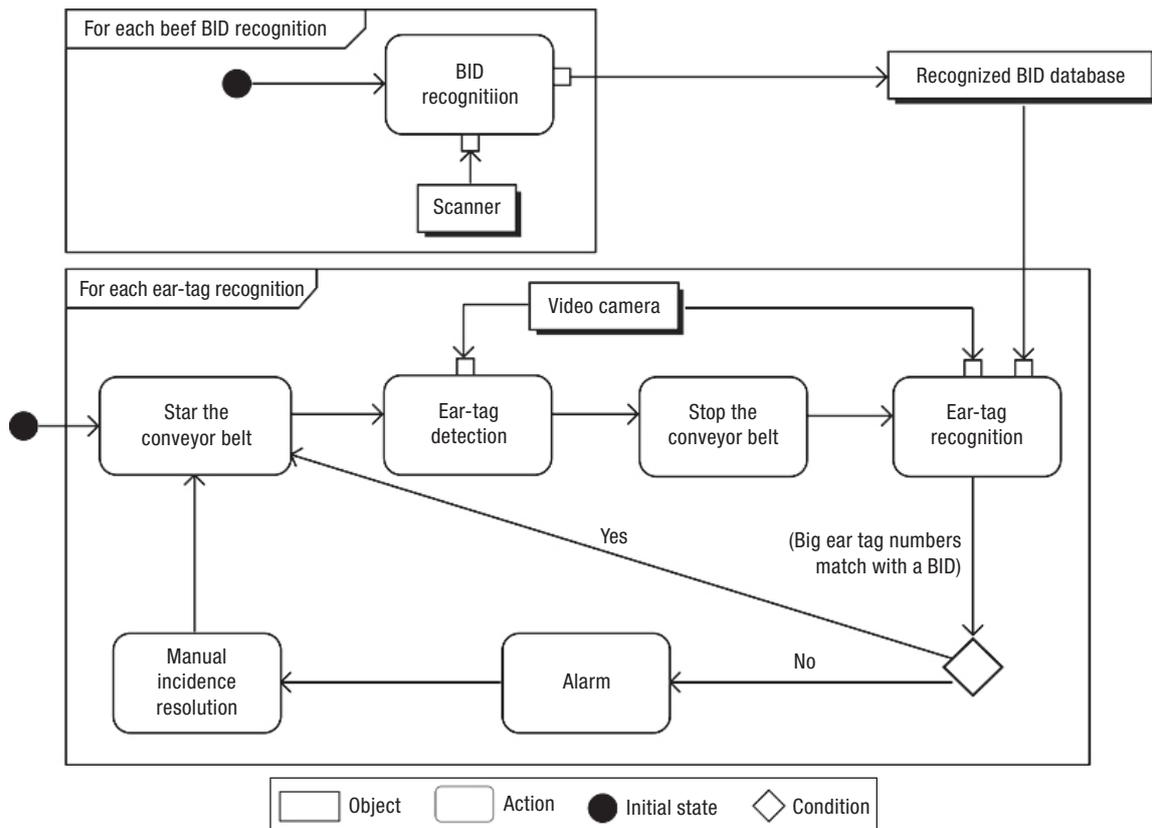


Figure 1. High-level UML activity diagram for the proposed beef recognition system in slaughterhouses.

BID contains three bar codes that incorporate the most relevant information in the document. So that an untrained person can read the information, this BID also includes most of its information (but not all of it) in the form of alphanumeric characters. Obviously, the goal of the bar codes is to make the automatic reading of the information easy. All this being so, the processing of these types of documents is based on the correct recognition of the three bar codes, as well as in the alphanumeric information contained in them. For the automatic reading of the BID, we have used the Atril Software (IPSA, 2011). Atril allows the conversion of paper documents in useful digital information, which is stored into an intermediate database (see Fig. 1).

The most relevant information in a BID for beef traceability is the Identification Number appearing on top of the document. That number is represented by a bar code type Code 128 which incorporates an error detection method. The importance of this Identification Number lies in the fact that it makes it possible to establish a match between the BID Identification Number and the digits of the ear-tag for each animal.

The Exploitation Code, containing the sex, breed, date of birth and herd of origin (related to the farm) of the animal, is codified as an Interleave 2 of 5 bar code. Since it does not contain any error detection codification, this bar code type is less reliable. In fact, as these documents contain different types of noise; many errors arise during the reading of these bar codes. For the validation of the bar code information reading it thus becomes necessary to compare it with the alphanumeric information also contained in the BID. If this comparison is not performed automatically, manual intervention by a human operator is required.

Optical segmentation of an ear-tag

An initial proposal consisted in using the video sequence of the animal passing through a corridor towards the abattoir. The deficient lighting conditions in the corridors, as well as the rapid and unpredictable head movements of the animals while running along the corridor, determined that this proposal was not feasible.

The final developed solution used the hardware system shown in Fig. 2 that was designed for the automatic ear-tag image capture. This device consisted in a conveyor belt where the ear-tag is placed by a human operator once the animal has been slaughtered and the ear-tag was cutting off. The ear-tag on the belt passes

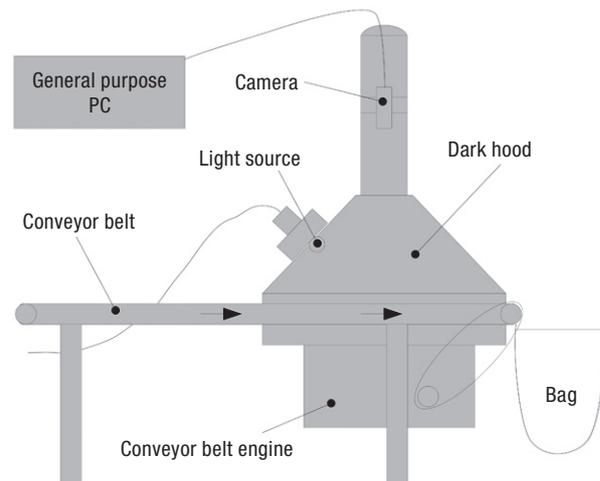


Figure 2. Diagram of the hardware system components for automatic ear-tag recognition.

through a dark hood which contains a vertically-placed camera at about 30 cm distance from the belt. We used a Sony XC-55 monochrome camera which has a progressive charge-coupled device (CCD) scan to provide full frame images (640×480 pixels, by achieving a 200 DPI effective resolution). The device also contains its own controlled lighting system (a 15 watt light bulb) for a better capture of the images.

The device works in two different stages, as follows. In the first stage, the conveyor belt is on and any ear-tag that is placed on it moves towards the dark hood component. When the system detects the presence of an ear-tag, the belt is automatically stopped in order to capture a good-quality image. On this image, the larger-sized digits contained in the ear-tag will be recognized. The analyzed ear-tags can present some variability (*i.e.* in some countries there are 4 larger-sized digits, while in others there can be 5 or more digits). Moreover, the dirt and deterioration of ear-tags also hinders their correct recognition.

Matching the information extracted from a BID to the corresponding information from an ear-tag

Ear-tag reading becomes a difficult task because of two main problems. One is the low resolution of the printed information in conventional ear-tags: due to its low cost, ear-tag information is commonly poorly-printed on a plastic card. The second problem is the dirt that is on the tag (mainly straw and mud). These difficulties mean that it is not easy to read smaller-size

alphanumeric characters and bar-codes (if they appear). For the current version of our system, it is important to highlight that just the larger-size numbers on the ear-tag need to be read. Only these digits are put in correspondence with the final four digits which appear in the Identification Number information of the BID [see Suppl. Fig. 1 (pdf online)]. After this process, we choose as the matching BID for a given ear-tag the one whose Hamming distance between the last digits of BID Identification Number and the corresponding ear-tag digits is the smallest one. If there exist several pairs having the same distance, operator intervention is required.

In the cases where there are ambiguities, we check whether or not a BID corresponds to another animal of the same shipment, since they are all slaughtered at the same time. This ambiguity is not usually produced among the animals belonging to the same shipment, since it contains only about 20 animals, and supposing that there are 4 larger digits, the collision probability is 1 in 500, so the probability of a shipment with no collisions is greater than 98%. We should underline that this digit-matching process takes only a few milliseconds; it is carried out while the ear-tag is passing through the dark hood; when that takes place, the conveyor belt is stopped.

If the ambiguity was unsolvable within the shipment, this situation is controlled by our system (see Fig. 1). In this case, the conveyor belt is started again, but the movement is now in the opposite direction. So, a human operator can retrieve this problematic ear-tag and he/she takes the appropriate action (*i.e.* clean the ear-tag and try again or solve the problem manually). Once a given beef ear-tag is correctly recognized, a set of identification labels are put on the slaughtered animal during its cutting process.

Ear-tag recognition using machine vision techniques

The automatic reading task of larger-sized digits in ear-tags (see Fig. 3) can be broken down into two main stages: ear-tag detection (where the conveyor belt is in movement) and digit recognition (where the conveyor belt is stopped).

Ear-tag detection

This task is based on the analysis of the histogram provided by the ear-tag image while the conveyor belt is

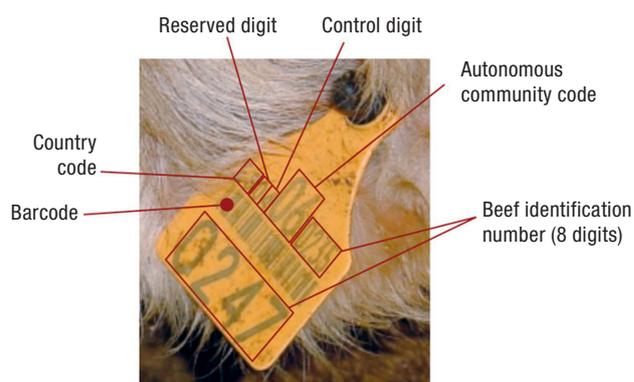


Figure 3. Spanish ear-tag and description of the information contained on it. The background color of the ear-tag can vary from one country to other country.

in movement. First of all, the intensity level corresponding to the rubber of the moving belt is determined. After this calibration, when the histogram values from the captured images are outside a threshold interval that corresponds to the rubber intensity, the system decides that an ear-tag is detected. As the velocity of the conveyor belt is constant, it is easy to adjust the system so it can be stopped automatically in order to capture good ear-tag images which make it easy to analyze them later.

False positives are commonly due to some dirt accumulated on the conveyor belt (*i.e.* straw residues). That makes it important to adjust the brightness thresholds for each installation properly, depending on the lighting conditions inside the dark hood device containing the camera.

Ear-tag recognition

The recognition of the large-sized digits appearing in an ear-tag image is solved by the application of the processes presented in Fig. 4. First, an adaptive threshold-based binarization of the image is computed. Then, a low-pass filtering to remove some noise is carried out. The next step consists in detecting the ear-tag base for orientation correction and large-sized digits segmentation. Finally, the recognition of the large-sized digits is carried out. We will now go on to describe each of these steps in detail.

Image thresholding

As the original ear-tag image is a grey-level one, an initial thresholding step is applied to convert it into

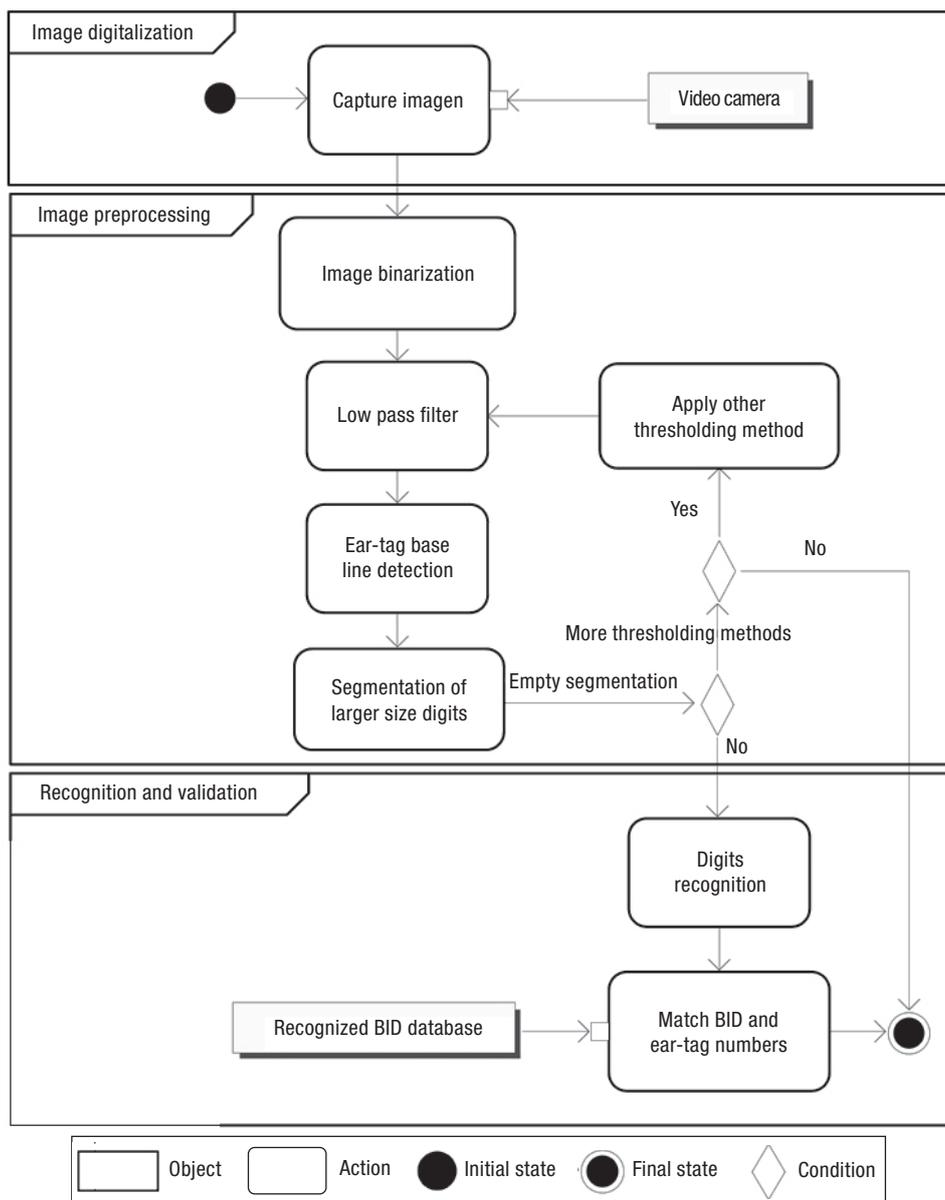


Figure 4. Stages in the ear-tag recognition process.

binary: the printed characters and pixels of the conveyor belt are turned to black, and the remaining ear-tag background pixels are turned to white ones.

For the case of Spanish ear-tags, as shown in Fig. 3, the pixels corresponding to the alphanumeric characters have an intensity value of around 40, while the pixels corresponding to the plastic material of these pieces present an intensity value of around 135. So, a fixed threshold value of 110 produces acceptable binarization results. However, we need an adaptive thresholding approach to handle ear-tags from different countries, since their color variability produce varia-

tions in their histograms. In general, an ear-tag image histogram can be modeled by three Gaussian distributions where one corresponds to the pixels of the belt, the second one to the ear-tag plastic background pixels, and the third one to the pixels of ink-printed information. To convert our images into binary ones, we considered two additional approaches: one is based on the Logarithm Likelihood-Ratio Test (Log LRT) and the other on the *k*-means algorithm.

The Log LRT test binarization approach is based on the hypothesis that the pixel intensities of the three classes considered have Gaussian distributions. To

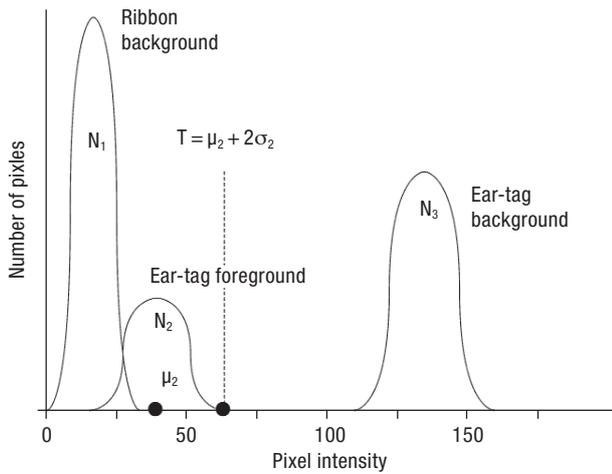


Figure 5. Selection of threshold T using the image histogram by the Log LRT approach.

model these distributions, a Log LRT is applied (Tse & Viswanath, 2005). Fig. 5 illustrates the threshold value selection using Log LRT. Three distributions are thereby obtained: $N_1(\mu_1, \sigma_1)$, $N_2(\mu_2, \sigma_2)$ and $N_3(\mu_3, \sigma_3)$, where N_1 corresponds to the belt pixels, N_2 corresponds to the ink ear-tag pixels and N_3 corresponds to the plastic-background ear-tag pixels. After some experimentation, the final binarization threshold T was chosen as: $T = \mu_2 + 2\sigma_2$. Fig. 6c shows the result produced by this approach on the sample ear-tag image of Fig. 6a. Common thresholding techniques like Otsu-based and median were also tested but they produced poor results. In consequence, a specific image binarization method was developed. Fig. 6b illustrates the application of Otsu method to the image of Fig. 6a.

The k -means binarization approach uses the k -means algorithm (with $k=3$) to find the three clusters of pixels considered (belt, ear-tag printed information and ear-tag background, respectively) which are related to their intensity values. To minimize errors coming from random elections, the k -means initial points are set to the

values: 0, 128 and 255, respectively. Finally, the threshold is set using the mid-point value between the centroid of the two clusters, corresponding to ear-tag ink-pixels and ear-tag foreground pixels, respectively. Fig. 6d shows the result produced by the k -means approach on the test image. The visual results produced by the Log LRT and k -means were, in general, similar.

Low-pass filter application

The accumulated dirt and deterioration of ear-tags produced some noise in the original images after their binarization. A filtering stage for removing all connected components which have a size smaller than N in the image was applied (our experiments determined that a value $N=100$ was appropriate for the resolution of our images). This filtering aims to take off those non-ink pixels of the binary image which have a value similar to the characters to be recognized and which could interfere in the ensuing segmentation and recognition processes. Fig. 7b shows the result of this filtering on a sample ear-tag image.

Ear-tag base detection

The skew angle of the ear-tag base in the image is detected and corrected. To achieve this, we first search for the perimeter pixels corresponding to the ear-tag base. A hit-and-miss morphological operation (González & Woods, 2008) using a binary mask of 10×1 pixels as shown in Fig. 7a is applied on the binary image to detect these contour pixels, as seen in Fig. 7b. After that, we used the Hough transform (González & Woods, 2008) on the pixels detected to extract the most probable line forming the ear-tag base (we also use the Hough transform to correct its skew). This line appears in red colour on the image of Fig. 7c.



Figure 6. Sample captured ear-tag image: (a) original grey-level image, (b) Otsu binarization, (c) result after Log LRT thresholding and (d) result after k -means thresholding.

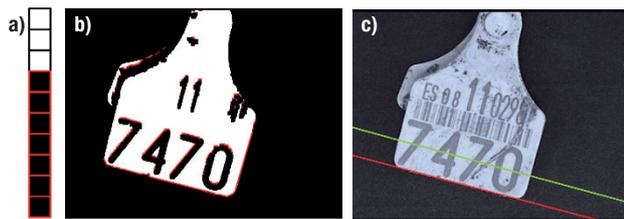


Figure 7. Ear-tag base detection: (a) morphological hit-and-miss mask used, (b) detected pixels (in red) using this mask over the result achieved after applying the low-pass filter described, and (c) corresponding straight line (also in red) detected by the application of Hough transform and parallel line (in green) at a distance of 1-cm from the ear-tag base.

Large digits ear-tag detection

Once the ear-tag base line is found correctly, the numbers to recognize correspond to the connected objects that are intersected by a parallel line to the base line, which is situated at an approximate distance of one centimeter above it (see green line of Fig. 7c). If any of these objects is touching the image borders, it means that the ear-tag is placed incorrectly on the conveyor belt. In this case, the conveyor belt movement reverses and the ear-tag is sent back so that it can be placed correctly.

Ear-tag digit recognition

Initially, we tried to use several generic OCR software tools. In particular, we made tests with ABBYY FineReader (<http://finereader.abbyy.com>) and Tesseract-OCR tools (<http://code.google.com/p/tesseract-ocr>). However, these OCR systems were discarded due to the errors performed in the digit recognition task. Many problems were caused by the types of digit fonts and the noise present in the ear-tags. Generic OCR software uses the context (*i.e.* dictionaries and standard fonts) to avoid this type of errors but in ear-tag image such context information is missing. Consequently, this recognition stage was carried out using machine learning techniques. In particular, as the problem of low-quality printed digit recognition has been successfully solved using different types of neural networks (Trier *et al.*, 1996), we explored the application of this classifier. After some experimentation, a trained feed-forward neural network with one hidden layer was used (and the corresponding parameters determined) for our approach. The images of the ear-tag digits resulting from the previous stage are now the inputs to the network. To fill possible holes, a morphological dilation using a 3×3 structu-

ring element mask is applied previously on the images. Now, each ear-tag number detected is directly segmented into its corresponding digit images.

The network used has an input layer with 256 neurons (corresponding to the pixels of a 16×16 ear-tag digit image to be classified), one hidden layer with 80 neurons and one output layer with 10 neurons (corresponding to the 10 possible digits to be recognized). Before the ear-tag digit image is presented to the network, it is re-scaled using bilinear interpolation. The scaled images maintain the original aspect ratio, but its height is fixed to 16 pixels.

The set of input neurons are partitioned into $s = 4$ disjoint subsets corresponding to four 8×8 disjoint sub-images (see Fig. 8). Each of the neurons of a sub-image are fully-connected to the corresponding subset s of k neurons in the hidden layer (where $k = 20$). The units of the hidden layer are fully-connected to the 10 neurons of the output layer. This network architecture decreases the training times since the number of links between the input and the hidden layer is reduced by $s = 4$ with respect to a fully-connected configuration. The architecture of the network used is presented in Fig. 8.

The network was trained using a sample consisted of 200 images of each of the 10 digits to be classified. These images were processed as described previously. The network was trained for 5,000 iterations until a 0.01 Mean Square Error (MSE) value was achieved. In the training process, the back-propagation algorithm with 0.1 for the learning rate parameter (μ) was used. When a new digit image is presented to the network, the highest value of the output neurons is used to determine the class assigned to such image. The value of the output neuron is used as a confidence level in such a digit character. The mean of the digit character confidences in a numeric string is used as the confidence of the string (*i.e.* the ear-tag string of digits).

Results

In this section, we present separately the tests performed in the laboratory from those tests carried out directly in the slaughterhouse.

Supervised experiments in the laboratory

These tests consisted in using the implemented system in an off-line mode (*i.e.* not working in practical

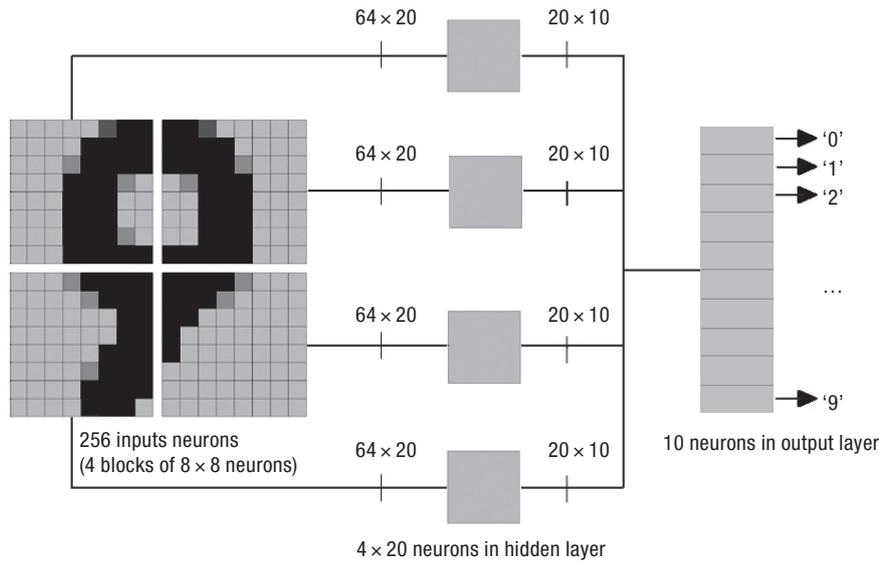


Figure 8. Structure of the feed-forward neural network used for the digits recognition task.

conditions at the slaughterhouse) for a sample of 9,970 ear-tags that correspond to 50 working days. These tags were previously washed and very few of them still kept some remains of straw and mud. After that, the ear-tags were placed in different positions at the conveyor belt (*i.e.* with varying inclinations), in order to emulate the further performance of the human operator at the slaughterhouse, for their digitization into images. Table 1 shows the different types of analysed ear-tag images that can be grouped into the following classes: correct (or intact), incomplete (due to bad placement of the ear-tags in the conveyor belt or to early stopping of the belt), dirty ear-tags, and bad-printed/damaged ones.

The main goals of the laboratory tests were to compare the different proposed ear-tag recognition approaches and also to adjust the binarization threshold T for the best classifier to be used at the slaughterhouse in practical conditions. In consequence, we have used the set of 9,970 images to create the Error-Reject (ER) curves (Simeone *et al.*, 2011) presented in Fig. 9. These

Table 1. Classification of ear-tag image samples for the laboratory tests

Type of ear-tag image	Number of images	Percentage (%)
Correct	8,913	89.40
Incomplete	1,045	10.48
Dirt	3	0.03
Bad-printed/Damaged	9	0.09
Total	9,970	100.00

curves plot the error rate against the reject rate and they respectively correspond to each of the different threshold-based binarization methods described in the previous section: (a) fixed threshold, (b) adaptive Log LRT, (c) adaptive k -means, and (d) the method that combines the three previous ones. This hybrid or combined method consists in using the result with highest confidence for the three previous binarization approaches. From the ER curves of Fig. 9, it can be noticed that the combined method produced the best ear-tag recognition results. For the collection of laboratory images and using the combined classifier, we experimentally adjusted the string confidence level threshold T to the value 0.93 (Fig. 9) and achieved for

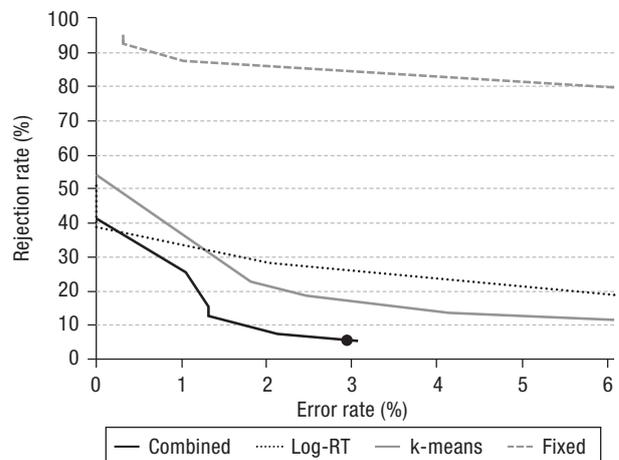


Figure 9. Error-Reject (ER) curves corresponding to the considered ear-tags recognition algorithms.

this value: a correct ear-tag recognition rate of 89.4% (*i.e.* those OCR results greater than or equal to T that are correct when compared to human visual inspection), a 7.7% of rejection (*i.e.* those results smaller than the confidence threshold T) and a 2.9% of error (*i.e.* those cases when the OCR values are greater than or equal to T that are incorrect when compared to human inspection).

System experiments in the slaughterhouse

The slaughterhouse tests aim to demonstrate the validity of the prototyped laboratory system when it is operative in practical conditions. For these experiments, we used 3,145 images corresponding to 10 working days. Table 2 presents the raw data corresponding to each day. Table 3 shows the number of error causes for the ear-tags images and also shows how many of them have generated rejections and errors. In short, 2,845 images correspond to correct ear-tag recognition cases (90.68%), 203 images to rejections (6.45%) and 90 images to errors (2.86%), respectively. This last error percentage is drastically reduced to 0.012%, being transformed into rejection, when the ear-tag recognition result is checked against with the BID recognition result by considering the collision probability (1/500), as explained in the M&M section.

Regarding the experiments carried out in the slaughterhouse, their corresponding results coincide with the simulated experiments in the laboratory (90.68% of correct ear-tag recognition in the slaughterhouse compared to 89.4% in the laboratory). Human

Table 2. Daily raw ear-tag image cases in the laboratory tests

Day	Number of images	Correct	Rejection	Error
1	397	369	21	7
2	140	123	10	7
3	305	275	19	11
4	519	479	25	15
5	239	201	24	14
6	189	171	16	2
7	221	207	7	7
8	137	111	18	8
9	504	451	41	12
10	494	465	22	7
Total	3,145	2,852	203	90

Table 3. Rejection and error causes of ear-tag image samples in the slaughterhouse tests

Error cause	Rejection cause		Error cause	
	Cases (#)	%	Cases (#)	%
Incomplete image	21	10.34	29	32.22
Dirt image	33	16.26	7	7.78
Bad-printing/Damaged	55	27.09	36	40.00
Other problems	94	46.31	18	20.00
Total	203	100.00	90	100.00

supervision of the system in the slaughterhouse was only required for 9.31% of the images (*i.e.* in the rejection cases), while key typing by the supervisor for 6.45% of the ear-tags. This last percentage corresponds to problems that cannot be solved by retries of the operators. Mainly, they are rejections due to bad-printed or damaged ear-tags (55 + 36 cases), and other cases correspond to misclassifications due to undetermined classifier errors (94 + 18 cases), as observed from Table 3.

To validate the concordance between laboratory and slaughterhouse results, we applied the statistical significance p -value test with the predetermined significance level of 0.05. Since the correct recognition rate in the laboratory was 89.4%, we assumed that the null hypothesis H_0 was “mean of correct recognition greater or equal than 90%” (and consequently the alternative hypothesis H_1 was “mean of correct recognition smaller than 90%”). As the achieved p -value is 0.39, we cannot reject the null hypothesis.

According to the slaughterhouse operators, who used the proposed system, it worked properly and they did not report any adverse incidents throughout the

Table 4. Solutions to possible problems when the system is working

	Error situations	Proposed solutions
Problems related to ear-tag detection	Detection of an ear-tag where none exists (false positive)	Clean conveyor belt
	Ear-tag not detected by the computer vision system installed	Revise system components (<i>i.e.</i> light bulb)
Problems related to BID identification number	Ear-tag recognition produces a number with no correspondence to recognized BID	System asks the operator to key in the complete number (delete ambiguities)
	There are two ear-tags with the same digits	If the problem persists the affected register is analyzed offline

whole working time of the system. Table 4 presents some possible operational problems when the system is working in practical conditions in the slaughterhouse and the corresponding proposed solutions given. Fribin reported us that human supervision of the system was only required in around 10% of the cases, and key typing in around 6% of the cases.

Discussion

This paper describes an operative machine vision-based solution for individual beef identification and traceability in slaughterhouses which includes the development of a specialized hardware system. The main tasks in the identification of the animals are the automatic extraction and further matching of some numerical information from the beef ear-tags to the information from the BID. Practical working conditions in slaughters (*i.e.* dirt or bad illumination) influence greatly the identification results. In these conditions, our recognition results are around 90. As we did not found published results on the same considered problem, we used the Automatic Number Plate Recognition (ANPR) problem for comparison purposes. The aspect of digits to be recognised could be compared to the digits of the car plate recognition problem, although the digits in the ear-tags are usually much dirtier. A paper from Parking Trend International (Keilthy, 2008) reported that system customers achieved below 80% of success in practical conditions using the implemented ANPR system, and consequently our presented results for ear-tag recognition are higher. Further, for the digit identification task in ear-tags, a validation method is applied which allowed to get a False Acceptance Rate (FAR) near to 0%. In consequence, the human operator can clean the tag and repeat the recognition process, which usually failed due to dirt problems.

Furthermore, it could be thought that the use of other referred animal identification methods could improve the recognition rates. Perhaps, a trade-off alternative is those based on RFID. Remote reading stations (*i.e.* antennas) are situated in strategic places in the slaughterhouse, such as the place where the cattle is weighted, the holding pen or the abattoir room. Some different types of passive tags (*i.e.* electronic ear-tags, ruminal boluses and injectable transponders) could be used (Marchant, 2002; EC, 2011). However, several problems arise when using RFID systems for beef identification.

These transponders are not “visible”, without there being an appropriate electronic reading device. Conventional ear-tags are always “visible” in absence of antennas. Moreover, a RFID system can not fully replace the use of physical ear-tags systems to identify each bovine, since this is the current legal solution adopted in Spain (and also in the EU). Consequently, the deployment of RFID devices to replace or complement the current solution would require a modification of the current legislation and would push up the economic costs of tracking each animal (EC, 2011).

It could be argued that the use of RFID technology seems a more accurate solution for the considered application, but it must be remarked that in slaughterhouses exists a big problem with interferences (IPSA, 2003; Scottish Government, 2008). For example, in the conveyor belts for transporting the animal pieces (*i.e.* when these have been quartered cut into pieces) or due the machinery present in these installations which makes the practical deployment of an RFID solution in these places very difficult. As reported in 2008 in a study of Scotland’s Environment and Rural Affairs Department (Scottish Government, 2008), the acoustic conditions in abattoirs produce short, high-intensity sound peaks (*i.e.* resulting from steel gates). These loud sounds seriously affect tag reader systems, such that their performance is degraded or completely inhibited. Moreover, the cost of using RFID could reduce the producers’ razor-thin margins.

The use of near field communication technology presents similar problems (*i.e.* in relation to visibility, cost and interference problems) for the considered application. Other works have pointed to the application of biometric solutions (Dalvit *et al.*, 2007; Allen *et al.*, 2008). These biometric proposals can produce high identification rates, but at the same time they present the problem of their high economic cost. Perhaps, these could be the reasons why the ear-tags are the main group of elements presented to the ICAR conformance test (ICAR, 2009) for animal identification.

The main advantages of our proposed system for automatic beef identification in industrial slaughterhouses are the following ones: (a) more accurate beef identification results in real production conditions (in particular, it reduces the number of identification errors while the animals are in the slaughterhouses); (b) there is no need of incorporating any additional elements in the body of the animals that are to be

slaughtered (*i.e.* electronic transponders), so it is better adapted to the traditional way the animals are handled in slaughters; (c) there is no need to modify the legal framework for beef traceability in slaughterhouses, since the proposed solution is based on the current Spanish and EU legislation.

Our framework considers the current legislation for beef traceability and does not increase the cost of individual beef identification. And, the presented application-oriented solution is general and it can be easily adapted to the common BID and ear-tag variations of the different countries. The complete system has demonstrated its effectiveness for a Spanish abattoir installation with practical working conditions, over a period of more than three years.

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