Intramuscular Fat Percentage Estimation through Ultrasound Images

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Abstract. This work presents a framework to estimate intramuscular fat percentage on live cattle based on ultrasound images. A procedure to automatically determine the region of interest is proposed. Given the determined ROI, feature extraction and dimensionality reduction is performed based on statistics measures, texture, local binary pattern, among others. A model based in Support Vector Regression (SVR) is trained to estimate the intramuscular fat percentage. A database of ultrasound images acquired by an beef industry expert is used; for each animal there are available the intramuscular fat estimation obtained by an expert using a commercial software, and by chemical analysis. The proposed framework shows good results for a fully automatic procedure.

Keywords: ultrasound images, feature extraction, intramuscular fat estimation, beef quality, support vector regression.

1 Introduction

Beef quality is a complex measure, among others, consumers highlight tenderness as one of the most determinant factors [14,17]. It has been show that intramuscular fat percentage (%IMF) is highly correlated with tenderness [17,2,4]. Therefore an automatic system for its measurement is fundamental.

Intramuscular fat percentage is the proportion of intramuscular fat in the rib eye. This quality measure are usually performed in slaughtered animals. However, is clear the importance and the utility of measuring them with the animal alive, for selective feeding, breeding, rearing [10]. For that reason is becoming important to develop automatic measurements and analysis algorithms on ultrasound images in livestock.

Ultrasound has been used in predicting beef quality for decades, allowing to measure animals' characteristics in a non invasive way and reaching objective measures [5]. It is simple and allows real time evaluations, easy to use in a large group of animals with reasonable costs and offers an alternative for data collection in progeny testing programs.

There are several previous work in this kind of applications, such as [6] addressing the estimation of the %IMF in ultrasound images for livestock. In [3] the rib area was used as a determinant factor in the estimation of beef quality.

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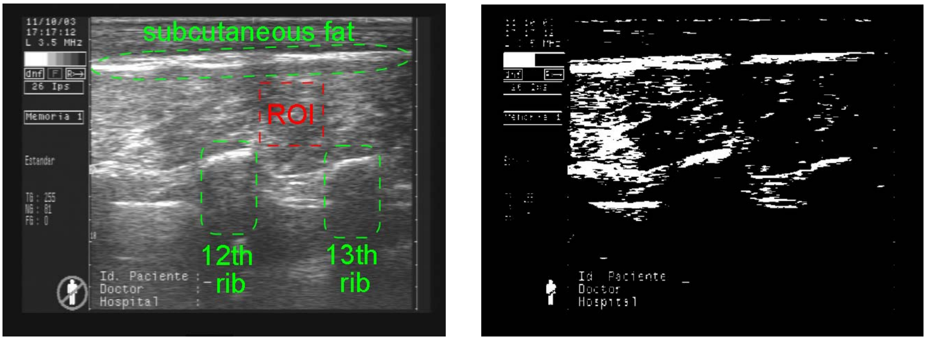


(a) (b)

Fig. 1. Image examples. Figure 1a shows an example image used as an input for the algorithm. Intramuscular fat appears on the top side, 12th and 13th rib are on the bottom and between them is the ROI. In Figure 1b can see the image in Figure 1a processed by the Otsu's method [15], the result is an binary image where the fat is contained in the white part.

The production method used in Latin America usually includes a high component of extensive farming (although feedlot is used too) impacting in the amount of %IMF, while in other regions the feedlot production is preferred [9,10,1].Therefore, the content of %IMF in animals analyzed in previous works such as [5,10,12,13] might be different from the animals analyzed in the present work and predictors should be adjusted to this case.

In this work we propose an automatic method for feature extraction from the ultrasound image, and adjust a model in order give an estimation of the %IMF. The remainder of the paper is organized as follows section 2 describes the framework, Section 3 presents the experiments and results, and Section 4 gives some conclusions and future work.

2 Framework

The proposed framework performs an automatic procedure for defining the region of interest (ROI) in the ultrasound image (see Figure 1a), and extract a set of features. Then Principal Components Analysis is performed with the extracted features in order to reduce its dimensionality. With this new space of features a Support Vector Regression (epsilon-SVR) was performed to obtain the intramuscular fat estimation. Details of this procedure are given next.

2.1 Defining the Region of Interest Detection

Our interest lies in measuring the %IMF in the *longissimus dorsi* muscle, therefore the ultrasound images are acquired around the 12th and 13th ribs and below the subcutaneous fat [9], only the muscle between the 12th and 13th rib under the subcutaneous fat is taken to determine the %IMF value.

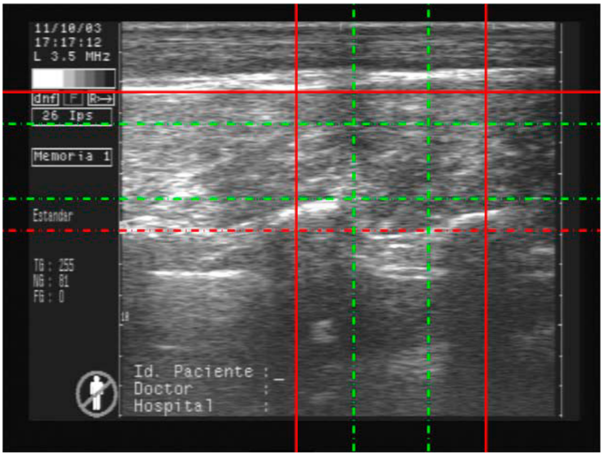


Fig. 2. An image example of the standard output from the automatic ROI detection procedure. Red lines represent subcutaneous fat and both ribs. The square in green is the ROI, an 80×80 pixels square set on the center of the delimited by the subcutaneous fat and the ribs.

In order to automatically determine the region of interest, middle points of both ribs (horizontally) and the upper point were detected, and the lower point of the subcutaneous fat as seen on the Figure 1a. For the subcutaneous fat location the Otsu method [15] was applied for thresholding the image (see Figure 1b). In the binary image we look for a region like the subcutaneous fat. A labeling algorithm was run on the image and then the labeled object with the highest ratio between the horizontal and vertical length was set as the subcutaneous fat. For locating the ribs, an algorithm based on anisotropic diffusion was applied in order to smooth the image without losing border information and restricting small variations of intensity in a same region [16].

Then, a correlation between the image and a synthetic template emulating a generic rib (see Figure 3b) was performed. The two local maxima in magnitude found in the correlation image represent the location of the ribs (see Figure 3a).

Finally, the ROI is defined as a 80×80 pixels square set on the center zone delimited by the subcutaneous fat and the ribs [12]. Figure 2 shows an example of the output from the ROI detection procedure.

2.2 Features Extraction and Selection

A set of forty two features were extracted from each ROI image. These features are based on several statistics and transformation on the ROI, for example, texture descriptors, local binary pattern, co-occurrence matrix, histograms, Fourier Transform, etc. [12,13,11,10].

Features:

Gradient	**Co-occurrence matrix**
- mean μ (45°,90°,135°,180°)	- correlation (45°,90°,135°,180°)
- std σ (45°,90°,135°,180°)	- homogeneity (45°,90°,135°,180°)
Gray Level	- contrast (45°,90°,135°,180°)
- mean	- energy (45°,90°,135°,180°)
- contrast ratio	
Histogram	**Local Binary Pattern (LBP)**
- percentile (each 20%)	- correlation
- skewness	- homogeneity
Fourier transform	- contrast
- variance coefficient	- energy
- power percentile ($\times$ 5)	

As a result of the feature acquisition stage we obtain a 42-dimension feature space. To reduce the space dimension in order to improve computational performance a feature extraction stage based on Principal Components Analysis was done, finding that 99% of the variance is accumulated in the first ten components. As a result of the PCA a new space of ten new features combinations was used to do the %IMF estimation model.

2.3 Estimation of the %IMF through Support Vector Regression

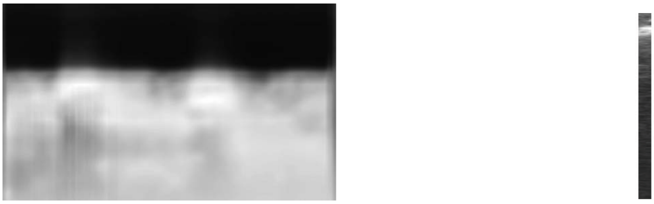
Support Vector Regression is a variant of the classic Support Vector Machine algorithm. The basic idea of SVR consist in make a mapping of the training data, $x \in \mathbb{X}$, to a larger space $\mathbb{F}$ via a nonlinear mapping $\Phi : \mathbb{X} \to \mathbb{F}$, where a linear regression can be performed. For more details on SVR see [7].

In this work, a radial basis function ($g(u,v) = e^{-\gamma|u-v|^2}$) was used as kernel type. Parameters γ and tolerance of termination criterion were optimized based on the data train set.

3 Experiments and Results

3.1 Database

We worked with a database of 283 ultrasound images (8-bits gray level) obtained from 71 live steers. Four images were taken per animal, and were analyzed independently [12]. Ultrasound images were collected at a cattle ranch in Uruguay. The ultrasound hardware used was the *Aquila Pro Vet*, an industry standard equipment. Based in the ultrasound images an estimation of the %IMF was performed by an expert from the beef industry using a commercial software. Also, the %IMF was measured by chemical analysis and used as *ground truth* to validate the regression results. The lipid extraction protocols used are described in [8]; its margin of error in the measurement is less than 0.3%.



(a) (b)

Fig. 3. (a) The result of the correlation with the image after the anisotropic diffusion and the template of a synthetic rib, in (b) shows the template who emulates a generic rib

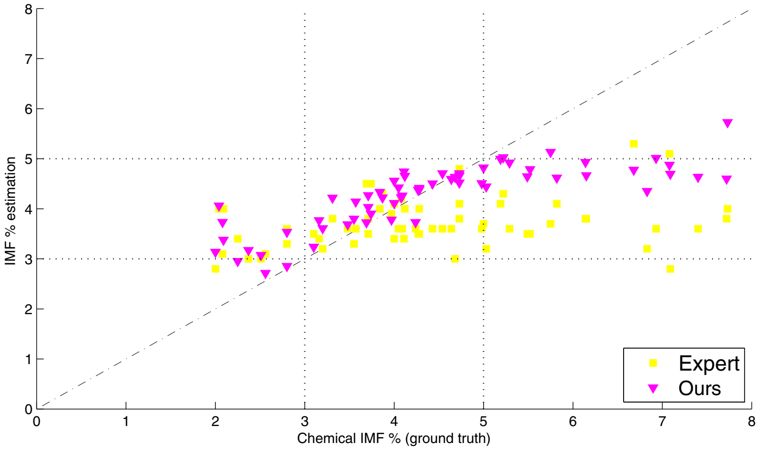


Fig. 4. Scatter plot between both, the %IMF estimation algorithm developed (in purple) and the estimation performed by the expert (in yellow), and the *ground truth* obtained by chemical analysis. The 71 animals are represented in the graphic.

3.2 Performance Analysis

The database was divided into two sets randomly drawn, one to train the algorithm and compute the linear regression coefficients (184 images, 2/3 of the dataset) and the other to test it (92 images, 1/3 of the dataset).

This procedure was repeated 100 times, varying the test and training set. The results were: $RMSE = 1.31$ and $R2 = 0.37$, where $RMSE$ is the root mean square error and $R2$ is the Pearson coefficient of correlation. Figure 4 shows the 71 animals in a scatter plot of the %IMF estimation vs. the *ground truth*. To contrast, the estimation of the %IMF made by the expert, which has an RMSE of 1.58 and a correlation coefficient of 0.23. Table 1 compares the result of the algorithm developed and the expert estimation.

Table 1. Quantitative evaluation of the %IMF estimation algorithm

	Ours	Expert
RMSE	1.31	1.58
R2	0.37	0.23

4 Conclusions and Future Work

A new procedure for estimating the intramuscular fat percentage was presented. First, the region of interest was automatically determined based in ultrasound images characteristics, from this region a set of features was extracted for fat estimation.

The performance of the automatic selection of the ROI was highly satisfactory, more than 96% of the database were well detected, in the reminder 4% where the ROI was wrong detected, the software gives an alert and allows for a manual definition.

The prediction of the intramuscular fat showed a better adjustment in the middle range of fat percentages (3%-5%). Meanwhile for the range of higher fat percentages the error is considerable, underestimating the intramuscular fat, however this error in our approach is lower than the error in the expert's estimation. The overall performance is promising, clearly a deeper analysis of the features considered is needed.

The average execution time is 15 seconds in a standard laptop, which is negligible in terms of industry requirements. Allowing fast estimation of the intramuscular fat percentage at industrial scale.

In future work we propose to study the impact of different parameters in the estimation, such as the ROI's area and location. We also want to explore new textures descriptors in the feature extraction and selection stage.

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