Research Article

Prediction of Pork Fatty Acid Content using Image Texture Features

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Abstract: The objective of this study was to investigate the usefulness of image texture features obtained from fresh (never frozen) pork backfat for the prediction of fatty acid content and Iodine Value (IV). Five image texture features (directionality, contrast, roughness, heterogeneity and line-likeness) were extracted from cross-sectional images of 9 pork loin chops with overlying subcutaneous fat. Texture features were extracted from images obtained on the subcutaneous fat using a digital camera. A full fatty acid profile was determined for each subcutaneous fat sample using AOAC and AOCS official methods. Linear and stepwise regression methods were utilized to establish the prediction models for oleic, linoleic and linolenic fatty acids and IV. Linear regression analyses produced higher coefficients of determination (R²) for all 3 fatty acids. Linear regression models for linoleic and linolenic acid generated an R² of 0.95. These preliminary findings suggest potential for use of image texture features for prediction of pork fatty acid values and subsequent pork fat quality.

Keywords: Fatty acid, image processing, iodine value, prediction, texture feature

INTRODUCTION

For customer expectations, pork processors put an emphasis on belly quality quantified via Iodine Value (IV), an indicator of overall fat firmness. The IV provides processors a numeric estimate of the level of unsaturation in the cut of interest by reacting iodine compounds to the samples’ C = C bonds (Hallenstvedt et al., 2012). Besides iodine titration, IV can be calculated from the samples fatty acid profile (Cd 1c-85 AOCS, 1998). Both methods to determine IV are time consuming and destructive; therefore, a consistent and non-destructive method that could be applied in an automated online situation would be desirable to quantify fatty acid profile (fat quality) in real-time.

Computer vision techniques have been previously investigated as an objective method to monitor lean and fat quality (Chen et al., 2010; Chmiel et al., 2011a, 2011b; Girolami et al., 2013). Furthermore, computer vision and image texture features have been used as method of evaluating lamb composition and quality (Chandraratne et al., 2006a, 2007, 2006b). Sun et al. (2012) predicted beef tenderness using color and image texture features and (Sun et al., 2014) recently published an image texture feature-based method to predict beef troponin-T post-mortem degradation product. These studies show the potential for image processing techniques to replace time consuming, expensive chemical methods of meat analyses.

The aim of this study was to investigate the analytical potential of computer image processing and texture analysis techniques to quantify fatty acids associated with soft pork (specifically oleic, linoleic, linolenic and IV). The specific objective was to develop a non-destructive, objective method to evaluate pork subcutaneous fatty acid parameters using image and texture features with two comparable regression models (linear and stepwise).

MATERIALS AND METHODS

Pork samples and fatty acid analysis: Fresh pork loins were obtained from 9 pork sides used in a separate research project that compared feeding obese swine a diet containing 16% corn oil (VEG) or 36% beef tallow (ANIM). The 3mo feeding strategy resulted in significant differences in fatty acid profiles of the subcutaneous fat. The Iodine Value (IV) and concentration of oleic, linoleic and linolenic acid expressed as percentage of total fat in a sample of subcutaneous fat collected adjacent the 10th thoracic vertebra were 85.8 (±5.1), 36.2 (±2.8), 26.9 (±3.6) and 2.4 (±0.4)% for VEG and were 60.2 (±3.5), 44.5 (±1.7), 9.8 (±1.2) and 0.6 (±0.2)% for ANIM, respectively. The iodine value in this study was calculated as:

After a 24h chill (2°C), each pork carcass was fully quartered at the 10th/11th rib interface and the blade and
Fig. 1: Segmentation of subcutaneous fat from a representative pork loin sample; (a): Original image; (b): Background segmentation; (c): Fat area

Iodine value = \[C16:1\times0.95+[C18:1]\times0.86+\]
\[[C18:2]\times1.732+[C18:3]\times2.616+\]
\[[C20:1]\times0.785+[C22:1]\times0.723\]  

Roughness relates to distances of notable spatial variations of grey levels, that is, implicitly, to the size of the primitive elements (texels) forming the texture. The proposed computational procedure accounts for differences between the average signals for the non-overlapping windows of different size. Roughness, \(F_{\text{rou}}\), can be computed as follows:

For image pixel area \(2^k\times2^k\), first calculate the average of the image grey value as:

\[
A_k(x,y) = \sum_{i=-2^{k-1}}^{2^{k-1}} \sum_{j=-2^{k-1}}^{2^{k-1}} (g(i,j)/2^k)
\]  

where, \(k = 0,1,...,5\); \(g(i,j)\) is the pixel value of \((i,j)\). For each pixel, calculate the average intensity, \(E\), of non-overlapping windows between the horizontal and vertical directions using:

\[
E_{h,k}(x,y) = |A_{k}(x+2^{k-1},y) - A_{k}(x-2^{k-1},y)|
\]  

\[
E_{v,k}(x,y) = |A_{k}(x,y+2^{k-1}) - A_{k}(x,y-2^{k-1})|
\]

where, each image pixel allows to set up a value \(E\), which reaches the maximum \(k\) to set the optimum size:

\[
S_{\text{best}}(x,y) = 2^k
\]  

with the maximum \(k\). In the end, the roughness equation can be calculated as:

\[
F_{\text{rou}} = \frac{1}{m\times n} \sum_{x=1}^{m} \sum_{y=1}^{n} S_{\text{best}}(x,y)
\]  

Contrast: Measures the manner grey levels “q” vary in the image “I” and to what extent their distribution is biased to black or white. The second-order and normalized fourth-order central moments of the grey level histogram (empirical probability distribution), that is, the variance, \(\sigma^2\) and kurtosis, \(\alpha_4\), are used to define the contrast where contrast, \(F_{\text{con}}\), can be computed as follows:

\[
F_{\text{con}} = \frac{\sigma}{(\alpha_4)^{0.25}}
\]
where,
\[\sigma^2 = (q-m)^2 Pr(q|l)\]
\[\alpha_4 = 1/\sigma^4 \sum_{q=0}^{\max}(q-m)Pr(q|l)\]

**Directionality** is measured using the frequency distribution of oriented local edges against their directional angles. The edge strength, \(e(x, y)\) and the directional angle, \(a(x, y)\) are computed using the Sobel edge detector approximating the pixel-wise x- and y-derivatives of the image:

\[e(x, y) = 0.5(\left|\Delta_x(x, y)\right| + \left|\Delta_y(x, y)\right|)\]  
\[a(x, y) = \tan^{-1}(\Delta_y(x, y)/\Delta_x(x, y))\]

where, \(\Delta_x(x, y)\) and \(\Delta_y(x, y)\) are the horizontal and vertical grey level differences between the neighboring pixels, respectively. The differences are measured using the following 3×3 moving window operators:

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1
\end{bmatrix}
\]

A histogram, \(H_{\text{dir}}(a)\), of quantized direction values, \(a\), is constructed by counting the number of the edge pixels with the corresponding directional angles and the edge strength greater than a predefined threshold. The histogram is relatively uniform for images without strong orientation and exhibits peaks for highly directional images. The degree of directionality relates to the sharpness of the peaks. Directionality, \(F_{\text{dir}}\), can be computed as follows:

\[F_{\text{dir}} = 1 - r m^{\text{peak}} \sum_{p=1}^{\text{max}} (a - a_p) H_{\text{dir}}(a)\]

The line-likeness feature, \(F_{\text{lin}}\), is defined as an average coincidence of the edge directions (more precisely, coded directional angles) that co-occur in the pairs of pixels separated by a distance, \(d\), along the edge direction in every pixel. Line-likeness, \(F_{\text{lin}}\), can be computed as follows:

\[F_{\text{lin}} = \sum_{i}^{N} \sum_{j}^{N} P_{\text{dir}}(i,j) \cos[(i-j)\frac{2\pi}{n}] / \sqrt{\sum_{i}^{N} \sum_{j}^{N} P_{\text{dir}}(i,j)}\]

**Heterogeneity:** Calculates the fraction of image pixels that is superior to the threshold value (10%) from the average intensity of the object. Image heterogeneity is defined by dividing the fat image feature into a window of size (n×m) and computing the window intensity mean on each window. Then, the texture of heterogeneous feature, \(F_{\text{het}}\), can be computed as follows:

\[F_{\text{het}} = \sum_{i}^{N} \sum_{j}^{N} P_{\text{dir}}(i,j) \cos[(i-j)\frac{2\pi}{n}] / \sqrt{\sum_{i}^{N} \sum_{j}^{N} P_{\text{dir}}(i,j)}\]

\[\sigma^2 = (q-m)^2 Pr(q|l)\]
\[\alpha_4 = 1/\sigma^4 \sum_{q=0}^{\max}(q-m)Pr(q|l)\]

\[F_{\text{het}} = \frac{\sum_{i}^{N} \sum_{j}^{N} I(i)/S}{\sum_{i}^{N} \sum_{j}^{N} I(i)/S}\]

where, \(|MI[w]-MI| > 10\%\); \(I(i)\) is the intensity of pixel; and \(S\) is the number of pixels.

**Fatty acid prediction using linear and stepwise regression methods:** Linear regression analysis was established to predict the quantity of oleic, linoleic and linolenic fatty acids as well as IV using the five texture features (contrast, roughness, heterogeneity, line-likeness, directionality) in the model.

Step wise linear discrimination and regression analysis were used to determine the most likely predictors from the five texture features. Unlike the linear regression analysis, the stepwise discrimination method was first performed to select the useful texture features from the five texture features using statistical software (SPSS 20.0) setting the significance level value at 0.05 for inclusion and at 0.15 for exclusion from the prediction model.

**RESULTS AND DISCUSSION**

The image texture features of contrast, roughness, heterogeneity, line-likeness and directionality were successfully extracted from images of the intact subcutaneous fat adjacent to the longissimus lumborum muscle at the 10th thoracic vertebra. The image texture features were utilized in linear and stepwise regression models to predict percentages of total fat for oleic, linoleic and linolenic fatty acids and IV (Table 1). Ripoche and Guillard (2001) used near infrared reflectance spectroscopy to determine the fatty acid composition and the results showed promising regards the R² value (above 0.90). But compared to the digital image acquisition method, the infrared method need 1 minute to acquire each sample, that will lead some potential time consuming issues to the future fatty acid detection requirement.

González-Martín et al. (2005) used near infrared spectrometer and regression methods to predict pork loin fatty acid attributes (C14:0, C16:0, C16:1, C17:0, C17:1, C18:0, C18:1, C18:2, C18:3, ε-polyunsaturated, Σ monounsaturated and Σ saturated). The results showed the highest correlation coefficients were 0.943 (ε-monounsaturated). De Marchi et al. (2012) predicted chicken meat fatty acid characteristics using near infrared spectroscopy at line in slaughterhouse which will fit the industry speed requirement. Results showed low significant correlation coefficients value (less than 0.60) to predict the fatty acid composition of chicken meat. In this research, for all predictions, linear regression models had a higher R² than stepwise regression models. For oleic acid, the linear regression model had an R² of 0.86 while the stepwise regression model had an R² of 0.65. For linoleic and linolenic, both linear regression models
resulted in an $R^2$ value of 0.95 while the stepwise regression $R^2$ values for linoleic and linolenic were 0.80 and 0.81, respectively. For IV, the linear regression model reached an $R^2$ of 0.95 while the stepwise regression only had an $R^2$ of 0.82. Due to the small sample size, no validation data was generated for the linear regression model.

Although the linear regression model produced effective results in this preliminary analysis, other analysis methods such as non-linear regression or artificial neural network should be investigated from a larger population of pork samples possessing more variability in fatty acid profile and subsequent fat quality.

**CONCLUSION**

This research shows the potential for the extraction of image texture features from pork loin images obtained in a processing plant environment as a means for quantifying fatty acids known to influence processing attributes of pork fat. From the satisfied results in this research, it showed imaging technology has significant ability of suitable the prerequisite of industry online application.

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