A non-stressful vision-based method for weighing live lambs

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Abstract

Accurate measurement of livestock weight is a primary indicator in the meat industry to increase the economic gain. In lambs, the weight of a live animal is still usually estimated manually using traditional scales, resulting in a tedious process for the experienced assessor and stressful for the animal. In this paper, we propose a solution to this problem using computer vision techniques; thus, the proposed procedure estimates the weight of a lamb by analysing its zenithal image without interacting with the animal, which speeds up the process and reduces weighing costs. It is based on a data-driven decision support system that uses RGB-D machine vision techniques and regression models. Unlike existing methods, it does not require walk-over-weighing platforms or special and expensive infrastructures. The proposed method includes a decision support system that automatically rejects those images that are not appropriate to estimate the lamb weight. After determining the body contour of the lamb, we compute several features that feed different regression models. Best results were achieved with Extra Tree Regression (R^2=91.94%), outperforming the existing techniques. Using only an image, the proposed approach can identify with a minimum error the optimal weight of a lamb to be slaughtered, so as to maximise the economic profit.

Keywords: computer vision, regression models, weight estimation, precision livestock farming

1 Introduction

Precision livestock farming is based on the use of new technologies and recent advances in order to automatize certain tasks and make the most demanding ones easier [1]. So, farmers can be assisted in cattle counting, analyse the behaviour of the animals, detect illness or monitoring breeding. All these aspects have a crucial influence on the achieved benefit [2] as well as on animal welfare [3], [4].

An important issue in livestock farming is the monitoring of animal growth, as it is known to provide useful information not only to prevent diseases, but also to optimize breeding and feed consumption. For industries that are not as profitable as lamb feedlots, it is important to determine the exact time of slaughter, as this increases the economic benefit. If it is too late, the lamb has consumed more feed than it should, which increases feed costs. If it is too early, the lamb has not reached optimal weight, which reduces the gain and therefore affects the economic profit.

In the context of sheep weight measurement, a stereovision system was proposed in [5] that estimates the size and weight of sheep from a front view with two cameras, although the sample is formed by just 27 live sheep and the system requires cameras perfectly aligned so it is not easy to set up. In [6], muscle mass is predicted using multiple regression models fed with features calculated from ultrasound images of live goats and sheep (also of the Rasa Aragonesa breed) and including the weight as an input. The requirement of complex and costly devices makes these approaches less attractive for broad use.

In [7], a regression model that used 11 attributes of a total of 30 extracted features combined with eight supervised learning algorithms was proposed. However, only 32 images of sheep in a small stall separation of about 3 square meters were acquired and evaluated, and the segmentation was done manually, redyieldind a MAE of 3.099 kg. A convolutional network formed by an encoder and a decoder was used in [8] for sheep weight estimation considering a dataset of 52 images taken with a mobile along with age and gender information. The method obtained only a R^2 score of 80%. In [9] lambs' weight was estimated using depth images combined with different features such as lamb sex. This method used depth information to segment the images and also included manual screening supervision to discard certain images, reducing the dataset from 272 lambs to 64. They achieved a MAE of 1.37 kg and a mean relative absolute error of less than 6%.

In this paper, we propose an efficient data-driven decision support system that speeds up the weighing process of lambs without requiring a particular infrastructure and, therefore, is cost-effective and usable. Moreover, lambs keep moving freely without suffering damage or stress during the process. The proposed system uses RGB-D machine vision and different regression models to estimate the lamb weight. This data-driven decision support system uses computer vision to determine the lamb weight and, thus, to assist the farmers to decide the slaughter time. The system is based on the processing of top shot images of the lambs, being able to detect automatically if an image has the proper appearance to determine the body contour of the lamb and estimate its weight. The proposed system speeds up the weighing process compared to the traditional manual process, enabling the monitoring of more animals. Moreover, lifting the lamb on the scale is not further necessary, which facilitates the operator's task and reduces stress on the lambs, which negatively influences the quality of the meat [10]. In addition to this, the proposed system does not need dedicated devices as the ones proposed in [9], [11] where a special camera or a WoW platform are required, respectively. For all these reasons, the proposed system is efficient for determining the lamb weight, maximizing the benefits, making easier and faster the weighing process, and also increasing animal welfare.

This paper is organised as follows. Section 2 presents the proposed method. Section 3 describes de dataset and the experimental setup. Obtained results are presented in Section 4. Finally, Section 5 draws the main conclusions of the paper.

2 Description of the machine-vision system

The proposed method processes RGB-D zenithal images of lambs in order to obtain the body contour (named mask) and compute a set of features that are used to feed different types of regression models that would estimate the weight in order to decide if it is the right time for slaughtering. Depth channel is only used to scale one of the features. The whole process pipeline can be seen in Fig. 1 and is discussed in detail in the following subsections.

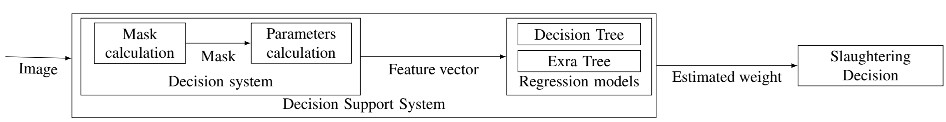

Figure 1: Scheme of the pipeline of the complete proposed data-driven decision support system

2.1 Body contour segmentation

The acquired color images are preprocessed in order to obtain a mask that outlines the body contour of a lamb. The complete data-driven decision support system is shown in Fig. 2. It should be noted that, unlike some existing approaches, this method is fully automatic.

First, the image I is normalised with 0 to 1 values. Then, a sharpen filter [12] is applied to refine the edges without increasing noise. The sharpened image I_S is converted to LAB color space to extract the luminosity (L) channel I_L. This I_L image is enhanced using Contrast Limited Adaptative Histogram Equalization (CLAHE) [13] (I_C). Next, an Otsu's threshold [14] is applied to obtain a binary image I_B. The obtained mask is cleaned

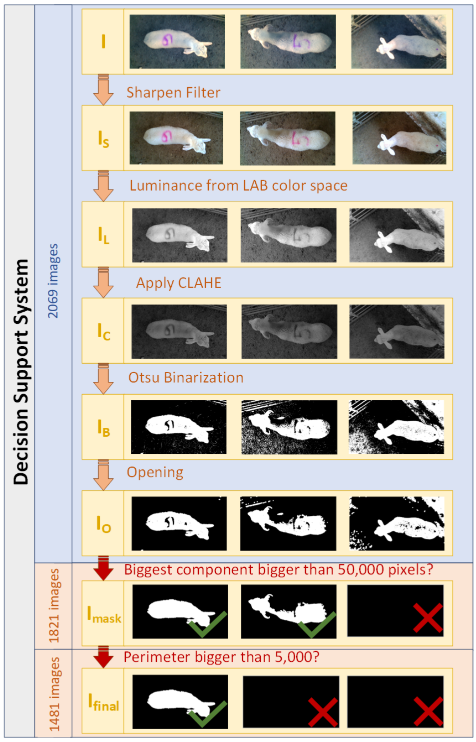

Figure 2: Data-driven decision support system to select the optimal mask.

with a opening operation with a disk-shaped kernel of 6-pixel size, which removes small groups of pixels of the background and fills the possible gaps existing within the body contour, preserving its original shape [15]. From I_O, we consider only the biggest region. Finally, the closed contours whose size is greater than 50,000 pixels and are not bounded by the edges of the image are automatically selected (I_{mask}). This process yields a binary image, which we call mask of the lamb, where white pixels correspond to the lamb and the background is black. If after these steps, the identified closed contour has less than 50,000 pixels, the image is discarded. Those values are determined empirically.

The final step of the proposed data-driven decision support system consists of filtering the data that feeds the regression models. Selected images must satisfy that the perimeter of the closed contour is smaller than 2,550 (I_{final}). If not, the images are automatically discarded, informing the operator if the acquired image is correct or not.

In order to decide the previously mentioned parameters such as kernel disk size or the minimum area of the connected component, a grid search of different configurations (see Fig. 3) has been carried out. Considering just 50 images of the training set, they were segmented manually and used to calculate the Intersection over Union (IoU) with the binary mask obtained with the machine-vision system. Results can be consulted in Fig. 3 which establishes that the best segmentation is obtained with a disk size with a diameter of 6 pixels and when the area of the closed contour has at least 50,000 pixels.

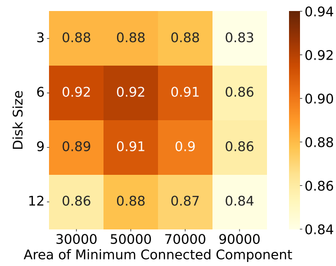

Figure 3: Grid search of configurable parameters of the machine-vision system: disk size and minimum area of the connected component, measured in IoU.

2.2 Feature extraction

Once the binary mask that corresponds to the lamb is determined, nine features are calculated, some from the bounding box, others from the connected component and the last ones from the ellipse that fits the body of the lamb. Fig. 4 shows an example of the mask obtained with the bounding box and the fitted ellipse are used to calculate the feature vector. For these regions, the following features are computed:

- Area: is the number of white pixels of the mask ($area\_cc$) scaled by α, which is the rate of the real bounding box area ($area\_depth$) in length unit measures read from the 3D information of the image, and the bounding box area in pixels ($area\_bb$). It is computed as in Eq. 1.
- Width and height of the bounding box.
- Mayor (MA) and minor (ma) axis of the ellipse.
- Eccentricity of the ellipse, which is the correlation between the focal half-distance d_f and the semi-major axis, as in Eq. 2.
- Perimeter of the white pixel region of the mask.
- Percentage of the number of white pixels of the mask ($area\_cc$) with respect to the bounding box area ($area\_bb$).
- Symmetry: it is measured along the mayor axis of the ellipse and is defined as the relation between the overlapping area ($area\_ol$) mirroring the axis and the number of white pixels of the mask ($area\_cc$), as in Eq. 3 [16].

$$Area = area\_cc * \frac{area\_depth}{area\_bb} \quad (1) \qquad Eccentricity = \frac{d_f}{\mathrm{MA}/2} = \frac{\sqrt{(\mathrm{MA}/2)^2 - (\mathrm{ma}/2)^2}}{\mathrm{MA}/2} \quad (2) \qquad Symmetry = \frac{2area\_ol}{area\_cc} \quad (3)$$

Finally, a feature vector is computed by concatenating the 9 previously described features.

2.3 Machine learning models

Several regression models were considered in the proposed system to predict the weight by considering the feature vector computed as it is explained in the previous section. The considered regression models are Decision Trees [17] , which organize decision rules hierarchically to optimize a given criterion, and Extra Trees Regressor, which averages the results of different decision trees improving the results and reducing over-fitting.

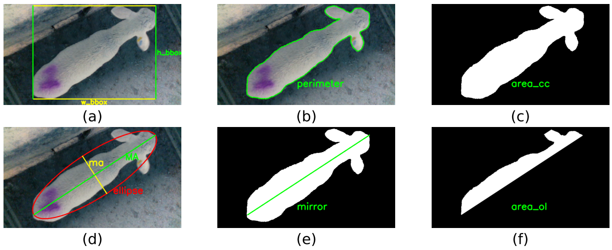

Figure 4: Example of how the feature vector is calculated from the bounding box (a), mask (c) and ellipse(d).

3 Experimental setup

A dataset of 2,069 images from a top shot view was used for experiments. The dataset is formed by top shot images of different lambs of farmers located at the northeast of Spain (breed -Rasa Aragonesa) whose live weight goes from 18 to 26 kg. Analysing the distribution of the weights and number of available samples for lamb, we have identified that the distribution is not normal. In order to keep a representative subset for training, we have selected the images as follows. We have considered a maximum of 30 images per lamb, so we have discarded the remaining images for those lambs with more than 30 images. Therefore, the final dataset has 618 images of 48 lambs. Table 1 shows the weights of the dataset used in our experiment, ranging from 14 up to 27.7 kg, and the distribution for each sex.

Table 1: Number of images and lambs splitted by range of weights (horizontal axis) and training set (vertical axis).

Range of weights			[14-16)	[16-18)	[18-20)	[20-22)	[22-24)	[24-26)	[26-28)	Total
Train	Female	Images	0	60	0	50	62	62	39	441
		Lambs	0	2	0	3	4	3	3	15
	Male	Images	30	3	30	9	17	34	46	169
		Lambs	1	1	1	2	1	3	5	14
Test	Female	Images	0	0	0	18	32	17	0	67
		Lambs	0	0	0	1	8	2	0	11
	Male	Images	0	60	0	0	0	16	0	76
		Lambs	0	2	0	0	0	4	0	6

Images were acquired using an Intel® Real Sense^{TM} Depth Camera D435 with a resolution of 848×480 and a distance from the camera to the lamb from 1.20 m to 1.45 m. Each shot includes an RGB image, a depth image and an identifier which helps us to assign the image to a specific lamb, including information about its sex and its weight (obtained with a weighing device). Fig. 5 shows some samples of the acquired RGB images in which different situations can occur: more than one lamb, different orientations, fences, etc. The dataset was also used in [9].

These images were processed to obtain the mask of the lambs, the bounding box and the fitted ellipse as it is explained in Section 2. Applying the data-driven decision support system, the images that yield an optimal mask are selected, whereas another images were automatically discarded. For the remaining images, a feature vector of 9 components is computed. Fig 6 displays the correlation matrix of the computed features for the final dataset calculated with the Pearson correlation coefficient, which represents no correla-

(a) (b) (c) (d)

Figure 5: Samples of the images employed in this method. The camera is located approximately vertically to the lamb in order to obtain its body and the environmental conditions are not fixed. Lambs roam free without using a particular infrastructure (a). The ideal situation is when they are alone (b), but sometimes they are close to other lambs (c) or fences (d).

tion when is near zero and correlation positive or negative depending on sign. As we can observe, the correlation between features is not too high, except between: MA and $width\_bbox$, $percent\_area$ and $height\_bbox$ and $eccentricity$ and ma, as none of then are repeated is not considered.

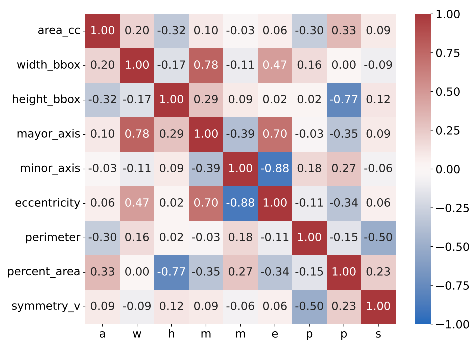

Figure 6: Correlation matrix of the features of the final dataset.

The regression models were trained through grid search on the training set. Therefore, the dataset was split into a training set, comprising 80% of the images, and a test set, with the remaining 20%. This test set serves as a hold out set to evaluate the quality of the final model.

The considered regression models were trained with Generalized Cross-Validation (CV), specifically with Stratified K-Folds cross-validator of 10 folds. By setting N as the number of samples, y as the real weight and $\hat{y}$ as the predicted weight, there are multiple regression metrics used to evaluate results:

- R Squared (R^2) , also known as coefficient of determination, measures the variability of a dependent variable. Values can go from 0 to 1, although can be interpreted as a percentage. (Eq. 4)
- Mean Absolute Error (MAE) is the mean of the absolute error between the predicted and real values. (Eq. 5)
- Mean Relative Absolute Error (MRAE) is the ratio of the mean error. (Eq. 6)
- Explained variance measures the discrepancy between model and real data. (Eq. 7)
- Maximum Error is the maximum difference between prediction and real. (Eq. 8)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

$$MRAE = \frac{1}{N}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \quad (6)$$

$$explained\_variance = 1 - \frac{Var\{y - \hat{y}\}}{Var\{y\}} \quad (7)$$

$$max\_error = max(|y_i - \hat{y}_i|) \quad (8)$$

4 Experimental results

The aforementioned classification algorithms are compared by tuning their parameters with grid search and 10-fold cross validation for the images of the training set. Regressors have been trained with different configurations in criterion selection to measure the quality of a split and maximum number of features to selected the best split. Table 2 gathers the obtained results. Note that the Extra Tree Regression achieved the highest R^2 score of 91.94% and an explained variance of 92.19% in the cross validation.

Table 2: 10-fold cross validation mean and standard deviation results on the training dataset

	Mean			Standard Deviation		
Regressor	R^2	Exp. Variance	Max. Error	R^2	Exp. Variance	Max. Error
Extra Trees	**91.94**	**92.19**	**-3.24**	14.37	12.97	2.15
Decision Tree	88.47	88.85	-4.82	37.22	36.91	3.50

The best performance model out of the 10 trained for the Extra Trees was selected by applying as a criterion the mean squared error (MSE), which minimises the L^2 loss using the median of each terminal node. This model displays a R^2 score on the test set equal to 0.9041, an explained variance of 0.9192, a maximum error of 4.08, a MAE of 0.75 and a MRAE of 0.04. That means the estimated weight $\pm$1.5 Kg in 85% of the cases, what satisfies the requirements according to the consulted experts. Table 3 displays the GINI impurity metric of the model which represents a higher importance of a feature with a higher value of the metric. In our case, area which is scaled with the depth channel represents almost half the importance of the model.

Few samples with different absolute errors and taken at different distances from the camera to the lamb are shown in Fig. 7. Some of the samples display errors in the mask due to the illumination and the background is similar to the animal's hair, but not by the purple stains made to distinguish lambs from each other. Nevertheless, some images are not properly captured showing a too lateral image, when it captures not only the body and head, but also the legs.

The acquired images also present different distances from the camera to the lamb, since they were not taken by the same person (two people of similar height have acquired images, and we have not taken into account this information for the experiment). Moreover, even if the same person took the images, the position of the camera can vary during

Table 3: Feature importance of the ExtraTree Regressor measured with the GINI impurity.

Feature	MA	ma	Eccentricity	Perimeter	Symmetry	Width bbox	Height bbox	Percentage area	Area
Importance	0.0448	0.0478	0.0478	0.0510	0.0544	0.0606	0.0958	0.1339	0.4639

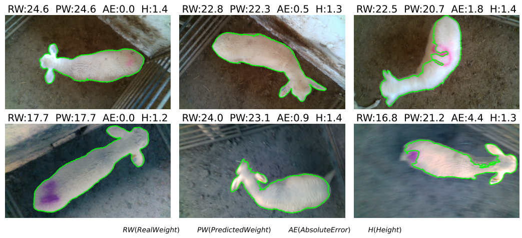

Figure 7: Test samples with the real (RW) and predicted weight (PW) and the absolute error (AE) with different AE less than 0.5 kilos (left column), between 0.5 and 1 kilo (middle) and bigger than 1 kilo(right column).

the acquisition due to the fast movements of the lamb through space. In addition, the lamb can freely move and its position may vary from being straight to being bent, additional factors such as the presence of a fence or variations in illumination conditions can also influence the data. Upon analyzing the obtained results we do not observe a correlation between the obtained error and the position of the lamb or the camera distance. In the latter case, since some of the features are scaled using depth information, the system is robust to changes in distance. Fig. 8 shows the distribution of the absolute error with the height of the captured image, revealing no correlation between them. [1].

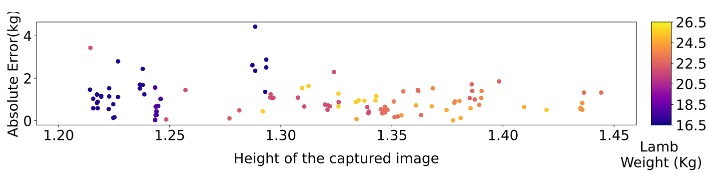

Figure 8: Distribution of the MAE and height distance from the camera to the lambs.

4.1 Discussion

Various approaches have been proposed to estimate the economic value of animals that may produce a high economic benefit, such as pigs. These approaches leverage phenotypic features and estimated breeding values (EBV) [18], as well as RGB-D images [19]for classification purposes. Neural networks [20], which require hardware that could not be used in a normal mobile phone, yielded a R^2 of 0.79 in pig weight estimation. With a more complex system than our proposal, which is formed by two calibrated Kinect cameras, pig weight estimation achieved a R^2 of 0.975 in [21]. Better results were obtained when the animal is quite stationary in a specific area with fences and limiting the entry to just one animal [22] but this approach limits the weighing time and provides more stress to the animal than our approach as well as it requires two cameras to obtain the binocular stereo images. Using another approach with ultrasounds, the R^2 goes from 0.52 to 0.64 [6]Other approaches considering different species as cows predict body weight with a R^2 of 0.80 [23]. In a controlled environment with a fixed background, [24] uses regression

[1] All the code and experimental results are available in https://github.com/uleroboticsgroup/morphology_lamb_weight_unizar

to predict the mass from the pig's volume with a standard error of 3.01 kg and an average absolute residual of 4.6% or 2.2 kg.

In [6], related to the Rasa Aragonesa breed, they obtained a percentage relative error (RE%) of 11.1 in the estimation of the muscle mass, although it is not comparable with this experiment as they take the weight as an input unit. Using WoW technologies and weight sensors (not images) in small ruminants as [11], a R^2 of 0.95 was achieved. Previous research [9] with the same dataset got the best results with a linear regressor but including a manual image selection. Results showed a MAE of 1.37 kg and a R^2 of 0.86 in the test set. Therefore, we have improved these results with the proposed method. Besides, we use the depth image only for scaling data, instead of for segmenting the lambs, which allow us to think in future experimentation with other acquisition devices like mobile phones. Depth information can be solved with a manual height established by operator. Also, transfer learning with Xception and the same dataset has been tested [25], achieving a MAE of 1.07 kilos and a R^2 of 0.8696 in the training set. As we can observe in Table 4,the proposed system that detects the body contour of the lamb, extracts a set of features as it is described in previous sections and classifies them with Extra Tree Regressor yields higher standard metrics than the state-of-the-art results, satisfying the livestock farm requirements in terms of accuracy and ease of procedure, according to the expert assessors consulted.

Table 4: Comparison of the state-of-the-art methods for lamb weigh estimation.

Method	R^2	MAE	MRAE	Acquisition system	Dedicated infrastructure	Completely automatic	#animals / #images
Menesatti et al. (2014) [5]		4.4		stereovision	No	Yes	27 / -
Dias et al. (2020) [6]			11.1	ultrasound	Yes	Yes	125 / -
Shah et al. (2020) [8]	0.8			RGB	No	Yes	52 / -
Sant'Ana et al. (2021) [7]	0.69	3.1		RGB	stall separation	No	32 / 32
Samperio et al. (2021) [9]	0.86	1.37		RGB-D	No	Yes	64 / 520
Riego et al. (2022) [25]	0.87	1.07		RGB-D	No	Yes	48 / 618
Our system	**0.90**	**0.75**	**0.04**				

5 Conclusions

This paper proposes a visual data-driven support system to enable farmers to estimate lamb weight automatically by using RGB-D images taken from the top view of the lambs. Masks obtained from morphological operations allowed to compute different characteristics from the bounding box and fitted ellipse, such as area, perimeter, eccentricity or symmetry, among others. Applying regression models, the Extra Tree provided the best result, with an R^2 of 91.94%, outperforming existing systems. Our method automatically discards unsuitable images without manual interaction. End users and field experts considered these results to be adequate for the needs of livestock farms in terms of accuracy as well as ease and speed of the system. Ultimately, an automatic system for lamb weigh estimation that reduces human-animal interaction at the farm, since it does not require to separate and place the animal in a specific area or the use of WoWs, could lead to higher welfare for the lambs.

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