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DETERMINATION OF MEAT QUALITY THROUGH PRINCIPAL COMPONENTS ANALYSIS

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ABSTRACT

In the present investigation, Principal Component Analysis (PCA) was applied to various variables to describe meat quality. Sixteen meat quality variables were examined, and the analysis showed that 60.71% of the total variation was explained by the first three principal components. L^*, a^*, b^* as colour data; odour, tenderness, flavour, acceptability as sensorial traits; hardness and chewiness as physical traits had the highest share in the total variation.

Key words: Principal component analysis (PCA), meat quality.

INTRODUCTION

With the increase in meat consumption during the last few decades, consumer's demand for quality meat has also increased. Several factors like genotype, sex, rearing technique, diet, transport and slaughtering of the animals and post mortem technological treatments of the carcasses affect the quality of meat. Meat being a complex heterogeneous product, its qualitative characteristics needs different kinds of analyses (chemical, physical and sensory) to describe it completely. Characteristics directly related to the physical components of meat products can be measured through instrumental methods that can provide reliable information about meat quality. In addition to these physical components, factors involved in chewing like appearance, flavor, and texture can be described by human subjects. Sensory panels are essential because of providing complementary information to instrumental methods. At the same time, more specific texture attributes that are not measured instrumentally may be identified and quantified by panels. A relationship might exist between instrumental measurements and sensory panel evaluations because each type of analysis contributes specific and important information on overall meat quality, a meat sample might be described with different techniques, resulting in many diverse characteristics (Liu *et al*., 2004; Santos *et al*., 2008).

With large number of variables, it is much difficult to reach at a reasonable conclusion about the overall quality using classical analytical methods. It is therefore imperative to reduce the number of quality variables through some statistical technique and analysis (Destefanis *et al*., 2000; Liu *et al*., 2004).

Principal component analysis (PCA), one of the multivariate statistical methods, a useful tool to analyze the variations among physical, color, and sensory properties of meat, able to identify the most important directions of variability in a multivariate data matrix and presenting the results graphically.

Principal components analysis (PCA), originally introduced by Pearson (1901) and independently by Hotelling (1933), is a multivariate ordination technique used to display patterns in multivariate data. It aims to graphically display the relative positions of data points in fewer dimensions while retaining as much information as possible, and explore relationships between dependent variables. It is a hypothesis-generating technique that is intended to describe patterns in a data table, rather than test formal statistical hypotheses.

This technique has already been used to assess relationships between carcass characteristics and between meat characteristics (Hernandez *et al*., 2000; Liu *et al*., 2004). In the present study, Principal Component Analysis (PCA) was applied to the various chemical, physical and sensory variables in order to describe meat quality to evaluate results visually and on more a wide angle.

MATERIALS AND METHODS

Thirty Holstein Friesian young bulls fattened under the similar management system from commercial beef farm were used in the present study. Animals were slaughtered. After carcass dressing, muscle pH and temperature were recorded in the *m. longissimus dorsi* (between 12th and 13th rib) on the left side of each carcass at 15 min ($pH_{15\ min}$, $T_{15\ min}$) with an electronic pH meter (Hanna: model 8314 with FC 200 probe).

Twenty-four hours post-mortem, the LTL was removed from the left side of the carcass, and the muscles were sliced for colour measurements, water holding capacity, texture analysis and sensory panel evaluation according to Sañudo *et al*. (2000).

Colour was measured using a Minolta CM 508d spectrocolorimeter. The first colour readings were taken after cutting the surface of sample and this measurement was accepted as 0h (Abril *et al*., 2001). Then this portion was placed in a styrofoam tray wrapped with permeable film and bloomed at 4° C for 14 days post mortem. During measurement, L* (Lightness), a* (red colour coordinate) b* (yellow colour coordinate) for each sample were recorded to computer using D65 illumination, and (10°) Standard Observer (CIE, 1986). The water holding capacity (WHC) of meat was assessed by a filter paper press method (Sierra, 1973). The weight loss was expressed as a percentage of initial weight for WHC.

To obtain thawing loss, cooking loss, textural attributes and sensorial attributes, the rest of the samples were weighed and then vacuum-packed in commercial barrier bags. Aged at 2 ^{0}C in the ageing room of the abattoir for 24h, 4, 7 and 14 days post-mortem, all steaks were frozen at −18 C until evaluation (Chrystall *et al*., 1994).

Thawing loss was determined after steaks were thawed in water during 4 h at 15-17 °C. Cooking loss was determined in the meat samples, individually placed inside polyethylene bags in water bath at 75 °C for 30 minutes until an ultimate temperature of 70 °C was reached and then cooled for 4 h. They were then taken from the bags, dried with paper and weighed (Purchas, 1990). The weight loss was expressed as a percentage of initial weight for thawing and cooking loss. Before and after cooking, TPA was performed on the meat samples (1 cm^3). Meat samples (five repetitions) were deformed parallel to the direction of muscle fiber and the hardness, chewiness, gumminess and compressibility measured. The tests were conducted using an Instron device. Full-scale load was set at 50 kg and chart drive and crosshead speeds were 200 mm/min (Bourne, 1982).

For sensory evaluation, frozen steaks 1.5 cm thick were thawed in water for 4 h at 15–17 °C and heated in a double-sided contact grill (200 °C), covered with aluminium foil (after external fat was removed) to an internal temperature of 70 °C (Campo, 1999). A temperature probe was used to monitor endpoint temperature. Grilled samples were cut into eight pieces (2 cm^3) and were covered with a loose piece of aluminium foil coded numerically. Sensory evaluation was conducted in a sensory room following standard sensory practices (Stone and Sidel, 1993). A total of 80 beef-eating consumers, were used to evaluate steaks. For cooked steaks, the odour, flavour, tenderness and overall acceptability were evaluated. Judgements were recorded by marking on a 10-point scale.

Statistical Analysis: The basic idea of Principal component analysis (PCA) is to describe the variation of a set of multivariate data in terms of a set of uncorrelated variables, each of which is a particular linear combination of the original variables. The new variables, namely principal components the total number of which equals the number of the original variables in the studied data, are derived in decreasing order of importance so that, for example, the first principle component accounts for as much as possible of the variation in the original data. The second component is choosen to account for as much as possible in the remaining variation subject to being uncorrelated with the first component, and so on. The usual objective of this type of analysis is to see whether the first few components account for most of the variation in the original data. If so, they can be used to summarize the data with little loss of information. A reduction in dimensionality is thus achieved which might then be useful in visual interpretation of the data represented by two-dimensional graphics.

Algebrically, principal components are particular linear combinations of the *p* random variables. Geometrically, these linear combinations represent the selection of a new coordinate system obtained by rotating the original system with *p* variables as the coordinate axes. When each sample is characterized with variables $X_1, X_2, ..., X_p$, then principal component Y_i can be presented as

$$Y_i = a_{i1}X_1 + a_{i2}X_2 + a_{i3}X_3 + ... + a_{ip}X_p$$

where a_{ij} is an element of the eigenvector a_i corresponding the eigenvalue λ_i so that $a_i^{'}a_j = 1$, $i = j$ and $a_i^{'}a_j = 0$, $i \neq j$ when $i = 1,..., p$ and $j = 1,..., p$. The variance of Y_i is given by

$$Var(Y_i) = Var(a_i^{'}X) = a_i^{'}Sa_i.$$

Principal components are orthogonal and thus independent of each other (Everitt and Dunn, 2001).

To maximize a function of several variables subject to one or more constraints, the method of *Langrange multipliers* is used. In this case this leads to the solution that a_i is the eigenvector of *S* corresponding to the *j*. largest eigenvalue. If the eigenvalues of *S* are $\lambda_1, \lambda_2, ..., \lambda_p$, then since $a_i^{'}a_i = 1$, the variance of the *i*th principle component is given by λ_i. The total variance of the *p* principal components will equal the total variance of the original variables so that

$$\sum_{i=1}^{p} \lambda_i = trace(S).$$

Consequently, the *j*th principle component accounts for a proportion P_j of the total variation on the original data, where

$$P_j = \frac{\lambda_j}{trace(S)}.$$

The first p^* principle components, where $p^* < p$ account for P^* of the total variation in the original data, where

$$P^* = \frac{\sum_{i=1}^{p^*} \lambda_i}{trace(S)}.$$

The variation in the original *p* variables is only completely accounted for by all *p* PCs. The usefulness of these transformed variables, however, stems from their property of accounting for the variance in decreasing proportions.

The number of components we need to provide an adequate summary of a given data set is determined to explain some specified, large percentage of the total variation of the original variables. Values between 70% and 90% are usually suggested, although smaller values might be appropriate as *p* or *n* increases. Those PCs whose eigenvalues are less than the average $\sum_{i=1}^{p} \lambda_i / p$ are excluded. Since $\sum_{i=1}^{p} \lambda_i / p = trace(S)$, the average eigenvalue is also the average variance of the original variables. When the components are extracted from the correlation matrix, $trace(R) = p$, and the average is therefore 1; components with eigenvalues less than 1 are therefore excluded. Cattel (1965) suggests examination of the plot of the λ_i against *i*, the scree diagram. The number of components selected is the value of *i* corresponding to a sharp bend in the curve, this point being considered to be where large eigenvalues end and small eigenvalues begin. A modification described by Jollife (1986) is the log-eigenvalue diagram consisting of a plot of $\log(\lambda_i)$ against *i*.

After deciding which of the first principal components are adequate to explain the total variation in the original variables, a loading plot can be drown for visual evaluation of the data. A loading plot shows the correlations among variables based on the correlation matrix by plotting loading vectors of two principal components against each other.

All the computational work, including the graphical presentations, was performed using SPSS (2004) package program.

RESULTS AND DISCUSSION

Table 1 summarizes the means±standard deviations and coefficients of variation of the variables of meat quality. The coefficient of variation were lower than 20% for pH, temperature, L*, odour, elasticity, flavour, acceptability, while drip loss, cooking loss, hardness, chewiness, compress power were higher than 30%.

Table 1: Mean, standard deviation (s.d.) and coefficient of variation (CV%) of the meat quality measurements

	Mean	SD	CV(%)
pH	6.61	0.20	3.04
Temperature (Tmp)	39.99	1.77	4.42
Water-holding capacity (WHC)	16.37	3.53	21.56
Lightness (L*)	38.19	4.74	12.42
Redness (a*)	15.49	3.05	19.73
Yellowness (b*)	14.06	2.98	21.22
Odour (Od)	5.74	0.83	14.49
Tenderness (Tnd)	4.85	1.24	25.70
Flavour (Fl)	5.32	0.87	16.36
Acceptability (OA)	5.53	1.03	18.64
Drip loss (DL)	6.28	2.09	33.29
Cooking loss (CL)	16.47	5.55	33.73
Hardness (ML)	11.28	3.58	31.76
Chewiness (Cw)	12.09	3.78	31.30
Elasticity (El)	1.62	0.12	7.30
Compressibility (CP)	13.91	5.68	40.85

The correlation coefficients between meat quality variables are shown in Table 2. There existed several significant correlations among variables, chemical, physical or sensorial, determined on raw or cooked meat. Besides the positive and moderate correlation with L*, a* and b*, WHC correlated with 4 sensory traits negatively and moderately. None of the color attributes, L*, a*, b*, was correlated significantly with sensory characteristics or instrumental texture. Color of meat is probably not related directly to actual texture and flavor but plays an important part in visual appraisal of meat prior to ingestion. Positive correlations between the colour parameters were observed, As expected, five sensory characteristics had positive and significant correlations with each other which is in agreement with Destefanis *et al*. (2000) and Hernández *et al*. (2000) who reported high correlation coefficients among sensorial parameters. Instrumental analysis such as hardness, chewiness and elasticity had insignificant correlations with sensory characteristics. Compress power are negatively correlated with flavour and acceptability.

The results of the PC analysis are presented in Table 3 for meat quality traits. Five principal components (PCs) were extracted that accounted for 75.3% of the total variation. The first 3 of these PCs accounted for 60.7% of the variance in the 16 variables. In the other words, 60.7% of total variance for meat quality, in the 16 considered variables can be condensed into three new variables (PCs). These results are similar with the results reported by other analogous studies with other species.

Table 2: Correlation coefficients between the meat quality variables

	pH	Tmp	WHC	L*	a*	b*	Od	Tnd	Fl	OA	DL	CL	ML	Cw	El
Tmp	0.23														
C	-0.12	0.22													
L*	0.06	-0.04	0.47**												
a*	-0.11	-0.16	0.38*	0.67**											
b*	-0.04	-0.12	0.50**	0.91**	0.90**										
Od	0.05	-0.08	-0.37*	-0.07	-0.30	-0.23									
Tnd	-0.04	-0.08	-0.48**	-0.04	-0.22	-0.18	0.75**								
Fl	0.02	-0.22	-0.42*	-0.01	-0.19	-0.13	0.69**	0.72**							
OA	-0.05	-0.24	-0.45*	-0.05	-0.16	-0.13	0.73**	0.79**	0.93**						
DL	0.02	-0.03	0.46*	0.59**	0.29	0.48**	-0.05	-0.03	-0.02	-0.04					
CL	-0.12	-0.27	0.08	-0.02	0.14	0.07	0.20	0.01	0.04	0.07	-0.13				
ML	-0.11	-0.48**	0.28	0.20	0.28	0.27	-0.19	-0.13	-0.12	-0.08	-0.02	0.18			
Cw	-0.17	-0.53**	0.20	0.26	0.36*	0.34	-0.09	-0.08	-0.05	0.02	0.07	0.18	0.89**		
El	0.17	0.15	-0.10	0.14	-0.15	-0.01	0.00	0.04	0.05	0.01	-0.17	-0.11	0.08	-0.12	
CP	-0.15	0.25	0.27	0.10	0.41*	0.27	-0.18	-0.23	-0.44*	-0.37*	0.12	-0.01	0.24	0.29	-0.09

* ($P<0.05$), ** ($P<0.01$)

Table 3: Results from the principal component analysis for the first five principal components

Component	Eigenvalues	Portion of variance (%)	Cumulative variance (%)
1	4.59	28.66	28.66
2	3.04	18.99	47.65
3	2.09	13.06	60.71
4	1.29	8.06	68.76
5	1.05	6.58	75.34

In beef, Destefanis *et al*. (2000) reported that 62.5% of total variation is explained by the first three components with meat quality measurements using 18 variables, including pH, meat colour, WHC, cooking loss, instrumental and sensory parameters. Laville *et al*. (1996) found the first ten PCs analyzing 76 morphometric variables from young Charolais bull carcass explained 80% of the total variability of those measurements. Cañeque *et al*., (2004) in lambs, and Santos *et al*., (2008) in goat kids analysed carcass and meat quality measurements as separate sets of variables and reported similar results. Hernández *et al*. (2000), analysed meat quality in rabbits, using 23 variables and found that the firs four PCs for meat quality explained 62% of the total variation.

Table 4: Coefficients in the eigen vectors (loadings) for the five first principal components (PC)

	PC1	%	PC2	%	PC3	%	PC4	%	PC5	%
pH	-0.09	1.21	-0.18	2.88	0.32	6.36	0.53	16.41	-0.12	4.24
Temperature	0.003	0.04	-0.58	9.27	0.54	10.74	-0.02	0.62	0.45	15.90
WHC	0.74	9.93	-0.09	1.44	0.18	3.58	-0.14	4.33	-0.03	1.06
L*	0.58	7.78	0.52	8.31	0.54	10.74	0.19	5.88	-0.06	2.12
a*	0.71	9.53	0.43	6.87	0.17	3.38	-0.09	2.79	0.06	2.12
b*	0.72	9.66	0.51	8.15	0.37	7.36	0.04	1.24	-0.02	0.71
Odour	-0.67	8.99	0.47	7.51	0.16	3.18	-0.13	4.02	0.26	9.19
Tenderness	-0.68	9.12	0.51	8.15	0.19	3.78	-0.05	1.55	0.27	9.54
Flavour	-0.68	9.12	0.59	9.42	0.19	3.78	0.04	1.24	-0.03	1.06
Acceptability	-0.69	9.26	0.64	10.22	0.12	2.39	-0.03	0.93	0.06	2.12
Drip loss	0.39	5.23	0.29	4.63	0.54	10.74	-0.19	5.88	-0.19	6.71
Cooking loss	0.02	0.27	0.29	4.63	-0.33	6.56	-0.26	8.05	-0.07	2.47
Hardness	0.44	5.90	0.44	7.03	-0.59	11.73	0.35	10.84	0.12	4.24
Chewiness	0.43	5.77	0.57	9.11	-0.56	11.13	0.18	5.57	0.13	4.59
Elasticity	-0.09	1.21	-0.08	1.28	0.14	2.78	0.79	24.46	0.21	7.42
Compr-80	0.52	6.98	-0.07	1.12	-0.09	1.79	-0.20	6.19	0.75	26.50

Table 4 shows that all variables of meat quality had similar proportion in the first PC except for pH, temperature, cooking loss, elasticity. After WHC, the most important variables for the first PC were meat colour parameters (L*, a* and b*) and sensory characteristics (odour, tenderness, flavor, acceptability). So, first PC is defined by the eating quality and colour parameters.

Fig. 1 shows the loading plot of the measurements of meat quality on the first two PCs. The measurements and PCs are interpreted according to the correlations between each parameters and each PC, thus measurements close to each other are positively correlated, measurements separated 180° are negatively correlated, whereas if they are separated by 90° they are independent.

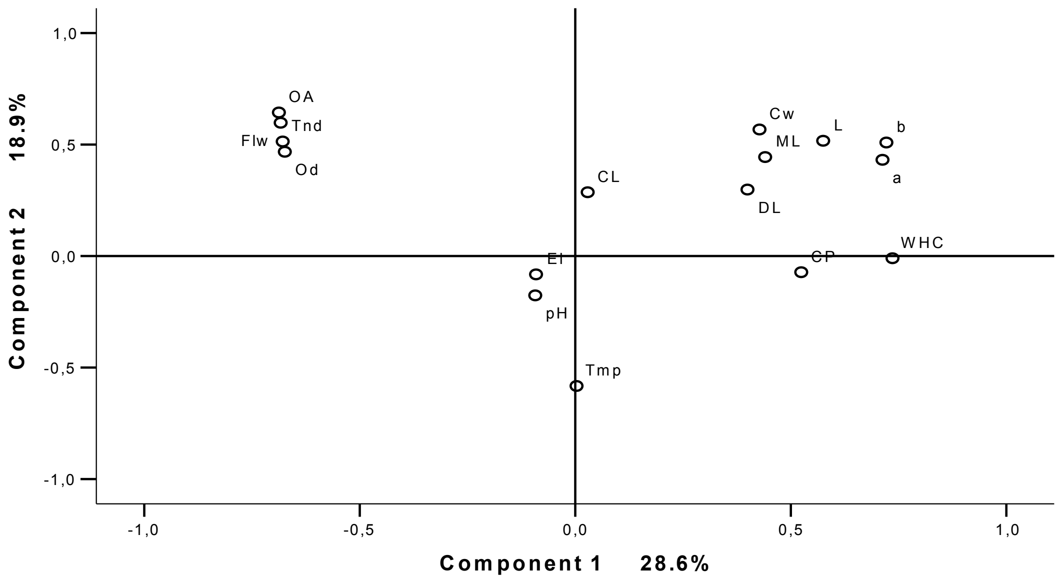

Fig. 1. Plot of the first two PC loading vectors. The labels correspond to sample notation given in the Table 1.

The loading plot displays that these measurements are placed far from the origin of the first PC and near each other indicating the high correlation among them (Fig. 1). The second PC is characterized by colour characteristics, eating quality, and two physical parameters (chewiness and temperature). They are placed in the loading plot far from the origin of the second PC. The third PC is defined by one colour characteristics (L*), two eating quality (dripp loss and cooking loss), and four physical parameters (pH, temperature, hardness and chewiness). Ultimatelly, the forth PC is characterized by three physical characteristics (pH, hardness and elasticity), which elasticity had little importance in the previous PCs.

The PCA has shown how meat quality characteristics are grouped in independent sets. The observed variation in the meat quality traits are explained by of the meat quality variables though the meat colour and sensory characteristics explain most variability. In other words, the meat colour and sensory characteristics explain a large part of the observed variation. In both PC1 and PC2, meat colour and sensory characteristics had the highest loadings, which show the value of these parameters as a predictor of meat quality.

It may be concluded that, by using PCA, although we can not obtain any analytical results to estimate any effects and explain differences between treatments the way other statistical methods do, we can better understand underlying relationships between a lot of variables affecting meat quality by reducing data and visualization.

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