PORK MEAT QUALITY EVALUATION FROM HYPERSPECTRAL OBSERVATIONS

By

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ABSTRACT

Little research has been reported on the use of visible and near infrared spectroscopy for the prediction of meat quality classes. Therefore, in this study hyperspectral reflectance measurements ranging from 350 to 2500 nm were made with the help of a spectroradiometer on fresh pork loin samples belonging to four different quality classes (Red, firm, non-exudative: RFN; Pale, firm, non-exudative: PFN; Red, soft, exudative: RSE and; Pale, soft and exudative: PSE). The samples were collected from a local cutting house in Quebec, and they were classified by a meat specialist. Data collected from the samples was analyzed using a stepwise approach to identify wavebands useful in differentiating pork quality classes. Discriminant Analysis was used to evaluate the usefulness of the selected wavebands and to classify meat samples into four quality classes. An overall classification accuracy of 76% was obtained for the prediction of pork meat quality classes for unseen data. These results confirmed the possibility of the prediction of meat quality classes rather than the prediction of quality attributes, as is commonly reported in literature.

Various classification methods have been used to utilize hyperspectral data for meat quality evaluation. Selection of the best method is crucial in extracting the valuable information contained in hyperspectral observations. Therefore, the performance of four classification methods, Artificial Neural Networks, Decision Trees, k-Nearest Neighbor, and Discriminant Analysis, was compared in classifying pork meat quality using hyperspectral data. Models were developed to sort meat into four quality classes (PFN, RFN, RSE, and PSE), into two classes (pale and red), and finally further into two classes (soft and exudative, and firm and non-exudative) within the pale and red meat samples. Overall, the Discriminant Analysis achieved the highest classification accuracy for sorting meat into four quality classes, its performance was followed by ANNs, k-NN and DTs.

In order to explore the industrial applicability of the technique, hyperspectral observations were acquired at five different locations along the same meat samples. The data collected at each location was analyzed separately. Stepwise regression and

Discriminant Analysis were used for the selection of important wavebands and for the classification of samples into quality classes, respectively. Classification accuracies as high as 99% were obtained. The results suggest the possibility of developing on-line sensors for automated pork meat quality assessment.

RESUMÉ

L'utilisation de la spectroscopie visible et infrarouge pour la qualification et la classification de la viande a fait l'objet de peu de recherche jusqu'à présent. Dans cette étude, avec l'aide d'un spectroradiomètre, des mesures de facteurs de réflexion hyperspectrale entre 350 et 2500 nm ont été faites sur des filets de porc frais appartenant à quatre différentes catégories (RFN: rouge, ferme, non-exsudatif; PFN: pâle, ferme, non-exsudatif; RSE: rouge, tendre, exsudatif; et PSE: pâle, tendre, exsudatif.) Les échantillons à analyser, fournit par un abattoir du Québec ont d'abord été classés par un spécialiste en viande. Les données recueillies sur les échantillons furent analysées afin de déterminer les longueurs d'onde significatives pour différencier les quatre catégories de viande porcine. L'analyse discriminante a servi afin d'évaluer l'efficacité des longueurs d'onde sélectionnées et de classer la viande dans les quatre catégories. Au total, les prédictions du modèle utilisé pour la classification d'échantillons inédits se sont avérées juste dans 76% des cas. Cette thèse se distingue par des résultats qui confirment non seulement la possibilité de qualifier une viande mais également de prédire la catégorie à laquelle elle appartient.

En ce qui à trait à l'analyse de données hyperspectrales, plusieurs méthodes sont utilisées, d'où la nécessité de choisir la méthode la plus appropriée afin d'extraire l'information essentielle dans les données recueillies. Les méthodes suivantes: réseau de neurones, arbre de décision, k plus proches voisins et analyse discriminante ont été évaluées selon leur performance à classer la viande de porc en utilisant les données hyperspectrales fournies. Les modèles furent développés afin de classer la viande dans l'une des quatre catégories (PFN, RFN, RSE, et PSE) puis en deux sous-catégories (pâle/rouge) et ensuite en deux groupes (tendre et exsudatif/ferme et non-exsudatif.) L'analyse discriminante fût la plus performante en terme d'exactitude de classification des échantillons, suivie par l'ANN, k-NN et DT.

Afin d'analyser la capacité d'appliquer cette technique de façon industrielle, les mesures hyperspectrales furent prises à cinq différents endroits sur le même échantillon. Chaque mesure fût analysée individuellement. Méthodiquement, la régression et l'analyse discriminante furent utilisées pour la sélection des longueurs d'onde

significatives pour le classement des échantillons. L'exactitude de la classification de certains échantillons atteint 99%. Les résultats obtenus suggèrent la possibilité de developper des capteurs en ligne afin d'automatiser le contrôle de la qualité de la viande de porc.

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CONTRIBUTION OF AUTHORS

This thesis was written according to the rules and regulations of the Faculty of Graduate Studies and Research of McGill University Guidelines for a Manuscript Based Thesis, where-in it is stated the following:

"As an alternative to the traditional thesis format, the dissertation can consist of a collection of papers of which the student is an author or co-author. These papers must have a cohesive, unitary character making them a report of a single program of research. The structure for the manuscript-based thesis must conform to the following:

1. Candidates have the option of including, as part of the thesis, the text of one or more papers submitted, or to be submitted, for publication, or the clearly-duplicated text (not the reprints) of one or more published papers. These texts must conform to the "Guidelines for Thesis Preparation" with respect to font size, line spacing and margin sizes and must be bound together as an integral part of the thesis. (Reprints of published papers can be included in the appendices at the end of the thesis.)

2. The thesis must be more than a collection of manuscripts. All components must be integrated into a cohesive unit with a logical progression from one chapter to the next. In order to ensure that the thesis has continuity, connecting texts that provide logical bridges between the different papers are mandatory.

3. The thesis must conform to all other requirements of the "Guidelines for Thesis Preparation" in addition to the manuscripts. The thesis must include the following:

(a) a table of contents;

(b) an abstract in English and French;

(c) an introduction which clearly states the rational and objectives of the research;

(d) a comprehensive review of the literature (in addition to that covered in the introduction to each paper);

(e) a final conclusion and summary;

4. As manuscripts for publication are frequently very concise documents, where appropriate, additional material must be provided (e.g., in appendices) in sufficient *detail to allow a clear and precise judgment to be made of the importance and originality of the research reported in the thesis."*

Manuscripts based on the thesis:

1. Monroy, P. M., Prasher, S. O., Ngadi, M. O. and Karimi, Y. 2007. Pork Meat Quality Classification from Hyperspectral Observations. Trans. ASAE. (Submitted for publication)
2. Monroy, P. M., Prasher, S. O., Ngadi, M. O. and Patel, R. 2007. A Comparison of Different Methods of Classifying Pork Meat Quality Evaluation, Using Hyperspectral Observations. Canadian Biosystems Engineering (Manuscript based on this chapter is under preparation).
3. Monroy, P. M., Prasher, S. O., Ngadi, M. O. and Patel, R. 2007. Importance of the place of measurement in pork meat quality classification from hyperspectral data. *Trans. ASAE*. (Manuscript based on this chapter is under preparation).

All the sample collection, experimental works, data analyses, and the preparation of the manuscripts were completed by the candidate, under the supervision of Dr. Shiv O. Prasher and Dr. Michael Ngadi. Yousef Karimi and Ramanbhai Patel provided additional help and guidance in this study.

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LIST OF SYMBOLS

The most commonly used abbreviations, symbols and acronyms are listed below.

ANNs	Artificial Neural Networks
CDA	Canonical Discriminant Analysis
DA	Discriminant Analysis
DFD	Dark, Firm and Dry
DTs	Decision Trees
FN	Firm and Non-exudative
IMF	Intramuscular fat
k	Number of nearest neighbors
k-NN	k-Nearest Neighbor
LDA	Linear Discriminant Analysis
MLR	Multiple Linear
MPLS	Modified Partial Least-Squares
NIR	Near infrared
NIRS	Near infrared spectroscopy
NPB	National Pork Board
PCA	Principal Component Analysis
PCR	Principal Component Regression
PFN	Pale, Firm, and Non-exudative
PLS	Partial Least Squares
PSE	Pale, Soft, and Exudative
PSS	Porcine Stress Syndrome
RFN	Red, Firm, and Non-exudative
RSE	Red, Soft, and Exudative
SE	Soft and Exudative
SSV	Separatability of Split Value
SVM	Support Vector Machines

VIS	Visible
VI/NIRS	Visible near infrared spectroscopy
WHC	Water-holding capacity

CHAPTER 1

INTRODUCTION

The meat industry needs to obtain reliable and accurate information about meat quality during the production process in order to reduce economic losses and provide guaranteed quality of fresh pork and pork products to the consumers. Moreover, the pork meat industry is going through diverse challenges, including emerging new quality classes and market segmentation. As a result, there is a critical need for new methods of meat quality evaluation (Monin, 1998). Traditionally, pork meat quality is defined by various combination of three main quality parameters; color, texture and drip-loss. Good quality of pork is typically red, firm and non-exudative (RFN). Other quality grades are described as RSE (red, soft and exudative), PSE (pale, soft and exudative), DFD (dark, firm and dry) and PFN (pale, firm, and non-exudative).

In practice, pork meat quality can be assessed by a specialized grader, or by using quality charts and standards. These methods are time consuming and subject to human errors. Objective evaluation of pork meat can be done by determining certain physical and chemical quality attributes with the help of laboratory methods. However, laboratory-based methods tend to be time-consuming, expensive, and sample destructive. They are also unsuitable for on-line application and are usually unable to characterize all types of pork meat. Thus, development of rapid, accurate and non-destructive techniques, suitable for on-line application is desired.

Near infrared spectroscopy (NIRS) has taken its place among the proven spectroscopic tools, especially for determining physical and chemical properties of foods and food products. As stated by Monin (1998), NIRS is one of the most promising techniques for large-scale meat quality evaluation, and its potential in a great range of applications has been broadly studied. Visible/near infrared spectroscopy (VIS/NIRS) allows obtaining a great amount of valuable information, which is most likely advantageous in the characterization of foods. In fact, Shackelford et al. (2004) noted that techniques should be developed to simultaneously evaluate visible and near infrared spectroscopy of meat. VIS/NIRS has been demonstrated to be an advantageous tool over traditional laboratory methods. It is a multi-analytical, objective, rapid, affordable technique, which is not sample-destructive, and its potential to characterize meats has been proven (Savenije et al., 2006; Liu et al., 2003; Liu et al., 2000).

The use of Visible (VIS) and near infrared (NIR) spectroscopy for the assessment of pork meat quality has been studied (Xing et al., 2007; Savenije et al., 2006; Shackelford et al., 2004). NIRS and VIS/NIRS techniques have been used to develop models for the prediction of pork quality traits such as drip loss, shear force, color, pH, intramuscular fat (IMF), subjective color, cook yield and XYZ tristimulus values (Lanza, 1983; Forrest et al., 2000; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Savenije et al., 2006; Xing et al., 2007). However, no exact correlation has been found between these attributes as to allow classifying pork meat into different quality classes. Xing et al. (2007) investigated the potential of using visible spectroscopy to classify different quality classes of pork meat. Their results suggested that visible spectral information is not sufficient to separate all quality classes. Thus, exploration of both VIS and NIR spectra seems more likely to yield higher classification accuracies.

Hyperspectral observations contain a great deal of physical and chemical information about the sample being analyzed. If this valuable, useful and abundant information is properly analyzed, it can be used to characterize the sample itself. However, meat being such a variable product with respect to muscle fiber arrangement, pH and connective tissue content, it is extremely difficult to standardize a way of interpreting the reflectance spectra (Swatland, 1989). Chemometric multivariate analyses have been commonly used for the qualitative and quantitative assays based on NIR spectra. Other Statistical methods such as Principal Component Analysis (PCA), Discriminant Analysis (DA), Partial Least Squares (PLS), Multiple Linear Regression Analyses, etc, allow understanding of the optical properties and allow classifying without making use of the chemical information (Ozaki et al., 2007). Advanced signal processing and pattern recognition techniques with high generalization capabilities have also been tested for this purpose, not only for meat products but also for other kinds of foods (O’Farrell et al., 2005).

Current literature reports a few studies in which the potential of spectral observations for the prediction of quality classes has been assessed (Xing et al., 2007). Moreover, since the development of a rapid VIS/NIRS technique for meat quality evaluation is intended to supply the pork industry with a means for meat classification in an on-line process, the method needs to be tested by simulating similar measurement conditions. To the best of our knowledge, present literature lacks information on the study of the impact of the location of measurements on meat for quality classification purposes. In addition, there is not enough work done on the comparison of the performance of different classification techniques that can be used to analyze VIS/NIRS data in such application (Curram and Mingers, 1994; Wang and Paliwal, 2006; Karimi et al., 2005).

1.1 Objectives

The main goal of this study was to develop a VIS/NIRS model for the evaluation of pork meat quality classes. The study also aimed to test the performance of different classification methods for the analysis of hyperspectral observations. More specifically, the objectives of this study were:

1. To select important wavebands for pork meat quality classification using a stepwise approach and then use discriminant analysis to classify pork meat quality on the basis of hyperspectral data,
2. To qualitatively assess hyperspectral data by using Canonical Discriminant Analysis,
3. To evaluate the classification accuracy of Discriminant analysis, k-Nearest Neighbor, Artificial Neural Networks, and Decision Tree methods,
4. To evaluate the importance of the location of measurement on the classification accuracy of pork meat quality from hyperspectral data.

To meet these objectives, hyperspectral observations from pork samples, belonging to different quality classes, were analyzed. Samples were collected at a local cutting house and the experiments were conducted at Macdonald Campus of McGill University. Spectral data was analyzed using different classification techniques. Once the best classification method was determined, hyperspectral observations were acquired at different sites along the samples, and the spectral data was analyzed.

1.2 Thesis Organization

This thesis consists of six chapters and three appendices. The first chapter provides an introduction to the subject, lists the objectives, and introduces the scope of the present investigation. Chapter 2 describes the general and basic concepts related to the subject, and presents a review of relevant and related literature. Chapter 3 provides information on the first experiment held in this study which focused on evaluating the potential use of hyperspectral observations for the prediction of pork quality classes. A spectroradiometer was used to acquire spectral observations from pork loin samples belonging to different quality classes. The focus of the chapter is the selection of important wavelength regions for the prediction of quality class using discriminant analysis. A paper based on this chapter has been sent for publication in the *Transactions of the ASAE*.

Chapter 4 focuses on the selection of the best classification method for the sorting of meat into quality classes. This chapter describes the performance of four classification methods [DA, Decision Trees (DTs), k-Nearest neighbor (k-NN), and Artificial Neural Networks (ANNs)]. A manuscript based on this chapter is under preparation.

Chapter 5 presents the results from the evaluation of the industrial applicability of the method proposed for meat quality class predictions. Reflectance measurements were taken at different sites along each sample and the spectral data from each location site was analyzed separately using discriminant analysis. A manuscript based on this chapter is under preparation.

Finally Chapter 6 presents a summary of this study and provides the general conclusions drawn from this work. Classification matrices from DA and ANNs models are provided in Appendices A and B.

1.3 Scope

Even though high classification accuracies were obtained from the calibration and predictive models described in this thesis, it is important to note that raw meat is a highly variable and heterogeneous material. For instance, the color of the meat samples can vary from place to place on the same sample, and even when the area measured is only 12.25 cm^2, it might not be a true representative of the class. An ideal sample under investigation should be identical in all its properties and as for meat samples, obtaining identical properties along the sample is not possible. As an alternative, the experimental setup could be modified in order to increase the scanned area.

The meat samples used in this study were classified by a meat specialist. The meat classification given was taken as true evaluation, and likelihood, the results obtained from the data analysis grasp the human error from a subjective evaluation. The use of well defined quality classes would allow increasing the classification accuracy due to a higher variation between the classes and elimination of possible outliers.

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CHAPTER 2
LITERATURE REVIEW

In this chapter the relevant literature on pork quality classification and the application of VIS and VIS/NIRS for pork quality assessment is reviewed. First the basics of pork meat quality, its causes and its impact in pork industry are introduced. The discussion continues with a general introduction on the subjective and objective methods for the evaluation of meat quality. Next, a brief introduction to the principles of VIS/NIRS is given, followed by an exploration on the related research on this technique and its use for pork meat quality prediction. Finally, various approaches used to analyze spectral information from meat samples are discussed.

2.1 Pork meat

Meat, in its broadest definition, is animal tissue used as food. It is composed of tissue or muscle fiber cells, fat and connective tissue; it can also be composed of pieces of bone (Miller, 2002). Since many factors affect the quality of the meat, for instance; age, breed sex, nutritional status, animal stress during transport, carcass refrigeration rate, postmortem age, pre-slaughter handling, etc. it is a highly unpredictable product.

Pork meat is classified as a "red" meat because it contains more myoglobin than chicken or fish and it is the most widely eaten meat in the world, providing about 38 percent of daily meat protein intake worldwide, although consumption varies widely from place to place.

2.1.1 Meat Quality

Many definitions of meat quality are found in literature. In fact, meat quality can be defined in various ways from palatability to technological aspects to safety (Mullen, 2002). For instance, Hoffman (1990) described meat quality as the sum of all quality factors of meat in terms of the sensory, nutritive, hygienic and toxicological and technological properties (Aaslyng, 2002). Meat quality can be defined as the suitability of meat for use in a specified product; in other words, the attributes that define the quality of the meat depend on the use for which the meat is intended (Aaslyng, 2002).

2.1.2. Pork Meat Quality

As for pork meat, the National Pork Board (NPB) has specifically defined the lean quality in fresh pork, which refers to a wide range of factors but focuses more on muscle color, texture, marbling and functionality (water holding ability) (Buege, 2001). These factors affect products attractiveness to potential consumers, processing characteristics for value-added products manufacture and the ultimate palatability and satisfaction of pork products to consumers.

Over the last few decades, strong industrialization of meat processing has created a need for technological meat quality assessment. As a response, evaluation of pork quality has focused on giving priority to variations in color, moisture retention and texture. In fact, the most commonly used subjective evaluation distinguishes three classes of meat, based on the combination of anomalies of the three main parameters mentioned above. The RFN (Reddish-pink, Firm and Non-exudative) meat is good quality pork that exhibits desirable color, texture, and water-holding capacity (WHC); it is described as reddish-pink in color, firm in texture, and free of surface wateriness(van Laack et al., 1994; Joo et al., 1995; Buege, 2001). On the other hand, PSE (Pale, very Soft and Exudative) meat has undesirable appearance, and lacks firmness due to excessive drip loss (Qiao et al., 2007). The third class, DFD, stands for dark, firm and dry pork, and is a dark-colored low quality meat that has a very firm and dry texture. Two other quality designations have been recognized over the past few years; during the 1990's RSE (Red, Soft and Exudative) meat class was identified (Kauffman et al, 1992; Kauffman et al., 1993; Joo et al., 1995). This meat has desirable reddish-pink color, but is Soft and Exudative, and finally; PFN (Pale, Firm and Non-exudative) meat, which has the texture of good quality meat, but has undesirable color and poor water-holding capacity (van Laack et al., 1994). As shown in Table 2.1, these five classes of meat can be defined by certain parameters such as; color, L* value, pH and drip loss. The NPB has stated that it is not unusual to find varying degrees of the RFN, PSE, RSE, and DFD conditions in pork cuts displayed in a retail market case, and in primals destined for further processing (Buege, 2001).

Table 2.1 Pork qualities characteristics (van Laack et al., 1994)

Quality class	Color	L* (measurement of the lightness of the sample's color)	pH	Drip loss (%)
DFD	Dark	≤52	High ultimate (>6.0)	<5.0
PSE	Pale	≥58	Fast pH decline	≥5.0
RFN	Red	52-58	Normal (5.5-5.7)	<5.0
RSE	Red	52-58		≥5.0
PFN	Pale	≥58		<5.0

2.2 Causes of Low Quality Meat

The final quality of the meat is mainly defined by the chemical and physical changes that occur in the muscle before, during, and after the slaughter of the animal. The conversion of glycogen (muscle sugar) to lactic acid that takes place after the pig has been slaughtered plays an important role in meat quality attributes. Decrease and the ultimate pH influence meat quality in terms of color and water-holding capacity.

During the post mortem, in adequate conditions, the conversion of glycogen to lactic acid occurs at a moderate rate in a long time process. As the temperature of the muscle decreases with chilling, the pH of meat declines (Buege, 2001). This optimal conditions, result in good quality meat (RFN meat). On the other hand, if the lactic acid is produced at an accelerated rate after slaughter when the temperature of the carcass is still high, there will be a rapid falling of the pH. Buege (2001) indicated that the combination of an acidic environment with high carcass temperatures results in the denaturation of proteins present in the meat (such as myoglobin which is mainly responsible for the color of the meat). The denaturation of the pigmented protein myoglobin, as well as the accumulation of free water on the cut muscle surface produces a pale appearance in the meat (NPB, 1999).

When proteins are denatured, they can no longer retain water, and therefore the meat will have lower water holding capacity and a pale color (PSE meat). Offer and Knight (1988) suggested there is strong evidence that denaturation of myofibrillar proteins, especially myosin, is the cause of the low water-holding capacity (WHC) of PSE pork. Moreover, PSE meat appears pale because of a high degree of light scattering caused by a low pH; it is soft because of free fluid between the muscle fibers and other factors, and it is exudative due to the loss of weight by drip and evaporation (Swatland, 2002).

Low level of glycogen in the muscle before slaughter of the pig results in DFD meat. In this case, little or no acid production in the muscle is observed. Since the decrease in the pH is null or limited, no proteins are denatured. As a result, meat presents a dark red color and increased WHC (Buege, 2001). The muscle proteins tightly bind the water and contribute to the characteristic firm texture of DFD meat. DFD meat appears dark because it has a high pH and scatters less light than normal; it is firm because its fluid-filled muscle fiber is still turgid, and it seems dry when eaten. The dryness is misleading because DFD meat has lost less fluid than normal. However, water is held tightly between meat proteins at the micro-structural level. Therefore, when DFD meat is eaten a lack of juiciness is experienced (Swatland, 2002).

Various factors are determinant for the quality of the meat such as handling of pigs before slaughter and hereditary factors. For instance, PSE is related to the Porcine Stress Syndrome (PSS), a heritable condition in which the gene transmitted causes pigs to show intolerance to stress and to exhibit accelerated muscle metabolism. PSS contributes to the chemical conditions which strongly favor the development of PSE meat (Buege, 2001). PSS condition could also lead to DFD pork, in case the pig is exposed for a long time to stress depleting its muscle glycogen. As for the handling before slaughter, if the stress is not minimized and certain conditions are not suitable for the pig to be in a cool environment, the conversion of the energy stored in the muscle is augmented (Buege, 2001). Thus, declining the pH and favoring the condition of PSE meat.

The stressors contributing to the depletion of meat quality are various, and therefore, need to be properly managed and controlled. There are specific guidelines for proper handling of the pigs before slaughter which mainly focus on factors such as: facility design, environment (lighting, sounds and smells, temperature and humidity, and vibrations), physical abuse, stocking density, mixing with unfamiliar pigs, total time of feed/water withdrawal during transport and lairage, and rest in lairage after transport (Murray, 2000).

2.3 Pork Industry in Canada

Canada is a major producer and exporter of pork meat. Canadian pork is related to meat with high quality standards; factor that has contributed to the leadership in the market of pork industry. In 2006, the meat industry was the largest sector of the Canadian food manufacturing industry with annual sales worth $15 billion. In the same year, Canada exported $2.5 billion of pork to over 130 countries (Canadian Meat Council, 2007). Exports are an important source of growth for the industry and bring in more than $1 billion annually in foreign revenues.

2.3.1 Pork Industry Challenges

Quality control in the meat industry plays a predominant role. Both consumers and industry are interested in having a reliable technique that can predict the quality of fresh meat. While the consumer is expecting to be offered good quality meat, the industry is hoping to be able to discriminate between the different classes of meat. The later aims to minimize economic losses, optimize plant process, and maintain quality standards. Pork processors have encountered an increasing demand of good quality pork due to market segmentation. In response to the many specialized markets, the meat industry needs to provide meat based upon the quality standards and preferences of every different market.

A major problem facing the modern meat industry is the difficulty of predicting the quality of the meat from an outward inspection (Swatland, 2002). Thereby, the effects of using low quality meat for processing have been studied, more specifically for the PSE condition. It has been found difficult to use PSE meat in the formulation of hams (boneless and bone-in) sectioned and formed, chunked and formed or country-cured hams. This is mainly because there are no functional proteins (able to retain water) present in the meat, and the color formations are hard to achieve (Marriott and Schilling, 2002). In addition, PSE meat yields very low quality products when used for the processing of certain types of sausages. Meats with low WHC will tend to produce processed meats with cracked texture. Moreover, the overall production yield of these meats is lower than for good quality meat.

It is worth to mention that consumers make their purchase decisions mainly based on the color and appearance of the meat. Variations in the color of the meat, whether the meat is too pale or too red, and/or excessive fluid accumulation, will most probably influence and/or affect the selection of the meat purchased by the consumer.

Inadequate muscle color and water holding capacity rank second, after excessive fat, as the primary industry concern about pork quality (Warriss et al., 2006). Precise and reliable estimates for most countries are difficult to obtain; however, Murray (2000) and Johnson (1998) reported that in Alberta, approximately 13% of pigs produce loin muscles that are PSE, and a somewhat higher number of loins exhibit one of these traits: pale, soft or exudative. It was also indicated that approximately 10% of loins were darker, and 5% were firmer and dryer than normal (Murray, 2000). The study on the economic losses in the pork production by Murray (2000) estimated that the PSE condition decreases the value of a pig carcass by about $5. Swatland (2002) reported that the costs of increased exudation from PSE meat may be measured in millions of dollars for a major pork packer, and that this low quality meat attribute has been a long-standing problem.

2.4 Meat Quality Evaluation

Pork industries that process fresh pork cuts for national or export markets need to sort meat in different classes. For this purpose, most pork processors utilize visual examination performed by a meat specialist. Quality indicators such as color, firmness, and wateriness of the cut lean surfaces are typically evaluated, making the classification time consuming and subject to human error.

2.4.1 Subjective Evaluation of Meat Quality

Fresh quality meat indicators such as; physiological maturity, marbling, color, texture and firmness of lean, wateriness of cut lean surfaces and firmness of fat are typically evaluated by a visual inspection. Graders and evaluators use color, texture, wetness and marbling standards which are available in photographic and/or color chip form. Most commonly, meat color is visually determined using various scales such as; the Japanese color standards (Nakai et al., 1975), and the color evaluation scale developed by the National Pork Board Council (NPB, 1999).

Even though subjective evaluation is helpful in eliminating major quality defects, it cannot assure that all the meat in the plant has been sorted. In the worst case scenario, subjective evaluation cannot assure that meat has been accurately classified, since it is subject to human error. Moreover, it is difficult to overcome the inconsistencies associated with any visual assessment considering; 1) the need of an intensive training program for the assessors, 2) the cost of training and employing graders, 3) the variation between the judgments made by different specialists, and 4) the lack of standardization in assessment procedures and quality grades among countries (Ferguson, 2004). On the basis of the wide margin of error found in any subjective judgment of individual carcasses (Swatland, 2002), subjective evaluation of meat cannot assure sufficient accuracy and repeatability.

2.4.2 Objective Evaluation of Meat Quality

Many objective methods for characterizing meat quality have been developed to overcome the inconsistencies associated with any visual evaluation, and to aid the comprehensive assessment of quality attributes. For decades, laboratory analyses have been extensively used for meat quality classification (Mullen, 2002). Probably, pH has been the quality attribute most commonly measured in fresh meat; however, Channon et al. (2001) stated that the measurement of pH was poorly related to pork eating quality. This study suggested that in addition to ultimate pH, other meat quality attributes may be needed to provide industry with a useful model for sorting pork into different eating quality classes. As a result, other meat quality traits such as tenderness, WHC, color, cook yield, and enzymatic activity were evaluated in an attempt to improve pork meat classification.

2.4.2.1 Laboratory-based Methods for Meat Quality Evaluation

Chemical methods for the analysis of water, protein and fat have been developed and have become more sophisticated. Due to the expansion of meat industries, traditional methods have been switched to methods which are faster, easier and usually provide good accuracy and precision (Mullen, 2002). However, these methods need to be reviewed for the specific product type, sample size and other factors involved in the experimental setup. The analysis of meat for quality evaluation encompasses the determination of certain quality parameters, among them the most common ones are: pH, water holding capacity, color, and intramuscular fat.

pH measurement has commonly been considered as an essential element in meat quality assessment mainly because of its profound effect on the color, firmness and water holding capacity of the meat. Early post mortem pH measurement has been considered as the most effective predictor of the occurrence of PSE condition (Somers et al., 1985). pH can be determined by direct measurements with a glass or solid electrode in the meat to measure pH electrochemically, or, a sample can be homogenized before determination. The two classical measuring times are 45 min and 24 h post-mortem (Swatland, 2002).

The determination of water-holding capacity of meat can be performed in many different ways (see Honikel and Hamm, 1994 for a review on the techniques). Whatever method is used for this purpose, the overall objective is to measure the inherent ability of the cellular and sub-cellular structures of meat to hold on to parts of its own and/or added water (Mullen, 2002). The WHC can be determined by three techniques: (i) using external forces to drive out the water, such as centrifugation or filter press method, (ii) by letting the water drip out of the meat over a certain period of time, such as the "Honikel bag method", or (iii) by heating the meat and measuring the cooking loss (Honikel, 1989; Honikel and Hamm, 1994; Rasmussen and Anderson, 1996; Christensen, 2003).

The color of the meat is a combination of the reflection due to protein denaturation as a result of the pH change and the concentration and oxidative status of myoglobin. Color is the primary criterion by which consumers evaluate fresh meat quality (Cornforth, 1994; Faustman and Cassens, 1990). Color is commonly considered the most important sensory characteristic in the appearance of meat, and can be determined instrumentally or visually (Hunt and Mancini, 2002). Various systems exist for the objective measurement of color with CIE L*a*b* (color space coordinates). However, it has been stated that instrumental metamerism is a common and serious defect in colorimeters (AMSA, 1990). The color can also be subjectively assessed by color standards.

The content of intramuscular fat or, fat marbling plays an important role on the eating quality and the consumer's preferences. IMF can be measured subjectively in a visual way as fat marbling using different scales; however, IMF can also be measured objectively by chemical analyses (acid hydrolysis followed by an extraction) (Mullen, 2002).

2.4.3 Emerging Technologies for Meat Quality Evaluation

The laboratory tests have become more sophisticated and accurate. However, laboratory-based methods are time- and labor-intensive and expensive. They are no longer sufficient for the large volume of meat and the high-speed production facilities that are found nowadays in meat processing plants. Meat industry needs accurate, fast, non-invasive, objective techniques for meat quality evaluation. As a result, emerging technologies, which include both physical and biochemical techniques, have been developed, such as: ultrasound, nuclear magnetic resonance, image analysis, auto-fluorescence spectroscopy (see Mullen, 2002 for a review on these techniques) and Near Infrared spectroscopy (NIRS).

2.5 Visible/Near Infrared Spectroscopy

Spectroscopy is the study of the interaction between electromagnetic radiation and atoms, molecules, or other chemical species (Mohan, 2004). Near Infrared (NIR) technology derives its name from the use of portion of the electromagnetic spectrum, and it was first introduced in 1960’s to determine the composition of meat products (Ben-Gera and Norris, 1968). The NIR region goes from 780 to 2500 nm, and it is based on molecular overtone and combination of vibrations. It provides complete information about the molecular bonds and chemical constituents in a sample scanned. However, the electromagnetic spectrum includes a much wider region that NIR. The visible region is the portion of the electromagnetic spectrum that is visible to the human eye and ranges from 400 to 700 nm. Advances in instrumentation now allow the use of a single instrument to scan not only the NIR region, but also the entire visible spectrum (McCaig, 2002).

The use of spectroscopy has increased tremendously in the last few decades as it has appeared that detection and estimation of a number of food constituents and properties may be achieved by measuring the amounts of the radiation that is absorbed or emitted at different wavelengths. NIRS is a convenient tool not only for characterizing foods, but also for quality measurements and process control (Andres et al., 2007).

2.5.1 Visible/Near Infrared Spectral Analysis of Meat

As stated by Monin (1998), NIRS is one of the most promising techniques for large-scale meat quality evaluation, and its potential in a great range of applications has been broadly studied. Application of NIRS as a proximate analysis tool has been assessed. Common applications with meat include estimating moisture, fat, or protein content, pH, energy contents, hydroxyproline and sodium chloride in meat products (Chen and Marks, 1998).

The use of NIRS has also been evaluated for the prediction of diverse pork meat quality traits such as drip loss, shear force, protein, caloric content, color, pH, intramuscular fat, subjective color, cook yield and XYZ tristimulus values among others (Lanza, 1983; Brøndum et al., 2000; Forrest et al., 2000; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Savenije et al., 2006, Xing, et al., 2007).

Diverse and contrasting results have been obtained from the studies related to prediction of pork quality attributes from NIRS. For instance, Geesink et al. (2003) reported a correlation value of 0.71-0.74 for the prediction of drip loss, and 0.74 correlation value of NIRS with a combination of ultimate pH, filter paper tests and L* value. Hoving-Bolink et al. (2005) did not get the expected results for the prediction of intramuscular fat content by VIS/NIRS, neither for the prediction of color, observing an R^2 of 0.35. On the other hand, the study by Forrest et al. (2000) on the use of NIRS for the prediction of drip loss in fresh pork in the early post mortem stage resulted in a correlation higher than 0.8. However, in the later study, spectral measurements were acquired during a 6 min period, that is too long considering the possibility of an industrial application. As for the results obtained by Chan et al. (2002); quality traits such as XYZ tristimulus, moisture, and fat and protein composition were well predicted with VIS/NIR, with the highest $R^2 > 0.88$ obtained for XYZ tristimulus prediction. This study also reported marginally poor R^2 values for other characteristics (shear force, cook yield, pH, water-holding capacity, color, marbling and firmness) with R^2 values ranging from 0.584 to 0.002. Certainly there are important factors contributing to these variations, such as;

sampling conditions, nature, and methodology, experimental design, instrument type, and the data analysis performed for each study.

NIRS has also been used for the estimation of physical characteristics and evaluation of other meats. Common applications include quantitative prediction, chemical composition (fat and protein), and physical characteristics, such as drip loss, color, juiciness, hardness, and tenderness (Lanza, 1983; Mitsumoto et al., 1991; Park et al., 2001; Andres, et al., 2007). Mitsumoto et al. (1991) obtained correlation coefficients of 0.8 and 0.83 when testing the potential of NIRS for the prediction of Warner-Bratzler shear value in beef cuts. In the research done by Park et al. (2001) on the prediction of beef tenderness using NIRS, an R^2 of 0.633 was attained. Savenije et al. (2006) assessed the prediction of pork quality traits using VIS/NIRS and reported prediction accuracy as high as 84% for pH. In contrast, the lowest prediction accuracy documented in the former study was of 56% for drip loss.

The use of NIRS in meat products has also been evaluated, for instance; Ellekjaer et al. (1994) evaluated NIRS as a potential means for determining the sensory quality of sausages. In fact, it was found that NIRS mainly described the color and texture variations in this product (Chen and Marks, 1998). Liu et al. (2003) framed the feasibility of VIS/NIR spectroscopy to predict shear values, color and sensory characteristics of beef steaks during the aging process.

As for chicken, Chen and Marks (1998) evaluated the use of NIRS for the prediction of specific physical attributes in wholesome and unwholesome chicken carcasses obtaining promising results. Oxen meat samples were also used by Prieto et al. (2006) to assess the potential of NIRS for the estimation of chemical composition. Good to moderate correlation values for some parameters and poor predictive accuracy for some others were reported. More recently, Andres et al. (2007) assessed the potential of NIRS for the prediction of sensory characteristics related to the eating quality of lamb meat. The authors suggested a possibility for the use of NIRS for the discrimination between samples but only when extreme scores for sensory quality attributes existed.

To our knowledge, few studies have focused on the use of spectral measurements, from the VIS/NIR region for the prediction pork meat quality class itself, rather than the prediction of quality attributes (Xing et al., 2007) and the urge of a quality classification system is still in demand.

2.5.1.1 Limitations of VIS/NIRS Technique

VIS/NIRS has shown its potential as an accurate, rapid and non-destructive technique for meat evaluation. However, a few studies have focused on the industrial applicability and the limitations of the technique. Olsen et al. (2007) evaluated the repeatability and variation caused by the scanning conditions in on-line assessment of pig carcass. The results from this study described sources of variation responsible for the different results obtained in the determination of fat. On the other hand, Shackelford et al. (2004) developed an optimal protocol for the use of VIS/NIRS in meat quality evaluation. Different experimental conditions were tested and results were compared. The optimum number of spectral observations per samples and the effect of blooming were defined. The study also evaluated the effect of using various equipments for spectral measurements in the accuracy of predictive models. Both Olsen et al. (2007) and Shackelford et al. (2004) agreed on the importance of examining the applicability of NIRS in the industry. As stated by O'Farrell et al. (2005), the great potential of Visible and NIRS would be of no use if the technique cannot be applied in an on-line application.

2.5.1.2. Importance of the location of measurement

To the best of our knowledge all studies done so far have considered meat to be homogeneous. As aforementioned, meat is a highly unpredictable product. Limited information on the effect of the place of the spectral measurement along the sample is available. For instance, Forrest et al. (2000) repositioned the measuring probe in three different locations (between the 4^{th} and 5^{th} lumbar vertebrate) of the pig carcass. The later was made in order to obtain a large volume of spectral information to average out possible heterogeneities. Great variation was found in the spectral values obtained from different locations. As a result, prediction of WHC and drip loss in fresh pork was developed without relocation of the measurement site.

2.6 VIS/NIRS Analyses Methods

Hyperspectral data contains spectral response information that provides detailed chemical, moisture, and other descriptions of constituent parts of an item (Casasent and Chen, 2003). It is well known that spectral and hyperspectral data are very powerful and contain invaluable and detailed information about the sample analyzed; however, it usually happens that the chemometrical or statistical method used for the data analysis is not the best one. In fact, if the approach used to analyze the data is not the adequate or the best, important information about the sample might be lost.

2.6.1 Commonly used NIRS Analyses Methods

Multivariate data analysis has proven to be very useful for spectral analysis in the NIR region. In previous studies mentioned above, which involve datasets with spectral and in some cases hyperspectral data, different approaches have been used. Basically, these methods try to reduce the dataset in order to simplify the model and by this, acquire higher prediction accuracy. Mitsumoto et al. (1991) obtained considerable results in the prediction of physical and chemical attributes in beef cuts by using Multiple Linear Regression (MLR) analyses. Savenije et al. (2006) applied Modified Partial Least-Squares (MPLS) for the prediction of pork quality traits. In contrast, Chen and Marks (1998) combined MLR with PCA. They reported a correlation coefficient as high as 84% for pH in pork meat. On the other hand, Barlocco et al. (2006) and Andres et al. (2007) applied PCA to the dataset, followed by PLS. In the former studies, models were developed for the prediction of proximate and physical parameters of pork meat samples with different presentations and for the prediction of sensory parameters of lamb meat respectively. Besides already mentioned methods, some other different approaches have been used for this kind of data, for instance; Principal Component Regression (PCR), Stepwise Regression, Stepwise Multiple Linear Regression, and PLS (Lanza, 1983; Park et al., 2001; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Xing et al., 2007).

As for other techniques, Artificial Neural Networks have been widely used for pattern recognition and classification. More recently, ANNs are beginning to play an increasingly significant part in the food industry. For instance; O'Farrell et al. (2005)

combined the use of PCA with ANNs in their study on the online quality assessment of food from spectral readings. The former study emphasized the need of applying advanced signal processing pattern recognition techniques with high generalization capabilities to categorize the spectral reading taken from the food products and eliminate any interfering parameters. Similar approach was used by Qiao et al. (2007) in which ANNs was used for pork quality classification. However, in the former study, not only spectral observations, but hyperspectral images were analyzed.

2.6.2 Classification Techniques for VIS/NIRS Data

There are two broad classification procedures: supervised and unsupervised classification methods. In the unsupervised methods no target variable is identified as such, instead, the data mining algorithm searches for patterns and structure among all the variables. Most commonly, in supervised methods there is a particular pre-specified target variable and the algorithm is given many examples where the value of the target variable is provided, so that the algorithm may learn which values of the target variable are associated with which values of the predictor variables (Johnson, 1998). In this section, the classification methods that were used in the presents study will be described.

2.6.2.1 k-Nearest Neighbors

k-Nearest Neighbors (k-NN) is a supervised method which was first introduced by the researchers E. Fix and J. Hodges in their paper: "Discriminatory Analysis: Nonparametric Discrimination: Consistency Properties", in 1951 (Silverman and Jones, 1989). The k-NN rule is one of the oldest and simplest methods for pattern classification. Nevertheless, it often yields competitive results, and in certain domains, when cleverly combined with prior knowledge, it has significantly advanced the state-of the-art (Weinberger et al., 2006).

k-NN is a distance-based system in which the training dataset is stored, so that a classification for a new unclassified record may be found simply by comparing it to the most similar records in the training set (Larose, 2005). The k-NN method tends to classify new samples by calculating their proximity to individual samples in the training set (Wolf and Parsons, 1983); it remembers all training data and selects most similar vectors at the moment it is asked to make a prediction. However; defining the number of nearest neighbors to be considered, as well as the distance function for the classification of a new record is of great importance to achieve a good performance of the method.

When using the k-NN algorithm, it is necessary to compute the distance between two records (the new sample to be classified and the reference sample). The most common distance metric used is the Euclidean distance (the ordinary distance between two points). The best choice of k depends upon the data; generally, larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct. A good k can be selected by using parameter optimization, for example, cross-validation (Ghostminer, 2004).

The k-NN decision rule makes no assumption on the underlying probabilistic distribution of the samples points and of their classification. The difference to most other techniques for classification is that when using k-NN, training points are used during the classification, whereas in other methods, usually they are needed only during the training. The accuracy of the k-NN algorithm can be severely degraded by the presence of noisy or irrelevant features, or if the features scales are not consistent with their relevance (Larose, 2005).

2.6.2.2 Canonical Discriminant Analysis

Canonical Discriminant Analysis (CDA) is a procedure that creates new variables containing all of the useful information for the discrimination that is available in the original variables (Johnson, 1998). These new variables often lead to simpler rules for actually classifying experimental units into different classification groups. CDA is similar to principal component and factors, however, they do not compute in the same way. CDA often allows the visualization of the distribution or distances between the populations being studied in a reduced dimensional space.

The key assumption of CDA is that all individuals can be assigned to one and only one group in advance, through some means external to the data being analyzed While PCA maximizes the total variation explained by each principal component, CDA maximizes the among-group variance explained by each canonical variant; as such, it focuses not on the overall variation in the data, but on the extent to which that variation is partitioned among groups (Johnson, 1998)

2.6.2.3 Stepwise Regression and Discriminant Analysis

As stated by Johnson (1998), the STEPDISC procedure uses the stepwise approach for variable selection, which uses a combination of the forward selection and the backward elimination procedure. The stepwise approach starts by selecting the single best discriminating variable. At each step of the process, an F-test is performed and the variable that results to be the most discriminant is included, the discriminant power of all the variables will be evaluated and before including a new variable, it will make sure that all the variables previously chosen remain significant, if this is the case, the variable or variables that are no longer significant will be eliminated. The selection continues until no more variables meet the criteria to be included. The Stepwise method is commonly used as a tool for the reduction of the set of variables to be included in the classification function developed by the DISCRIM procedure.

Johnson (1998) noted that a small subset of well-chosen variables often allows a better discrimination between treatments than the entire set of variables, and that it is possible that all statistically significant variables chosen in a selection procedure might not be required, or that they may even result to be not useful for discrimination, so basically there is no such guarantee that the selected variables would represent the best set of variables, particularly when there is high collinearity in the data (Karimi et al., 2005; Johnson, 1998).

The Discriminant Analysis performed by the DISCRIM procedure is a multivariate technique primarily used to build rules that can classify individuals within a population; produce a rule that will allow predicting the class membership of an individual from a specific population. The basic prerequisites to perform a discriminant analysis are that two or more groups exist which are presumed to differ on several variables and these variables can be measured at the interval or ratio level (Klecka, 1980). Discriminant analysis is able to distinguish between groups and/or provide the means to classify any case into the group it most closely resembles.

2.6.2.3.1 Estimation of the probability of misclassification

When performing a discriminant analysis it is necessary to estimate the probabilities of misclassification of new observations. Three basic methods exist for this purpose: Resubstitution estimates, Estimates from holdout data, and the Cross-validation estimates. The resubstitution estimates method applies a discriminant rule to the data used to develop the rule and observes how often the rule correctly classifies these observations. The disadvantage of this method is that since all the data is used to develop the rule, the probabilities of correct classification are usually overestimated. The holdout method uses a test or holdout dataset for testing the rule developed from other data. This method has been proven to produce unbiased estimates of the probabilities of correct classification; however, it has the limitation that the rule developed might not be the best discrimination rule since a reduced number of samples are used for its development. The leave-one-out Cross-validation method, which is more frequently used than the first two methods described, consists of developing a model using all data except one, the model is tested on the one data record not seen by the model. Next, the first observation is replaced and a second one is removed, a new rule is then developed and it is now tested on that second observation that was removed. This process is repeated for all data records. According to Johnson (1998), Cross-validation estimates have been shown to be nearly unbiased estimates of the true probabilities of correct and incorrect classifications.

A variation of the leave-one out or Cross-validation methods is the x-fold Cross-validation method. The latter requires that the complete dataset be divided in x equal sub-sets, aftwerwards a first discriminant rule is created using x-1 subsets and the model is tested on the one remaining subset that was not included for building the rule. This process is repeated x-1 times and in each case, the subset that is left out of the model construction is changed, so that each one of x subsets is used for the testing of the model at least once.

2.6.2.4 Decision Trees

Decision Trees are logical predictive models represented by a flow-chart-like tree structure that shows how the value of a target variable can be predicted by using the values of a set of predictor variables (Larose, 2005). Within the tree structure, the internal nodes denote tests on an attribute, branches represent an outcome of the test, and leaf nodes symbolize class lables or class distribution. DTs are a collection of decision nodes, connected by branches, extending downward from the root node until terminating in leaf nodes. DTs are built in a cyclical process by dividing the feature space into two or more parts. The divisions or splits are made in such a way that the best separation of objects belonging to different classes is achieved. At each stage of the DTs construction process a certain criterion is used to estimate the usefulness of a particular split from the point of view of the final classification tree (Ghostminer, 2004).

The estimation criterion in the Decision Tree algorithm is the selection of an attribute to test at each decision node in the tree. The goal is to select the attribute that is most useful for classifying objects. DTs models use a statistical measure called "Information gain", which allows measuring how well a given attribute separates the training samples according to their target classification (Ghostminer, 2004), this measure is used to select among the candidate attributes at each step of the tree development.

DTs are powerful and popular tools for classification and prediction. The attractiveness of DTs is due to the fact that, in contrast to Artificial Neural Networks, decision trees represent rules, which are easier to human understanding. In some applications the researcher is only interested in the accuracy of the predictive model, in this cases, it seems unnecessary to understand the reasoning or the way the models works, for some other applications, however, the ability to explain the reason for a decision, is crucial.

DTs present some advantages over other classification models, such as their ability to generate understandable rules without requiring much computation. Decision Trees are able to handle both continuous and categorical variables and they are able to provide a clear indication of which fields are most important for prediction or classification. As for their main disadvantages, (1) DT models are less appropriate for estimation tasks where the goal is to predict the value of a continuous attribute, (2) they are prone to errors in classification problems with many class and relatively small number of training examples, and (3) DT models can be computationally expensive to train (Larose, 2005).

2.6.2.5 Artificial Neural Networks

Artificial Neural Networks are an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information.

The key element of this paradigm is the novel structure of the information processing system. Artificial Neural Networks are an interconnected group of processing elements called neurons that work together to create an output function; these mathematical functions are able to convert inputs into desired outputs, they are basically a simplified model of the way the human brain processes information (Larose, 2005). In a Neural Network the basic units, neurons, are typically organized into layers.

ANNs can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. They are systems trained to learn how to solve complex problems from a training set and create generalizations that will be able to make estimations and/or predictions from unseen data (Larose, 2005). All the individual neurons involved in the network need to work as a team for the output to be consistent and robust. The complexity of the network will be determined by the connections between the processing elements and element parameters. ANNs learn by example, so they cannot be programmed to perform a specific task. On this basis, the examples must be selected carefully otherwise the network might function incorrectly.

2.6.2.5.1 Types of ANNs

As stated by Larose (2005), the commonest type of artificial neural network consists of three layers of units; a layer of input parameters is connected to a layer of hidden units, which is in turn connected to a layer of output units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units (Larose, 2005). ANNs can be generated with different architectures. The Feed-forward Neural Network works in such way that it allows the signal to travel only in one direction, as stated by its name, there is no feedback, so the inputs are only associated with the outputs (Larose, 2005). The Feedback Networks, on the contrary, tend to be more powerful networks due to the fact that they can have signals traveling in both directions; however, they can get to be extremely complicated. Feedback networks are in constant change until they reach the equlibrium, where-in they remain until the input changes and a new equilibrium needs to be found.

2.7 Concluding Remarks

It may be concluded from the above review that NIRS and VIS/NIRS can be used to evaluate pork meat quality attributes such as WHC, tenderness, pH, protein, color, IMF, cook yield and XYZ tristimulus values among others (Lanza, 1983; Brøndum et al., 2000; Forrest et al., 2000; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Savenije et al., 2006, Xing, et al., 2007). However, very little information was found on the use of spectral measurements for the prediction of pork meat quality class (Xing et al., 2007). In fact, to the best of our knowledge, there is a lack of information on the use of both visible and near infrared regions for the prediction of meat quality classes.

Limited information was found on the industrial application of the technique. An optimal protocol for the use of VIS/NIRS in meat quality evaluation has been developed (Shackelford et al., 2004). Optimum number of spectral readings, variation between various equipments, and blooming effects were assessed. However, to the best of our knowledge, no study has evaluated the effect of the place of measurement in pork meat quality evaluation from spectral observations.

It can also be concluded that spectral and hyperspectral data may contain valuable information about the sample being analyzed. Thereby, the selection of an appropriate classification method is crucial for the extraction of the valuable information which will allow eventual development of predictive models.

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PREFACE TO CHAPTER 3

According to the literature on the application of VIS and NIRS in pork meat quality evaluation, many studies have worked on the prediction of pork meat quality attributes. However, research is urgently needed to evaluate the potential of using VIS and NIRS to develop a model able to predict pork meat quality classes.

Fresh pork loin samples from different quality classes were collected over a period of 6 months. Hyperspectral observations were acquired from a spectroradiometer in 2150 wavebands (350 nm to 2500 nm). A stepwise approach was used to select important variables. Discriminant analysis was used to evaluate the usefulness of the selected wavebands for discrimination purposes. The aim of the study was to evaluate the potential of hyperspectral observations in the prediction of meat quality class.

Research paper based on the chapter:

Monroy, P. M., Prasher, S. O., Ngadi, M. O. and Karimi, Y. 2007. Pork Meat Quality Classification from Hyperspectral Observations. Trans. ASAE. (Submitted for publication)

CHAPTER 3

PORK MEAT QUALITY CLASSIFICATION USING HYPERSPECTRAL DATA

3.1 Abstract

Canada is a major exporter of pork meat. Currently, pork meat is classified into five quality groups, based on the combination of three main quality parameters, namely color, texture and exudation. For this study, 60 samples of pork loin from four quality classes of meat were assessed. To evaluate the capacity of near infrared spectroscopy as an accurate technique for pork quality prediction, a spectroradiometer measured hyperspectral reflectance at wavelengths ranging from 350 to 2500 nm with a resolution of 1 nm. Stepwise regression analysis was used to select the most significant wavebands and this was followed by a discriminant analysis to investigate the ability of the selected wavebands to classify pork meat samples into different categories. Leave-one-out and five-fold cross-validation methods were used to validate the procedure. Meat pork quality classes were correctly classified with 79% accuracy, when a smaller subset of selected wavebands was used. The results highlighted the potential application of hyperspectral analysis in pork meat classification.

3.2 Introduction

Canada is a major processor and exporter of pork meat, which is a highly variable raw material. As a result, accurate evaluation of pork meat quality is needed to move the pork industry forward, minimize economic losses, and assure Canada's global leadership in its pork meat production. Pork quality affects product attractiveness to potential customers, processing characteristic for value-added product manufacture, and the ultimate palatability and satisfaction of pork products to consumers (Buege, 2001).

Pork quality can be defined in various ways since the attributes that determine quality depend on the use for which the meat is intended (Aaslyng, 2002). Technological assessment of pork quality has been typically related to differences in moisture retention and color, which are critical characteristics that determine the consumer's choice.

Currently, pork meat quality classification consists of five quality groups, based on the combination of three main quality parameters namely color, texture and exudation. Good quality pork is described as reddish-pink, firm and non-exudative; the common designation of this pork is RFN. The second group includes the pork that is extremely soft, poor in both color and water holding properties; it is classified as pale, soft, and exudative (PSE). The third class, DFD, is dark, firm and dry as the acronym suggests. The fourth class (RSE) refers to red, soft and exudative meat, which has a normal reddish-pink color, but a soft texture and low water holding capacity (Kauffman et al, 1992; Kauffman et al., 1993; Joo et al., 1995). The fifth class of meat reported in the literature (van Laack et al., 1994), is known as PFN; pale, firm and non-exudative meat.

The pork meat industry is facing diverse challenges i.e., emerging classes of meat, the growth of the meat processing industry, market segmentation, and the lack of quality systems appropriate for meat plants, among others. The meat industry producers and consumers face a permanent need for new methods of quality evaluation. Consequently, effective systems for meat classification should be objective, reproducible, accurate, automated, rapid, affordable, and simple to use (Seman, 2002). Laboratory analyses are routinely used to determine pork meat quality, but tests tend to be time consuming, sample destructive, and expensive. Therefore, new, rapid and automatable methods need to be developed in order to assess pork meat quality.

Despite several attempts to develop an effective method for the evaluation of pork meat, such as optical probes, ultrasonic or video image analysis (VIA), limitations are not yet overcome. Near Infrared Spectroscopy (NIRS) is one of the most promising techniques for large-scale meat quality evaluation (Monin, 1998). Visible near infrared (VIS/NIR) spectroscopy has shown enormous potential in the assessment of food quality, and it has proved to be an objective, non-destructive and accurate method that is able to identify the presence and quantity of chemical constituents in specific wavelengths (Mullen, 2002; Monin, 1998; Osborne et al., 1993). Since these factors are mainly responsible for meat attributes, spectral measurements can be related to meat quality.

Although many studies have been performed on proximate analysis of meat products and by-products, lesser work has been done for unprocessed meat products. NIRS is being investigated for the prediction of meat quality using chemical parameters, characteristics, and attributes. For instance, Forrest et al. (2000) evaluated the ability of NIR measurements with fiber optic sampling for drip loss prediction in fresh pork, and obtained good results (R=0.71-0.74) but the process was quite time consuming. Geesink et al. (2003) worked on the prediction of pork quality attributes from NIRS data; reasonable results were obtained for the prediction of drip loss and no useful models could be constructed for shear force. A similar study was presented by Hoving-Bolink et al. (2005) and by Chan et al. (2002) where, in both cases, the potential of NIRS was investigated for predicting quality attributes. Park et al. (2001) were able to identify specific wavebands for fat (1212, 1722 and 2306 nm), water (1153 and 1910 nm), and protein (1240, 1385 and 1690 nm), while trying to predict beef tenderness. More recently, both spectral and spatial data were used by Qiao et al. (2006, 2007) for the development of predictive models for pork quality attributes, such as drip loss, pH, and color, and for classifying pork quality groups. In this study, feature wavebands were selected and quality attributes could be predicted with correlation coefficients ranging from 0.55 to 0.86. Qiao et al. (2007) reported 87.5% accuracy for classifying pork quality groups using hyperspectral imaging. Visible spectroscopy has been used to classify intact pork meat into two classes (based on color) with an accuracy of 85% (Xing et al., 2007).

Although visible and near infrared spectroscopy have shown their potential for the prediction of pork quality attributes, and in few cases, for the prediction of a quality class itself, there is the need to develop a more robust classification model using larger and more heterogeneous dataset. The overall objective of this study was to investigate the use of hyperspectral observations in pork meat classification. The specific objectives were to select important wavebands for pork meat quality classification using a stepwise approach, and to use discriminant analysis to determine pork meat quality on the basis of hyperspectral data, from samples collected over widely different sampling dates.

3.3 Materials and Methods

3.3.1 Sample Preparation

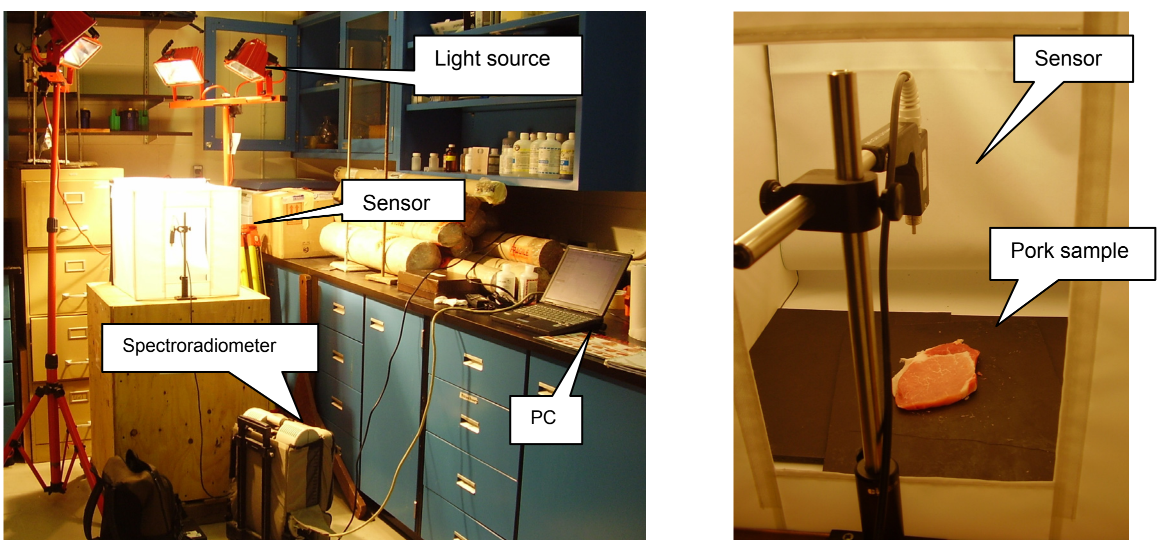
Fresh pork loins (24-h post-mortem) from the 11^{th} rib were obtained from a cutting house (Olymel S.E.C./L.P., St Hyacinthe, Quebec, Canada). The samples were collected at different times from November 2005 to April 2006. A total of 240 samples were collected, 60 samples from each one of the four different categories (PSE, RSE, PFN and RFN). The DFD class was not evaluated since there were insufficient samples in this category. The samples were classified by a meat specialist at the cutting house and then they were transported from the cutting house to the University Campus in an ice bag. The loin samples were sliced into 1 cm thick chops for further analysis.

3.3.2 Spectral data acquisition

Hyperspectral reflectance was measured using a spectroradiometer (FieldSpec® Pro, Analytical Spectral Devices, Boulder, CO, USA) in 2151 wavebands. The spectroradiometer measured reflectance at wavelengths from 350 to 2500 nm with 1 nm increment. The spectroradiometer had a field of view of 15° and the sensor was located within a distance of 14.3 cm from the 1-cm thick samples. As a result, the hyperspectral measurements were an averaged response for an area of 12.25cm^2. Reflectance energy was referenced to a pure white standard.

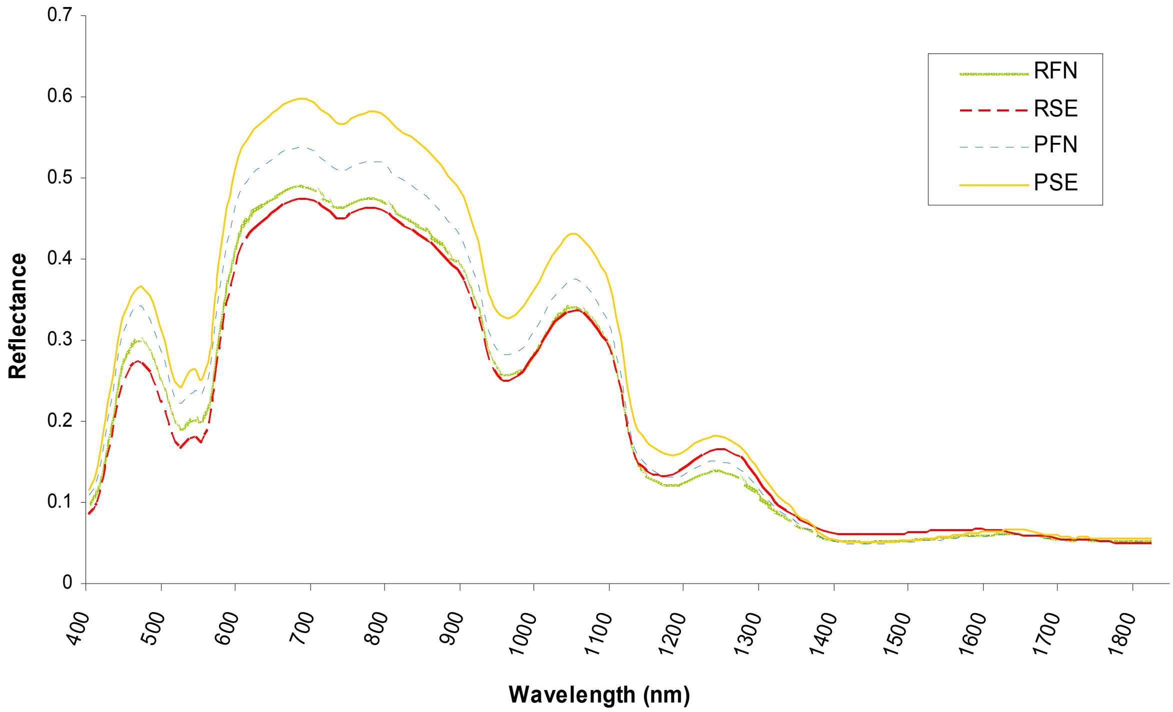
The complete spectral system as shown in Figure 3.1, consisted of a spectroradiometer, a DC fiber-optic illuminator (Fiber-Lite PL900-A, Dollan-Jenner Industries Inc, MA, USA) which was used as a light source, a platform, a white frame (surrounding structure used to distribute uniformly the light directed to the sample), and a PC.

Figure 3.1 Spectroradiometer and experiment setup



Six reflectance measurements were taken at the center of each slice and a mean value was calculated for each sample. Typical spectral responses of the four pork meat classes are shown in Figure 3.2.

Figure 3.2 Measured spectral response for four classes of pork meat quality, assessed from samples collected in March 2006



3.4 Data Analysis

Spectral data were analyzed using SAS® 9.1 (SAS Institute Inc., Cary, NC, USA) statistical software package. Firstly, to identify the most important wavebands, stepwise approach (STEPDISC procedure) was employed. Next, discriminant analysis (DISCRIM procedure) was used to evaluate the usefulness of the selected wavebands in classifying samples into different categories.

The STEPDISC procedure performs a multivariate discriminant analysis, combining forward selection and backward elimination methods. The forward selection is used for the inclusion of a variable, and backward elimination is employed for the exclusion of variables which are no longer significant in the model, based on the significance level for inclusion of variables in the F test. From this procedure, the most significant variables, suitable for discrimination of treatments, classes or different attributes, are selected.

From the wavebands selected in the stepwise regression, a smaller set of variables was chosen. The subset was chosen based on the order in which the variables initially entered into the STEPDISC procedure. The variables that were selected first are presumed to be more important than those that are selected later. The suitability of the selected wavelengths and of the subset of selected wavebands was examined with discriminant models using the DISCRIM procedures of SAS. The DISCRIM procedure can determine if a subset of wavelengths is suitable for building a rule for the classification of pork meat into the appropriate quality category.

The final model was evaluated by using the leave-one-out and five-fold cross-validation methods. The final model, developed by DISCRIM procedure, in each case, for the leave-one-out and every fold of the five-fold cross-validation methods, was based on the best subset of selected variables. In the leave-one-out method, all data except one are used to develop the model, and the model is tested on the one data record not seen by the model during model development. This process is repeated for all data records. In the five-fold method, dataset is divided into five equal subsets. In the model development process, one distinct set was used each time for testing and the remaining four sets for training [80% of the data is used to develop the model and an unseen dataset (20%) is used to validate the model], and the process was repeated five times. The five error estimates are averaged to get an overall error estimate

3.5 Results and Discussion

The reflectance measurements from 350 to 399 nm as well as from 1851 to 2500 nm were not included in the analysis because of consistent noise. Due to high collinearity of the data and in order to reduce the dataset size, spectral data was averaged every 10 nm, and so the bandwidth was expressed as 10 nm, instead of the initial 1 nm used in the measurement. For instance, the waveband 505 nm stands for the result average between 500 and 509 nm. As stated by Johnson (1998), the entry significance level for inclusion of variables is normally set somewhere between 0.25 and 0.5, and, 0.15 for variable elimination in the stepwise approach; however, in this study, for the selection of wavebands, the significance levels for the STEPDISC procedure were both set at 0.15, for the inclusion and removal of variables.

Taking into account the classes of pork meat, four populations were used for discrimination purposes. A summary of the results from the STEPDISC procedure, including the waveband selection for the complete dataset, is presented in Table 3.1. As can be seen, the training set #2 from the five-fold cross-validation method resulted in the highest number of wavebands, selected to be Discriminant. The STEPDISC procedure was able to select the most important wavebands among the 145 wavebands for discriminating between different treatments. These wavebands might be reflecting the underlying differences among various quality classes not visible to human eyes. Most of the wavebands selected in both validation methods are found in the visible region, however; some of the most discriminant wavebands, such as 1795 and 1785 nm, are found in the near infrared region.

A leave-one-out cross-validation method was performed to evaluate the predictive ability of the model. As can be seen in Table 3.2, better classification accuracy is obtained when a variable selection is performed by the STEPDISC procedure. According to the results, an increase in the overall classification accuracy rate of 15% is achieved when the model is evaluated using only the variables selected with the stepwise approach. In both matrices, it is clearly shown that the RFN meat quality class is more likely to be correctly classified, as compared to the three other remaining classes. In contrast, when the selected set of variables from the stepwise regression is used, a clear tendency of the PSE, PFN, and RSE classes to be misclassified into the RFN category is seen. In every fold, it can be seen that if there is no variable selection, more disparity appears in the misclassification. The observation above reveals that it is likely that the variable selection performed by the STEPDISC procedure could play an important role in achieving higher classification accuracy since it facilitates the elimination of those wavebands that cannot differentiate the quality classes and it allows the selection of the wavebands that are really necessary for an effective discrimination.

Table 3.1 STEPDISC results for waveband selection.

Complete dataset				Training set #2							
Number		Waveband		Number		Waveband		Number		Waveband	
U Step	In	Entered	Removed	Step	In	Entered	Removed	Step	In	Entered	Removed
1	1	595		1	1	595		43	27	1305	
2	2	575		2	2	1205		44	28	795	
3	3	415		3	3	1605		45	27		465
4	4	405		4	4	1225		46	28	635	
5	5	1215		5	5	1795		47	29	1065	
6	6	1205		6	6	1695		48	28		1205
7	7	605		7	7	585		49	27		585
8	8	455		8	6		595	50	26		1695
9	9	565		9	7	455		51	27	1075	
10	10	1225		10	8	1385		52	28	1045	
11	11	1305		11	7		1605	53	29	1785	
12	12	735		12	8	1265		54	30	1415	
13	13	845		13	9	1685		55	29		1305
14	12		1205	14	10	1735		56	28		1265
15	13	675		15	11	1505		57	29	585	
16	14	865		16	12	545		58	30	1575	
17	15	925		17	13	1715		59	31	1565	
18	16	905		18	14	1345		60	32	1115	
19	17	645		19	15	1255		61	33	1055	
20	18	1255		20	14		455	62	32		1565
21	17		1215	21	15	685		63	31		585
22	16		1225	22	16	1305		64	32	765	
23	17	1285		23	17	505					
24	18	1815		24	18	705					
25	19	1675		25	19	885					
26	18		455	26	20	465					
27	19	835		27	21	745					
28	20	975		28	22	725					
29	19		565	29	21		1305				
30	20	1365		30	22	925					
31	21	1055		31	21		695				
32	22	1045		32	22	825					
33	23	755		33	23	1485					
34	22		975	34	24	1455					
35	23	705		35	23		1345				
36	24	1655		36	24	1815					
37	23		1305	37	23		1795				
38	24	615		38	24	415					
39	23		605	39	25	405					
40	24	485		40	26	1595					
41	23		575	41	27	1535					
42	24	495		42	26		1505				

Table 3.2 Classification matrices for leave-one-out cross-validation method:

a) No variable selection was performed,

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	42 (70%)	9	8	1	60
	RSE	16	34 (57%)	6	4	60
	PFN	3	9	41 (68%)	7	60
	PSE	6	12	13	39 (65%)	60
	Total	67	54	68	51	240

b) Variable selection from the STEPDISC procedure

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	53 (88%)	3	3	1	60
	RSE	9	46 (77%)	1	4	60
	PFN	9	2	44 (73%)	5	60
	PSE	3	2	6	49 (82%)	60
	Total	74	53	54	59	240

Further selection of wavebands was performed mainly because there is no guarantee that the selected variables from the STEPDISC procedure would represent the best set of variables, particularly when there is high collinearity in the data (Karimi et al., 2005; Johnson, 1998; Murray, 1977). For reasons that are not fully understood yet, a small subset of well-chosen variables often allows a better discrimination between treatments than using all possible variables (Karimi et al., 2005; Johnson, 1998).

No variable reduction was possible for the cross-validation method. In other words, it was not possible to decrease the number of variables from the ones chosen by the STEPDISC procedure. Trying to obtain a smaller subset only resulted in a decrease in the 80% classification accuracy already achieved; as a result, no changes in the set of variables were made.

In the five-fold cross-validation method, the model was developed for each fold with a dataset containing 192 data records (80%), and then was tested using the remaining 48 (20%) unseen data records. For every fold, different combinations of wavebands were selected from the STEPDISC procedure, and in every case, a subset of wavebands was chosen to increase the prediction accuracy. The criterion used for the elimination of wavebands was the same as for the leave-one-out method; it was based on the order in which the variables initially entered into the STEPDISC procedure.

The classification matrices for two folds of the five-fold cross-validation method which resulted in the highest and lower classification accuracy are shown in Table 3.3. Little variation is found among the folds, resulting in no more than 10% difference between the best and the worst cases obtained in the five-fold cross-validation. As can be seen in both cases, the PSE class is the one which is more accurately predicted, achieving up to 100% classification accuracy even in the worst fold from the five-fold cross-validation. No trend is seen with respect to misclassification of any other class.

Table 3.3 Classification matrices for five-fold-cross-validation method

a) Fold with higher classification accuracy

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**10** (83%)	**0**	**2**	**0**	**12**
	RSE	**3**	**10** (83%)	**0**	**1**	**14**
	PFN	**1**	**0**	**8** (80%)	**1**	**10**
	PSE	**0**	**0**	**1**	**11** (92%)	**12**
	Total	**14**	**10**	**11**	**13**	**48**

b) Fold with lower classification accuracy

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**7** (70%)	**1**	**1**	**1**	**10**
	RSE	**4**	**8** (62%)	**1**	**0**	**13**
	PFN	**3**	**0**	**6** (67%)	**0**	**9**
	PSE	**0**	**0**	**0**	**16** (100%)	**16**
	Total	**14**	**9**	**8**	**17**	**48**

Table 3.4 shows the accuracy rate for the five-fold cross-validation method in two cases: first, when using all the variables selected by the STEPDISC procedure and second when using a smaller subset of wavebands. In the first case, results were rather poor for the testing set in every fold (overall accuracy of 71.6%), ranging from 52.8% to 79.3%. However, the overall classification accuracy improved substantially to 79.0% when subsets of wavebands were used for model development and testing.

Table 3.4 suggests that there is no direct proportion between the number of variables reduced from the original set and the increase in the accuracy rate. Furthermore, as seen in the first fold and in the cross-validation results, there are cases in which no variable reduction is possible; thus, it will only result in a decrease in the classification accuracy.

Table 3.4 Accuracy rate for the five-fold-cross-validation method.

Fold	**# of Wavebands selected by STEPDISC**	**Accuracy rate using all the wavebands selected by STEPDISC (%)**	**# of Wavebands in subset**	**Accuracy rate using the subset for the prediction (%)**
1	21	79.3	21	79.3
2	33	77.7	23	81.6
3	17	52.8	6	74.6
4	18	74.6	16	83.3
5	24	73.7	15	76.1
Average		**71.6**		**79.0**

Table 3.5 lists the wavebands selected by the STEPDISC procedure for leave-one-out cross-validation and the subsets selected from the five-fold cross-validation method. Based on the results, the wavebands 575, 595, 405, 935 and 735 nm seem to be consistent in most of the selected subsets, for both cross-validation methods used. Furthermore, wavelengths 585, 1795, 1205, 1785 and 1215 nm appear in at least two or more than two subsets selected for the five-fold cross-validation, but they do not appear in the leave-one-out method. The results show a clear tendency in the selection of adjacent wavebands, such as 575, 585, 595 as well as 405 and 415 or 1205 and 1215 nm, in response to the high collinearity.

Table 3.5 Subset of selected wavebands by the Stepwise operation

Table 3.5 Subset of selected wavebands by the Stepwise operation **Method**	**Subset**	**Wavebands selected for the subset**	**Number of wavebands**
leave-one-out Cross-Validation	-	595, 575, 415, 405, 735, 845, 675, 865, 925, 905, 645, 1255, 285, 1815, 1675, 835, 1365, 1055, 1045, 755, 705, 1655, 615.	23
First fold / five-fold Cross-Validation	1	595, 575, 405, 555, 585,855, 925, 785, 415, 1195, 865, 1615, 1065, 1075, 1045, 1145, 915, 1375, 1015, 1005, 995, 985.	22
Second fold / five-fold Cross-Validation	2	1205, 1795, 1225, 1695, 585, 1265, 1385, 1685, 1735, 1505, 545, 1715, 1345, 685, 505, 705, 885, 465, 745, 725, 925, 825, 1455.	23
Third fold / Fivefold Cross-Validation	3	595, 575, 1795, 1215, 1205, 1785.	6
Fourth fold / five-fold Cross-Validation	4	575, 405, 1205, 1215, 445, 1305, 1795, 1785, 1285, 1175, 1155, 1185, 475, 965, 605, 425.	16
Fifth fold / five-fold Cross-Validation	5	585, 405, 495, 465, 1305, 435, 425, 735, 885, 675, 925, 895, 1255, 895, 1265.	15

As shown in Table 3.5, each one of the wavebands from subset #3, appear at least once in each one of the other subsets, including the set from the leave-one-out method. Subset #3, with only six wavebands has the ability to classify pork meat into four quality classes with an accuracy of almost 75%. The use of few wavebands is preferable as it can lead to the development of a fast sensor system for monitoring the quality of pork meat. When few wavebands are used to develop a model, the total time needed per sample is reduced. Therefore, if this study was to be a useful tool for the development of a scientific apparatus for monitoring the on-line quality of pork meat, subset #3 would be the most suitable set.

It can be seen from (Table 3.5) that some spectral bands, selected in this study to be discriminant for pork meat evaluation, were related to certain chemical components in previous studies done on quantitative analysis of meat with spectral measurements. For instance, the wavelengths 1205 and 1215 nm, which appear in three of the five subsets from the five-fold cross-validation, correspond to an overtone for fat components, as reported by Osborne et al. (1993) and Park et al. (2001). The spectral bands 1155 nm and 1385 nm, selected for their discriminatory power in this study, are practically the same bands reported by Park et al. (2001), as water and protein absorption bands, respectively, for beef tenderness prediction. Forrest et al. (2000) and Hoving-Bolink et al. (2005) had a similar selection of variables for the prediction of chemical parameters of pork meat. Above all, the wavebands 405, 415, and 425 nm were the most predominant ones in all the subsets selected, and these spectral bands are considered to be myoglobin absorption bands (Millar et al., 1996), a chemical compound which highly influences the color of meat.

Qiao et al. (2006) reported various selected feature wavebands which were also selected in the present study; at least 9 wavelengths were found to be the same, or at least to be within the same wavelength regions, considering the average made of groups of ten consecutive wavelengths to reduce the number of variables to enter in the model. Good similarity was also found when comparing the wavebands reported by Xing et al. (2007) to the wavebands selected in this study. The wavebands 420 nm and 580 nm were reported, among others, as discriminant for the classification of pork meat into pale and red meat classes; on the other hand, one of the wavelengths chosen for the discrimination of samples within the pale class was 600 nm. These three wavelengths (420, 580 and 600 nm) are among the most important wavelengths in the present study, due to their discriminatory power.

3.6 Conclusions

In this study, the applicability of hyperspectral observations to classify pork meat into four quality classes was investigated. Classification models were developed using the stepwise and discriminant analysis methods. Two different cross-validation procedures were used to evaluate the predictive ability of the model. For the leave-one-out method, the classification accuracy was 80%, while with the five-fold cross-validation method; an accuracy of 79% was obtained for the unseen data. The subsets containing few variables suggest the possibility of using this study for the development of an on-line adaptation system. Our results clearly show the potential of using hyper-spectral observations in pork meat quality classification.

3.7 Acknowledgements

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PREFACE TO CHAPTER 4

The results of Chapter 3 indicated that hyperspectral observations could be used for the prediction of pork meat quality class. Classification models were developed using the stepwise and discriminant analysis methods. The study was focused on using the selected wavebands for discriminating between four pork meat quality classes.

Once the potential use of hyperspectral data for pork meat classification was ascertained, the next step was to evaluate the performance of different classification methods. The hyperspectral observations acquired in the first experiment were re-randomized, and analyzed using different approaches, i.e., k-Nearest Neighbors, Artificial Neural Networks, Discriminant Analysis, and Decision Trees. The overall goal of the study was to identify the most suitable method for the sorting pork meat into four quality classes.

Research paper based on the chapter:

Monroy, P. M., Prasher, S. O., Ngadi, M. O. and Patel, R. 2007. A Comparison of Different Methods of Classifying Pork Meat Quality Evaluation, Using Hyperspectral Observations. *Canadian Biosystems Engineering.* (Manuscript based on this chapter is under preparation).

CHAPTER 4

A COMPARISON OF DIFFERENT METHODS OF CLASSIFYING PORK MEAT QUALITY USING HYPERSPECTRAL OBSERVATIONS

4.1 Abstract

Hyperspectral data was qualitatively assessed by Canonical Discriminant Analysis (CDA). Four methods were used to assess pork meat quality classes (RFN, RSE, PFN and PSE). Artificial Neural Networks (ANNs), Decision Trees (DTs), k-Nearest Neighbors (k-NN) and multivariate Discriminant Analysis (DA) models were developed and tested using a hyperspectral dataset of 240 independent spectral observations within the VIS/NIR region. The best results were obtained from DA models which were developed using selected sets of wavebands from a Stepwise Regression. DA resulted in an overall classification accuracy of 76% for unseen data. In an effort to improve the classification accuracy, the 240 samples were regrouped into just two classes: pale and red meat. The data analysis showed that it was possible to separate pale meat from red meat, with classification accuracies attained by k-NN, DTs, ANNs and DA as high as 81%, 80%, 85% and 89% respectively. Since DA approach yielded the highest classification accuracy, it was then used to classify meat as Soft and Exudative (SE) or Firm and Non-exudative (FN), given that it was previously classified as Pale or Red. Classification accuracies of 91% and 84% were obtained for the discrimination of SE and FN classes within the pale and red classes, respectively. The classification accuracy of DA method could not be increased from regrouping the samples. An overall classification accuracy of 76% was obtained for the classification of pork meat into four quality classes.

4.2 Introduction

Canada is a major producer and exporter of pork meat and its leadership is related to the high quality of the meat produced. Due to the market segmentation, the concept of meat quality has become very specialized and specific for every market that needs to be supplied. In response to the many specialized markets, the meat industry needs to provide meat based upon the quality standards and preferences of every different market. Pork processors also need to be able to classify the meat before its processing. The quality and characteristics of a processed meat product could be affected if poor quality meat is used for processing (Marriott and Schilling, 2002).

In an attempt to classify pork meat, subjective and objective methods have been used. Fresh quality meat indicators such as physiological maturity, marbling, color, texture and firmness of lean, wateriness of cut lean surfaces and firmness of fat are typically evaluated by visual inspection. Unfortunately, visual evaluation is subject to human error. Laboratory-based methods, on the other hand, have focused on the determination of quality traits such as water-holding capacity, pH, shear force value, and color (See Mullen, 2002 for a review on the techniques). However, these methods tend to be time-consuming, sample destructive, time- and labor-intensive and expensive.

Visible and Near Infrared Spectroscopy (VIS/NIRS) has shown great advantages over both visual evaluation and traditional laboratory methods. This technique has demonstrated an enormous potential as an objective, accurate, and rapid tool for meat quality evaluation (Savenije et al., 2006; Liu et al., 2003; Liu et al., 2000).

Near Infrared Spectroscopy (NIRS) is one of the most promising techniques for large-scale meat quality evaluation and its potential in a great range of applications has been broadly studied (Monin, 1998). The technique has been used for the prediction of quality traits of different meats such as beef, lamb, chicken and oxen (Lanza, 1983; Mitsumoto et al., 1991; Park et al., 2001; Chen and Marks, 1998, Prieto et al., 2006; Andres, et al., 2007). Prediction of diverse pork meat quality attributes has also been evaluated using NIRS (Lanza., 1983; Forrest et al., 2000; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Savenije et al., 2006; Barlocco et al., 2006; Xing, et al., 2007). To the best our knowledge, very few studies have focused on the use of spectral measurements for the prediction of a pork meat quality class itself, rather than the prediction of quality attributes. Xing et al. (2007) investigated the potential of using visible spectroscopy to classify different quality classes of pork meat. Results suggested that visible spectral information is not sufficient to separate all quality classes. Thus, exploration of both VIS and NIR spectra seems more likely to yield higher classification accuracies.

In the aforementioned studies, which involve datasets with spectral and, in some cases, hyperspectral data, different approaches have been used for data analysis. For instance, Mitsumoto et al. (1991) obtained satisfactory results in the prediction of physical and chemical attributes in beef cuts by using Multiple Linear Regression (MLR) analyses. Savenije et al. (2006) applied Modified Partial Least-Squares (MPLS) to their data for the prediction of pork quality traits. Chen and Marks (1998), on the contrary, combined Principal Component Analysis (PCA) with MPLS, and obtained a correlation coefficient as high as 84% for pH in pork meat. Barlocco et al. (2006) and Andres et al. (2007) applied PCA to the dataset, followed by PLS. Barlocco et al. (2006) developed models for the prediction of proximate and physical parameters of pork meat samples with different presentations. Andres et al. (2007) used the same methodology for the prediction of sensory parameters of lamb meat. Chen and Marks (1998) also used PCA as a dimensionality reduction technique prior to development of MPLS to develop models for the prediction of cooking loss and yield deformation of chicken patties. Other approaches such as Principal Component Regression (PCR), Stepwise Regression, Discriminant Analysis, Stepwise Multiple Linear Regression, and Partial Least-Square Regression have been used for analyzing this kind of data, where-in a dataset reduction is usually intended in order to acquire a higher prediction accuracy, i.e., (Lanza, 1983; Park et al., 2001, Forrest et al., 2000; Chan et al., 2002; Geesink et al., 2003; Hoving-Bolink et al., 2005; Xing et al., 2007).

ANNs have been widely used as a means of pattern recognition and classification and, more recently; it is increasingly being used in the food industry. For instance, O'Farrell et al. (2005) emphasized that spectral observations should be preprocessed before applying for pattern recognition or classification purposes. In their study, they used PCA before the development of ANNs' models for food quality assessment. A similar approach was used by Qiao et al. (2007) in which ANNs was used for pork quality classification from hyperspectral images.

Curram and Mingers (1994) compared the performance of ANNs, Linear Discriminant Analysis (LDA) and DTs methods applied to real and artificially generated datasets, and obtained similar results for LDA and ANNs' techniques. Both methods yielded similar results except in the case when the dataset did not satisfy the assumptions required for LDA application. Wang and Paliwal (2006) evaluated discriminating techniques for the classification of wheat varieties from spectral observations and found that Linear and Quadratic discriminant analysis combined with PCA gave better results than k-Nearest Neighbor (k-NN), Probabilistic ANNs, and Support Vector Machines (SVM). In another study by Karimi et al. (2005b), multivariate discriminant analysis was found to offer the best classification accuracy of almost 75% for weed and nitrogen stress detection in corn, when compared to ANNs and DTs. Since the datasets vary from one another, it is not possible to rely on the comparison of techniques from other studies to select a classification method; different methods need to be evaluated to determine which method is able to classify pork meat quality classes more accurately.

4.3 Objectives

The overall objective of this study was to develop an automated and reliable technique for the classification of pork meat into four quality classes from hyperspectral observations. The specific objectives were 1) to qualitatively assess hyperspectral data by using Canonical Discriminant Analysis, 2) to compare the performance of Stepwise Regression and Discriminant Analysis, k-Nearest Neighbor, Artificial Neural Networks, and Decision Tree methods in the development of a classification model for pork meat quality assessment, and 2) to distinguish important wavebands for meat quality classification.

4.4. Materials and Methods

4.4.1 Meat Samples

The meat samples used in this study were obtained from a local cutting house (Olymel S.E.C./L.P., Ste Hyacinthe Quebec, Canada) from November 2005 to April 2006. A total of 240 fresh pork loins (24 hours after slaughter) from the 11th rib were collected.

Pork quality classification is based on color, texture, and exudation. Generally, the classification is done by specialists through visual observations. In this study, four different classes of pork meat; PSE, RFN, PFN and RSE, classified by a meat specialist, were assessed. RFN (Reddish pink, Firm and Non-exudative) pork has desirable color, normal texture and water-holding capacity (WHC). PSE (Pale pinkish, Soft and Exudative) pork has undesirable appearance and, because of the excessive drip loss, it has very soft texture (NPB, 1999). RSE (Reddish, Soft and Exudative) pork has normal color, but a softer texture and poor WHC (Kaufman et al., 1992). Finally, the PFN class stands for pale, firm and non-exudative meat (Nam et al., 2002).

Sixty samples were collected for each class. The loin samples were sliced into 1-cm thick chops for making spectral measurements.

4.4.2 Spectral Data Collection

Hyperspectral data were obtained from the pork samples using a spectroradiometer (FieldSpec® Pro, Analytical Spectral Devices, Boulder, CO, USA) with 2151 wavebands from 350 to 2500 nm (1.0 nm bandwidth) and a field of view of 15°. The hyperspectral measurements were an averaged response for an area equal to 12.25 cm^2.

The complete spectral system consisted of a spectroradiometer, a DC fiber-optic illuminator (Fiber-Lite PL900-A, Dollan-Jenner Industries Inc. MA, USA), a platform, a white frame, and a PC. Reflectance energy was referenced to a pure white standard. The spectroradiometer was recalibrated every 10 minutes. The measurements were taken approximately ten minutes after the slice was cut. Six successive scans were made at the center of each slice at the same location.

4.4.3 Data Pre-processing

Reflectance values were calculated and for each sample, an average value was calculated from the scans taken from 6 successive scans at the center of sample. Visual examination of reflectance spectra showed consistent noise in the region between 350 to 399 nm as well as from 1851 to 2500 nm. As a consequence, these regions were excluded from analysis. Thus, there were 1450 reflectance values between 400 to 1850 nm inclusive. To facilitate computations, reduce spectral noise, and reduce collinearity, the dataset was reduced by averaging groups of ten consecutive wavelengths; the dataset was then reduced to 145 wavebands per sample.

4.4.4 Data Analysis

Canonical Discriminant Analysis was used to determine the possibility of using the hyperspectral data collected for pork meat quality classification. Once the results showed the potential of the data for classification purposes, predictive models were generated using four different techniques: Stepwise Regression and Discriminant Analysis (DA), k-Nearest Neighbors, Decision Tree, and Artificial Neural Networks.

Stepwise approach (STEPDISC procedure) was employed to identify the most important wavebands for discrimination among various classes of pork meat. Next, Discriminant Analysis (DISCRIM procedure) was used to evaluate the usefulness of the selected wavebands in classifying samples into four quality classes. DA, CDA, and Stepwise Regression were performed via SAS® 9.1 (SAS Institute Inc., Cary, NC, USA) statistical software package. The spectral dataset was used to generate and validate DTs and k-NNs models using Ghostminer® 3.0 (FQS, Fujitsu Kyushu System Engineering, Poland) software, an advanced data-mining tool. ANNs were developed with Clementine® 8.5 (SPSS Inc., Chicago, IL, USA) data mining workbench.

Models were developed to identify four classes (RFN, RSE, PFN, and PSE), and then cross-validated. Once the best method for pork meat quality classification was determined, it was investigated in more detail to see if classification accuracy could be increased further.

4.4.5 Classification Methods

The classification methods used in this study are described below. Since CDA was used first to visualize the class-wise distribution and to determine if hyperspectral data collected in this study could be used for classification purposes, this method is also described briefly.

4.4.5.1 Canonical Discriminant Analysis

Canonical discriminant analysis is a dimension-reduction technique used to provide a representation of various populations in a subspace of smaller dimensions

(Khattree and Naik, 2000). Thus, CDA creates new variables by taking linear combinations of the original variables (Johnson, 1998). The canonical variables contain all the useful information that can be extracted from the set of original variables. From a large number of possibly correlated characteristics on which measurements are taken, CDA tries to obtain only a few new variables that can help describe the differences between various populations (Khattree and Naik, 2000). The new variables obtained are named canonical variables (See Johnson, 1998, and Khattree and Naik, 2000 for a more detailed review on the technique).

4.4.5.2 Stepwise Regression and Discriminant Analysis

The STEPDISC procedure uses a stepwise approach for variable selection: a combination of the forward selection and the backward elimination procedure. The stepwise approach starts by selecting the single best discriminating variable and adds new variables in stepwise manner. At each step of the process, a statistical F-test is performed and the variable that is found to be the most discriminative one is included. The discriminant power of all the variables is evaluated and before including a new variable, it is made sure that all the variables, previously chosen, remain significant. If at this stage, any of the variables previously selected are no longer significant, they are eliminated. The selection process continues until no more remaining variables meet the criteria for inclusion.

Johnson (1998) noted that a small subset of well-chosen variables often allows a better discrimination between treatments than the entire set of variables, and that it is possible that all statistically significant variables chosen in a selection procedure might not be required, or that they may not to be useful for discrimination. So there is no guarantee that the selected variables would represent the best set of variables, particularly when there is high collinearity in the data (Karimi et al., 2005a; Johnson, 1998).

DA is a multivariate technique primarily used to build rules that can classify individuals within a population (Klecka, 1980). When performing a DA, it is necessary to estimate the probabilities of misclassification of new observations. The leave-one-out method consists of developing a model using all data except one, and the model is tested on the one data record, not seen by the model. This process is repeated for all the data records. In a five-fold Cross-validation method, the dataset is divided into five equal sub-sets. Then, a discriminant model is created using four subsets and the model is tested on the one remaining unseen subset that was not included in model building. This process is repeated four more times, and in each case, the subset that is left out of the model construction is changed, so that each one of the five subsets is used for the testing of the model at least once. The accuracy ratios are averaged, and overall classification accuracy is determined. (See Klecka, 1980, Johnson, 1998, and Khattree and Naik, 2000 for more details on DA)

4.4.5.3 k-Nearest Neighbors

k-NN is a distance-based method in which the training dataset is stored so that a new record may be classified simply by comparing it with the most similar records in the training set (Larose, 2005). The k-NN algorithm looks at the similarity of the new data with reference samples. Thus, it remembers all training data and selects most similar vectors at the moment it is asked to make a prediction. Defining the number of nearest neighbors to be considered (k) as well as the distance function for the classification of a new record is of great importance to achieve good performance with the method. For instance, when a k value of 1 is defined, the new variable will be classified according to the 1 sample from the training dataset which is nearest to it. As stated by Wang and Paliwal (2006), if more neighbors are involved in deciding a class, more reliable results could be obtained. (See Larose, 2005 for a more detailed description of the method)

4.4.5.4 Decision Trees

Decision Trees are predictive models represented by a flow-chart-like tree structure, where-in the internal nodes denote tests on an attribute, branches represent an outcome of the test, and leaf nodes symbolize class lables or class distribution (Larose, 2005). DTs are built in a cyclical process by dividing the feature space into two or more parts. The divisions are made in such a way that the best separation of objects belonging to different classes is attained. In every stage of the DTs, construction process, a certain criterion is used to estimate the usefulness of a particular split from the point of view of the final classification tree (Ghostminer, 2004).

The estimation criterion is the selection of an attribute to test at each decision node in the tree. The goal is to select the attribute that is most useful for classifying objects. For instance, the Separatability of Split Value (SSV) for discrete attributes works on the basis that the best split value is the one that separates the largest number of pairs of objects from different classes. As for other criterion used by DTs, the best-first mode (Ghostminer, 2004) works in a way that once the best split is found, and once the resulting subsets contain data belonging to more than one class, just then, the next node that is split is chosen based on the highest value for the split among all that may be generated at a given stage. (See Larose, 2005, and Ghostminer, 2004 for more details on the method).

4.4.5.5 Artificial Neural Networks

ANNs are an interconnected group of processing elements called neurons that work together to create an output function (Larose, 2005). These mathematical functions are able to convert inputs into desired outputs. They are, basically, a simplified model of the way the human brain processes information. In an ANN, the basic units are neurons, and they are typically organized into layers. Artificial Neural Networks are systems trained to learn how to solve complex problems from a training set and they create generalizations that will be able to make estimations and/or predictions from unseen data (Larose, 2005). For the output to be consistent and robust, all the individual neurons involved in the network, need to work as a team. The complexity of the network is determined by the connections between the processing elements and element parameters (Larose, 2005). There are two main options for ANN development: feed forward neural network and recurrent neural network. The feed forward network restricts the network to a single direction of flow and does not allow looping or cycling (Larose, 2005). The models are generally pruned when the modeling process starts with large network and then it removes the weakest units in the hidden and input layers as training proceeds.

In this study, the significance levels for the STEPDISC procedure were set at 0.15 for both variable inclusion and removal. A subset of wavebands from the ones selected in the STEPDISC procedure was chosen based on the order in which the variables are initially entered into the STEPDISC procedure, given the variables selected are in the order of importance (Karimi et al., 2005a). The suitability of the selected wavebands and/or a subset of selected wavebands were examined with discriminant models using the DISCRIM procedures of SAS. For this study, to test the validity of the discriminant model, both the leave-one-out and five-fold cross-validation methods were used.

Cross-validation tests were used to estimate the accuracy of the k-NN training sets. The number of nearest neighbors tested ranged from 1 to 5. However, the *k* value used for subsequent analysis was set to a maximum of five, which was the number that appeared more frequently in the cross-validation tests. The similarity measure was Euclidean distance. To guarantee that all predictors are measured on the same scale, as in all the other models, the dataset was standardized. To test the validity of the k-NN model a five-fold cross-validation was performed. To eliminate any bias in the way randomization is done, a ten-fold cross-validation procedure was used 10 times to ensure development of a well generalized model.

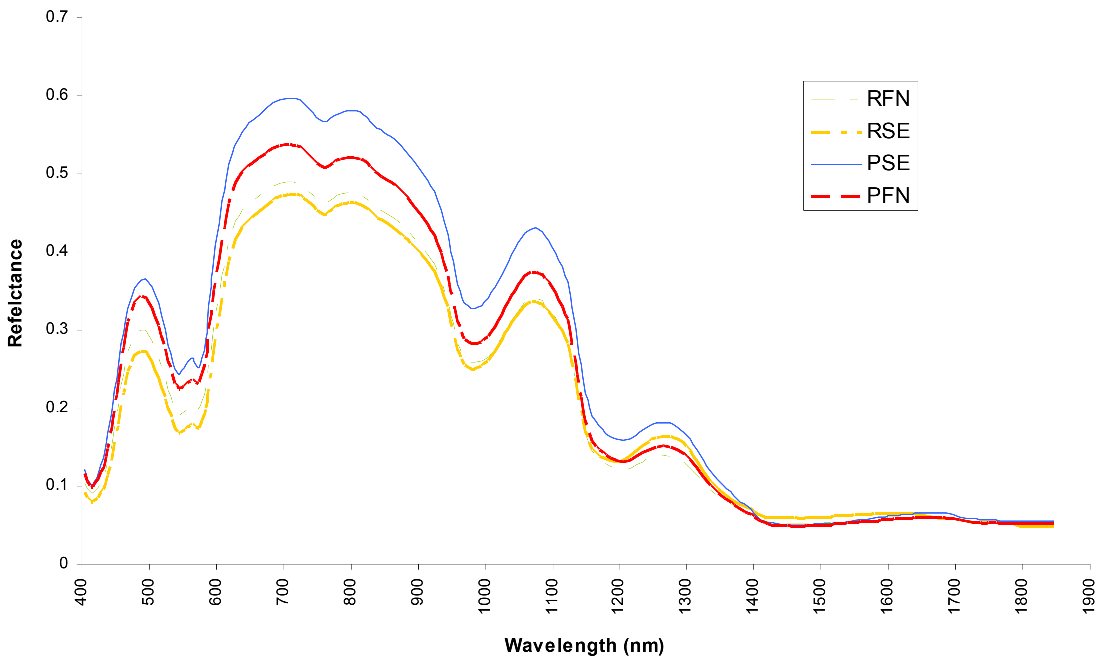
The criterion used in the decision tree algorithm for this study was the SSV. The best-first mode was selected for the configuration of the model. The given leaves count was set to five because it resulted in relatively smaller trees which were able to generalize the model. To test the validity of the DTs model a five-fold cross-validation was performed. A ten-fold cross-validation procedure was used 10 times to ensure development of a well generalized model.

The training method chosen for building the neural network was the feed forward neural network, combined with a prune method. The prune method was selected because it generally yields better results than the other methods available (Ghostminer, 2004). The ANN model was tested using a five-fold cross-validation procedure.

4.5 Results and Discussion

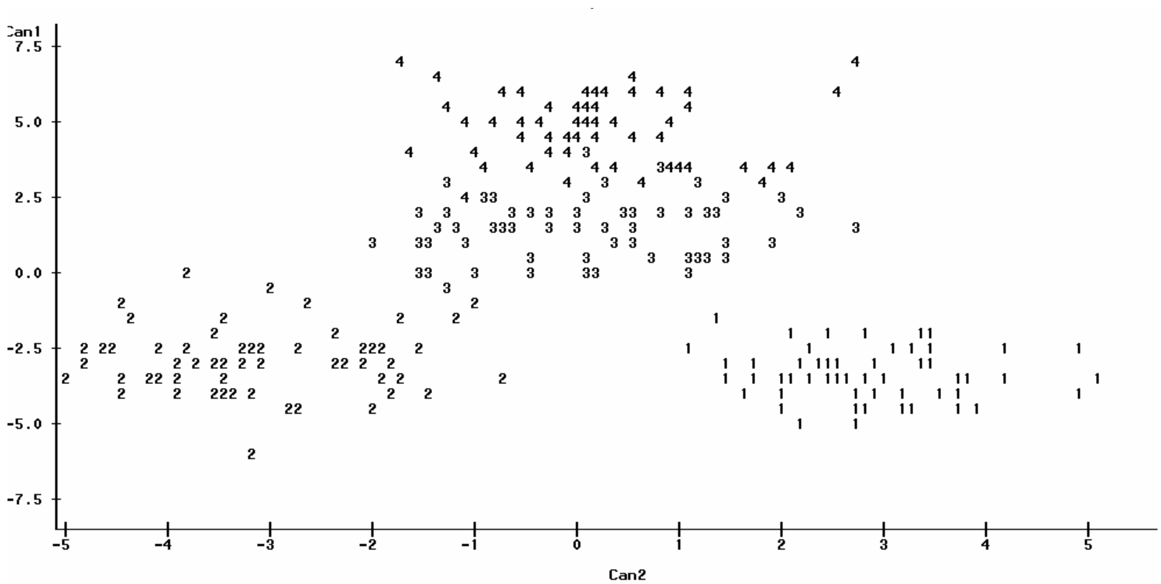
The average spectral response of the four classes of meat is illustrated in Figure 4.1. The figure clearly demonstrates the difference in the reflectance values among the four quality classes. It can be seen that there are regions in the spectra that show more differentiation between the classes of meat. The reflectance of the PFN and PSE classes appears to be higher than those of RFN and RSE classes; this behavior is due to the lighter color of the PSE and PFN classes. In the pale meat samples (PSE and PFN), myoglobin, which is the pigment mainly responsible for the color of the meat, is denatured, thus causing the paleness of the meat, and consequently a lower absorption of light.

Figure 4.1 VIS/NIR reflectance spectra of 24-h post mortem pork meat of four quality classes.



CDA allowed us to visualize the actual distances between the four classes of meat in a reduced dimensional space. The assessment of four classes of meat (RFN, PFN, RSE, and PSE) resulted in a canonical correlation of 0.92. Using two of the three canonical variables, the meat quality was distinguished among four different classes, as shown in Figures 4.2. Results from CDA suggested that the hyperspectral data could be used for classification purposes.

Figure 4.2 Plot of Canonical discriminant analysis of four classes of meat (Can 1*Can2), where-in 1=RFN, 2=RSE, 3=PFN and 4=PSE.



A summary of the results from the STEPDISC and the DISCRIM procedure are presented in Table 4.1. From the set of wavebands selected in the Stepwise regression, a smaller set of wavebands was selected based on the order in which the variables initially entered into the STEPDISC procedure. This was done because, as Johnson (1998) noted, a small subset of well-chosen variables often allows a better discrimination between treatments than the entire set of variables, particularly when there is high collinearity in the data (Karimi et al., 2005a; Johnson, 1998). However, variable reduction could not be achieved at all times. In these cases, the error estimate increased when the variables were removed. As a result, the number of discriminant variables in subset was the same as those selected by the STEPDISC procedure.

Table 4.1 Accuracy rates of testing data for the Cross-validation methods applied to the Discriminant Analysis performed with different subsets of wavebands for the classification of meat into four quality classes.

Cross-validation method	Fold	# of Wavebands selected by STEPDISC	Accuracy rate using all the wavebands selected by STEPDISC in unseen data (%)	# of Wavebands in subset	Accuracy rate using the subset for the prediction in unseen data (%)
Leave-one-out	-	23	80.0	23	80.0
Five-fold Cross-validation	1st	17	73.0	15	75.0
	2nd	22	69.2	7	84.0
	3rd	31	74.4	25	76.5
	4th	21	62.0	19	70.0
	5th	18	75.0	18	75.0
Average			**70.7**		**76.1**

DISCRIM procedure was used to discriminate four meat classes; RFN, PFN, PSE and RSE. Calibration accuracies of both leave-one-out and five-fold cross-validation methods for DA showed in Table 4.1. The leave-one-out cross-validation method resulted in 80% classification accuracy, and in this case, no variable reduction was possible. The five-fold cross-validation accuracies are also given in Table 4.1. An overall classification accuracy of 70% was obtained when using all the variables selected by the STEPDISC procedure. Results improved to 76% when using a subset of wavebands. The waveband reduction resulted in increased classification accuracy almost 8%. Table 4.1 suggests that there is no direct relationship between the number of variables reduced from the original set and the increase in the accuracy rate.

Table 4.2 displays the overall classification accuracies achieved by the four classification methods used in this study. The best classification accuracy was achieved by the DA classifier, combined with the STEPDISC procedure. DA method achieved 76% classification accuracy from unseen data. The second better performance was achieved by the Artificial Neural Networks algorithm with an overall classification accuracy of 66%, followed by k-NN with 62%. The lowest classification accuracy reported was obtained with the DT model.

Table 4.2 Classification accuracies obtained by the classification methods assessed for the evaluation of four classes of meat.

Classification Method	Overall Prediction Accuracy for Unseen Data (%)
Discriminant Analysis	**76.09**
k-NN	**62.42**
Decision Tree	**58.58**
Artificial Neural Networks	**66.25**

Table 4.3 displays a summary of the variables used for the development of the classification rules by DA, ANN, k-NN, and DT techniques for the sorting of meat into four quality classes. Both k-NN and ANN do not perform variable selection and therefore use all 145 variables to create a classification rule. The variables displayed as wavebands selected by the stepwise regression are those which consistently appeared in the five-fold cross-validation method of the DA (Table 4.3).

Table 4.3 Wavelengths selected by different methods in developing classification model.

Classification Method	Selected wavebands
Stepwise procedure *	585, 405, 445, 465, 1205, 565, 575, 1805, 1225, 1685, 685, 1065, 1795, 735, 1155, 845,1215, 1675
k-NN	All 145
DT	555, 1065, 635
ANN	All 145

*** The variables displayed are those found at least in two subsets from the five-fold Cross-validation.**

The better performance of DA over k-NN could be due to the fact that k-NN does not simplify the dataset at all; it provides no concise model of the relationship between the predictors and the response. Consequently, it is not as useful for visualization and knowledge discovery as DA.

The better performance of DA over ANNs could be due to the fact that ANNs could not identify the important wavebands in the dataset. It is also possible that the problem was too complex to solve for the size of the dataset. As compared to the DT method, it is possible that better performance of DA was due to the differences in the variable selection executed by each method. The variable selection performed by the STEPDISC procedure works in such a way that while a variable is selected to be discriminant, the discriminant power of the previously selected variables is evaluated to make sure that the final set of variables selected remains discriminant as a whole. On the contrary, DTs models are not able to eliminate any variable selected during the rule's development, thus, once a variable is selected there is no way back. Decision Tree's variable selection process might be the cause of its poor performance. In fact, forward selection has been found to be one of the best methods to order a set of features by which one best (Jain and Zongker, 1997). Consequently, if forward selection itself can perform so well, combining its potential with backward elimination suggests that the stepwise regression is a very powerful and useful tool for feature selection and that its use in the development of discriminant analysis models is very useful for achieving higher classification accuracies as compared to other classification methods.

The classification matrices for two out of five-fold cross-validation method for ANNs and DA are shown in Table 4.4 and 4.5, respectively. The folds displayed are those which resulted in the highest and lower classification accuracy. The classification matrices for the remaining folds are given in Appendix A. As can be seen, no clear tendency was found as for which class is the one which is more accurately predicted. No trend is seen towards any class for misclassification; however, it appears that RSE class is rarely misclassified into the PSE class as it happens with PFN and RFN classes. The same behavior is seen for the RSE class which was only once misclassified into the PSE class. The fact that the Soft and Exudative (SE) classes are not as frequently misclassified as the Firm and Non-exudative (FN) classes could be explained by the effect of light scattering. For instance, the denaturation of the pigmented protein myoglobin as well as the accumulation of free water on the cut muscle surface tend to increase light reflectance as compared to the FN samples, in which the muscle cells are swollen with retained water and tightly packed together thus absorbing more light rather than reflecting it as it happens with SE samples (Buege, 2001). Results suggest that, since more spectral information is obtained from SE samples, less misclassification appears within these classes.

Table 4.4 Artificial Neural Networks classification matrices from the five-fold cross-validation method between four quality classes of meat

a) Fold with highest classification accuracy

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**7** (64%)	**3**	**0**	**0**	**10**
	RSE	**2**	**7** (70%)	**1**	**1**	**11**
	PFN	**2**	**0**	**9** (75%)	**4**	**15**
	PSE	**0**	**0**	**2**	**10** (67%)	**12**
	Total	**11**	**10**	**12**	**15**	**48**

b) Fold with lowest classification accuracy

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**9** (82%)	**3**	**8**	**0**	**20**
	RSE	**1**	**7** (58%)	**0**	**0**	**8**
	PFN	**1**	**2**	**6** (33%)	**0**	**9**
	PSE	**0**	**0**	**4**	**7** (100%)	**11**
	Total	**11**	**12**	**18**	**7**	**48**

Table 4.5 Discriminant Analysis classification matrices from the five-fold Cross-validation method between four quality classes of meat.

a) Fold with highest classification accuracy

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	10 (100%)	0	0	0	10
	RSE	4	7 (58%)	1	0	12
	PFN	1	0	13 (87%)	1	15
	PSE	0	0	1	10 (91%)	11
	Total	15	7	15	11	48

b) Fold with lowest classification accuracy

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	11 (92%)	0	1	0	10
	RSE	1	12 (86%)	0	1	12
	PFN	3	0	3 (33%)	3	15
	PSE	1	1	2	9 (69%)	11
	Total	15	7	15	11	48

Since DA gave the best results in classifying pork meat quality classes, the method was investigated further. In order to improve the accuracy of the DA method, the meat samples were regrouped into pale (PFN and PSE) and red (RSE and RFN) meat classes.

4.5.1 Discriminating between the Pale and Red meat classes

Similar to the procedure previously followed, a variable reduction was performed by the STEPDISC procedure followed by DA. DA was used to select a smaller subset of variables from the already chosen wavebands by the STEPDISC procedure. A five-fold cross-validation was used for testing the DA model. A summary of the results from the STEPDISC and DISCRIM procedures are shown in Table 4.6. A classification accuracy of about 89% was achieved for both red and pale classes, for unseen data. The classification accuracies range from as low as 86% to about 94%, using only five and ten wavebands respectively as discriminators.

Table 4.6 Accuracy rates of testing data for the cross-validation methods applied to the DA performed with different subsets of wavebands for the classification of meat into pale and red meat classes.

Number of classes	Fold	# of Wavebands selected by STEPDISC	Accuracy rate using all the wavebands selected by STEPDISC in unseen data (%)	# of Wavebands in subset	Accuracy rate using the subset for the prediction in unseen data (%)
2 classes (Pale and Red meat)	1st	11	90.0	10	93.9
	2nd	14	91.5	14	91.5
	3rd	7	88.8	5	86.0
	4th	9	85.8	5	89.7
	5th	8	84.3	4	85.2
Average			**89.0**		**89.3**

The overall increase in the classification accuracy obtained shows that hyperspectral measurements are greatly influenced by the color of the sample. The classification matrices for two out of five-fold-cross-validation method from DA methods are shown in Table 4.7. The results of remaining folds are given in Appendix B. The folds displayed are those which resulted in the highest and lowest classification accuracy. No tendency was found as to which class, pale or red, is more accurately predicted.

Table 4.7 DA classification matrices from the five-fold cross-validation method between pale and red samples.

a) Fold with highest classification accuracy b) Fold with lowest classification accuracy

a)

		Predicted		
		Pale	Red	Total
Actual	Pale	21 (91%)	1	22
	Red	2	24 (96%)	26
	Total	23	25	48

b)

		Predicted		
		Pale	Red	Total
Actual	Pale	16 (80%)	3	19
	Red	4	25 (89%)	29
	Total	20	28	48

The classification accuracy improved when the meat was classified into pale and red meat samples. However, color alone does not fully describe the quality defects inherent in the pork. And above all, the main purpose of the present study was to classify the meat into four quality classes. Thereby, to improve the accuracy of the DA method further, and to be able to discriminate between four pork meat quality classes, meat was split in two sub-classes, Soft and Exudative (SE) and Firm and Non-exudative (FN) given that it was pale or red.

4.5.2 Discriminant Analysis of the samples within the Pale and Red meat classes

Once more, the STEPDISC procedure was used for a variable reduction, followed by the DISCRIM procedure, which was used to evaluate the usefulness of the selected wavebands for discrimination of meat samples. Since the dataset consisted of a smaller number of samples, a three-fold cross-validation was performed for testing the models.

Table 4.8 displays the classification accuracies obtained by DA; when using all the variables selected by the STEPDISC procedure, and when using a smaller subset of variables. There was no substantial increase in the classification accuracies after selecting a smaller subset of variables, however smaller subset can be useful for development of sensors. In the case of pale class, noticeable increase of 8% accuracy was observed with reduced number of wavebands. The classification matrices for the three-fold cross-validation are given in Appendix C.

Table 4.8 Accuracy rate for the cross-validation method applied to DA performed with different subsets of wavebands for the classification of meat into two classes based on Texture and Exudation parameters.

Classes	Fold	# of Wavebands selected by STEPDISC	Accuracy rate using all the wavebands selected by STEPDISC in unseen data (%)	# of Wavebands in subset	Accuracy rate using the subset for the prediction in unseen data (%)
Pale	1st	10	81.8	6	87.0
	2nd	11	88.1	9	95.0
	3rd	14	81.8	13	92.1
Average			**83.9**		**91.3**
Red	1st	7	77.5	7	80.3
	2nd	4	81.0	3	81.0
	3rd	6	89.1	5	90.5
Average			**82.5**		**83.9**

DA was able to discriminate SE from FN samples, within the pale meat, with an overall classification accuracy of about 91% on unseen data. As for the discrimination within the red meat samples, an accuracy of about 84% was achieved. Results seem to suggest that the overall classification accuracy was increased by regrouping the samples into pale and red classes, and further more into SE and FN. However, adding up the classification accuracies obtained through out the analyses did not result in an increase in the initial classification accuracy achieved for the discrimination of samples into four quality classes. The higher classification accuracies achieved when samples were regrouped into pale and red classes was expected, the same as it would be expected that a quality grader classifies more accurately meat samples according to their paleness or redness, rather than classifying into four quality classes. Overall, DA was able to classify fresh pork meat samples into four quality classes using hyperspectral observations with 76% classification accuracy on unseen data.

4.6 Conclusions

In this study, classification models were developed using hyperspectral observations from both visible and near infrared region for the classification of fresh pork meat samples into four quality classes. Classification accuracies from k-NN, DTs, DA, and ANNs models were compared. Overall, DA showed the best performance for the sorting of meat into four quality classes. The combination of Stepwise Regression and Discriminant Analysis resulted in an overall classification accuracy of 76% on unseen data. Results suggested the possibility to separate red meat samples from the pale class with an accuracy as high as 89% by DA.

The results show the potential of using DA to develop predictive models for pork meat quality classification from hyperspectral data. The results obtained suggest the possibility of developing a on-line adaptation system for meat quality grading.

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PREFACE TO CHAPTER 5

The better performance of the Discriminant Analysis method over ANNs, k-NN, and DTs methods for the classification of fresh pork meat samples into four quality classes using hyperspectral observations from both visible and near infrared region was described in Chapter 4.

In this chapter, hyperspectral observations from both visible and near infrared region were measured at five different locations along the meat loin. Fresh pork loin samples belonging to different quality classes (RFN, RSE, PSE, and PFN), collected in April 2006, were assessed. Stepwise regression and Discriminant Analysis were performed to evaluate the utility of hyperspectral data in pork industry.

Research papers based on the chapter:

Monroy, P. M., Prasher, S. O., Ngadi, M. O., and Patel, R. 2007. Importance of the place of measurement in pork meat quality classification from hyperspectral data. *Trans. ASAE*. (Manuscript based on this chapter is under preparation)

CHAPTER 5

IMPORTANCE OF THE LOCATION OF MEASUREMENT IN PORK MEAT QUALITY CLASSIFICATION FROM HYPERSPECTRAL DATA

5.1 Abstract

VIS/NIRS has shown a great potential for the evaluation of meat quality. Various models have been developed for the prediction of pork quality attributes obtaining good results; however, there is no clear relationship between quality attributes as to classify pork meat into quality classes (RFN, DFD, PSE, PFN, and RSE), based on color, and based on texture/exudation. Therefore a study was undertaken to investigate the utility of hyperspectral data in pork industry. Samples of pork loin from four quality classes of meat were assessed. To evaluate the industrial applicability of visible/near infrared spectroscopy as an accurate technique for pork quality prediction, hyperspectral reflectance at wavelengths ranging from 350 to 2500 nm with a resolution of 1 nm was measured in five different locations along the meat loin. Stepwise regression analysis was used to select the most significant wavebands for meat classification in each location assessed. A discriminant analysis was performed to investigate the ability of the selected wavebands to classify pork meat samples into different categories. High classification accuracies were achieved for the classification of meat in different locations. The results highlighted the potential use of hyperspectral analysis in pork meat classification in an on-line process.

5.2 Introduction

Pork meat quality is mainly described by the combination of anomalies of three quality attributes, color, texture, and exudation. On this basis, five pork meat quality classes have been identified (NPB, 1999; van Laack et al., 1994; Joo et al., 1995). Good quality pork is described as reddish-pink, firm and non-exudative; the common designation of this pork is RFN. The second group includes the pork that is extremely soft, poor in both color and water holding properties; it is classified as pale, soft, and exudative (PSE). The third class, DFD, is dark, firm and dry as the acronym suggests. The fourth class (RSE) refers to red, soft and exudative meat, which has a normal reddish-pink color, but a soft texture and low water holding capacity. The fifth class of meat reported in the literature, is known as PFN (van Laack et al., 1994); pale, firm and non-exudative meat, having textural and exudation desired characteristics but poor color properties.

The potential use of Visible and Near Infrared Spectroscopy (VIS/NIRS) in the assessment of meat quality has been studied. The advantages of this technique over subjective evaluation, laboratory tests, and traditional methods have increased the interest in spectral measurements as means of quality assessment. Diverse meat quality traits have been predicted from spectral observations (Chen and Marks, 1998; Forrest et al., 2000; Geesink et al., 2003; Park et al., 2001; Prieto et al., 2006; Savenije et al, 2006; Liu et al., 2000; Liu et al., 2003; Andres, et al., 2006; Barlocco et al., 2006; Xing et al., 2007). Results from various studies focused on the prediction of quality parameters of pork meat as a tool for the classification of meat class are inconstant, in fact, the prediction of certain quality parameters such as, water-holding capacity, color, shear force, pH, and intramuscular fat, have generally reported poor to moderate accuracies. As stated by Warriss et al. (2006), the relationships between ph, color, and water-holding capacity are complex and non-linear, and thus considering these isolated parameters to classify meat might not be accurate. To our knowledge, few studies have aimed to predict meat class as a whole (Qiao et al., 2006; Xing et al., 2007).

The meat industry faces a constant need of an objective technique to predict meat quality. Even though VIS/NIRS has shown its potential as accurate, rapid and non-destructive technique for meat evaluation, the ideal conditions for its use in practical applications is still limited. Shackelford et al. (2004) developed an optimal protocol for the use of VIS/NIRS in meat quality assessment. Results were compared for different experimental conditions; the optimal number of spectral observations per samples was defined, as well as the effect of blooming and differences due to the use of different equipments were evaluated. Olsen et al. (2007) focused on the study of the repeatability and variation caused by the scanning conditions in on-line evaluation of pig carcass. The results from this study described the sources of variation responsible for the different results obtained in the determination of fat. Both studies aforementioned converged in the importance of examining the applicability of NIRS in the industry. As stated by O'Farrell et al. (2005) the principal aim of the sensor systems developed for quality control in the food industry is that they are on-line, and unobtrusive to the product; however, the goal is not always achieved. The great potential of VIS/NIRS would be of no use if the technique cannot be applied in an on-line production.

NIRS methods have very good performance potential and among their advantages; rapidity of measurement, versatility, and they give a multi-component measurement which accounts information about fat, moisture, protein, and other quality traits. However, for NIRS methods, calibration is absolutely critical and if there is any change in the sample material that is out from the range of properties of the samples used for calibration, recalibration is needed. Once the calibration of the modes is made, it is important to consider that detectors must be precise, robust and fast enough to stand up to industrial conditions, in other words, practical for fast-paced production or processing environment.

All studies done so far, have considered meat to be homogeneous. This might not be the case, since meat is a highly variable and unpredictable material. For instance, marbling of the meat causes samples to be more heterogeneous. To the best of our knowledge, limited information on the effect of the place of the spectral measurement along the sample is available. Forrest et al. (2000) repositioned the measuring probe on three different locations between the 4^{th} and 5^{th} lumbar vertebrate of the pig carcass, in order to obtain a large volume of spectral information, to average out possible heterogeneities. They found great variation in spectral values at different locations. Therefore, prediction of water-holding capacity and drip loss in fresh pork were developed without relocation of the measuring probe. Thus it is important to know the effect of measuring point location on the hyperspectral response of meat. In our study, the main objective was to evaluate the impact of the place of measurement on the classification accuracy of pork meat quality from hyperspectral observations.

5.3 Materials and Methods

5.3.1 Sample Preparation

A total of forty fresh pork loins (24-h post-mortem) around the 11th rib were obtained from a local cutting house (Olymel S.E.C./L.P., Quebec, Canada). The samples were selected from four different quality classes by the meat inspector, before being transported to McGill University at a controlled temperature. The samples were collected in April 2006.

5.3.2 Spectral Data Collection

The pork loins were placed under the sensor for the spectral measurements one at a time, as shown in Figure 5.1. On each loin, five different location sites were scanned, and six measurements were made for each location. The location sites were approximately the same for every loin assessed starting from the left portion of the chunk (wider loin area) as shown in figure 5.1.

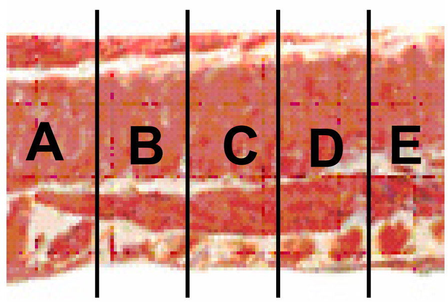

Figure 5.1 Measurement location sites along the chunk

The complete spectral system, as shown in Figure 5.2, consisted of a spectroradiometer, a DC fiber-optic illuminator (Fiber-Lite PL900-A, Dollan-Jenner Industries Inc, MA, USA) which was used as a light source, a platform, a white frame (surrounding structure used to distribute uniformly the light directed to the sample), and a PC. The spectroradiometer makes one full scan of the wavelength region in 1s approximately. The samples were not modified in any way before measurements.

Figure 5.2 Spectroradiometer and experimental setup.

Hyperspectral reflectance was measured using a spectroradiometer (Field Spec® Pro, Analytical Spectral Devices, Boulder, Inc, Colorado) in 2151 wavebands, at 1.0 nm increments of wavelength between 350 to 2500 nm. The spectroradiometer had a field of view of 15°, and it was held 15 cm above the sample to obtain an average reflectance signature for an area of 12.25cm^2.

5.4 Data Analysis

Spectral data were analyzed using SAS® 9.1 (SAS Institute Inc., Cary, NC, USA) statistical software package. The data collected from every location was analyzed separately, thus five datasets were analyzed. The STEPDISC procedure in SAS was used to identify the most important wavebands and the DISCRIM procedure was used to evaluate the usefulness of the selected wavebands in classifying samples into different meat categories.

The STEPDISC procedure performs a multivariate discriminant analysis, combining forward selection and backward elimination methods. The forward selection is used for the inclusion of variables, and the backward elimination is employed for the exclusion of variables which are no longer significant in the model, based on the significance level for inclusion of variables in an F test. From this procedure, the most significant variables of every dataset, suitable for discrimination the discrimination of quality classes, were selected.

For every set of selected wavebands, a smaller subset of variables was chosen. The reduction of variables was made based on the order in which the variables initially entered into the STEPDISC procedure. The variables that were selected first are presumed to be more important than those that are selected later. The suitability of the selected wavelengths and of the subset of selected wavebands was examined with discriminant models using the DISCRIM procedure.

The final models were evaluated by using the leave-one-out cross-validation method. In the leave-one-out method, all data, except one, are used to develop the model, and the model is tested on that one data record, not seen by the model during model development.

5.5 Results and Discussion

Due to extreme spectral noise, reflectance measurements from 350 to 399 nm as well as from 1851 to 2500 nm were not included in the analysis of any dataset. In order to evaluate if every scan could be used as an individual measurement for meat class prediction, every scan was considered (as opposed to average of six measurements used in previous work). Due to the high collinearity of the data and in order to reduce the dataset, spectral data was averaged every 10 nm, and so the bandwidth was expressed as 10 nm, instead of the initial 1 nm used in the measurement. Thus our dataset consisted of 240 observations and 145 variables. The significance levels for the STEPDISC procedure were both set at 0.15, for the inclusion and removal of variables.

A summary of the results from the STEPDISC procedure combined with a variable reduction, as well as the classification accuracies obtained in the discriminant analysis for every location site, are shown in Table 1. From the set of wavebands selected in the Stepwise regression, a substantially smaller set of wavebands was selected, based on the order in which the variables initially entered into the STEPDISC procedure. This was done for two reasons, 1) as Johnson (1998) noted, a small subset of well-chosen variables often allows a better discrimination between treatments than the entire set of variables and 2) the variables selected by the STEPDISC procedure were excessive if we consider that a smaller subset can be useful for development of on-line sensors. The classification accuracies slightly decreased when reducing the number of wavebands used for the development of the model. The slight decrease was preferable to an increased number of wavebands for two reasons; 1) the final classification accuracy was sufficiently high, and 2) for practical VIS/NIR applications the use of fewer wavebands is preferable as it can lead to faster sensor systems.

Table 5.1 Subset of selected wavebands by the Stepwise operation for every location

Location site	Number of wavebands in initial Subset	Accuracy rate using all wavebands selected by STEPDISC (%)	Wavebands selected for the subset	Number of wavebands in final subset	Accuracy rate using the subset for the prediction in unseen data (%)
A	61	100	605, 1485, 1445, 525, 1715, 985, 1005, 965, 975, 535	10	**99.98**
B	71	100	955, 1745, 925, 865, 965, 875, 1115, 805, 785, 945, 835	11	**99.98**
C	58	100	635, 865, 815, 965, 755, 735, 855, 1035, 1045, 885, 805	11	**99.98**
D	71	100	615, 535, 1495, 1445, 475, 565, 605, 445, 965, 1035, 1025, 1705, 1155	13	**99.6**
E	73	100	615, 1485, 535, 475, 565, 1455, 605, 455, 1775, 525, 1625	12	**99.95**

It can be seen from Table 5.1, that some of the wavebands selected were found in the spectral region between 540 and 580 nm which is related to respiratory pigments bands. Various studies have identified spectral bands similar to the ones displayed in table 5.1, for their use in the prediction of quality parameters, quality class, or as different component overtones (Park et al., 2001; Barlocco et al., 2006; Xing et al., 2007; Moss et al., 1999; Qiao et al., 2006; Forrest et al., 2000).

The classification matrices for the leave-one-out cross-validation methods are shown in Table 5.2. From this table, it can be seen that PSE class seems more likely to be misclassified either into PFN or RFN classes, for every location. RSE class was only once misclassified into RFN samples. Thus overall, RSE seems to be the class most accurately predicted.

Table 5.2 Classification matrix of the hold-out cross-validation method

a) From data collected in the location site A.

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**60** (100%)	**0**	**0**	**0**	**60**
	RSE	**0**	**60** (100%)	**0**	**0**	**60**
	PFN	**0**	**0**	**60** (100%)	**0**	**60**
	PSE	**0**	**0**	**3**	**57** (96%)	**60**
	Total	**60**	**60**	**63**	**57**	**240**

b) From data collected in the location site B.

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**60** (100%)	**0**	**0**	**0**	**60**
	RSE	**0**	**60** (100%)	**0**	**0**	**60**
	PFN	**0**	**0**	**58** (97%)	**2**	**60**
	PSE	**0**	**1**	**0**	**59** (98%)	**60**
	Total	**60**	**61**	**58**	**61**	**240**

c) From data collected in the location site C.

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	**60** (100%)	0	0	0	60
	RSE	0	**60** (100%)	0	0	60
	PFN	0	0	**59** (98%)	1	60
	PSE	0	0	3	**57** (96%)	60
	Total	60	60	62	58	240

d) From data collected in the location site D.

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	**60** (100%)	0	0	0	60
	RSE	0	**60** (100%)	0	0	60
	PFN	0	0	**59** (98%)	1	60
	PSE	0	0	0	**60** (100%)	60
	Total	60	60	59	61	240

e) From data collected in the location site E.

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	**58** (97%)	0	0	2	60
	RSE	1	**59** (98%)	0	0	60
	PFN	0	0	**60** (100%)	0	60
	PSE	4	0	3	**53** (88%)	60
	Total	63	59	63	55	240

Results suggest that it is possible to vary the location of the spectral measurement along the pork loin, and still, achieve good prediction accuracy. This study indicates that VIS/NIRS can be used in an on-line sensor system, and that it would not be necessary to average successive scans while trying to predict meat quality. Meat quality could be predicted with an accuracy of almost 100% with single scans at a few locations of the loin.

5.6 Conclusions

In this study, the applicability of hyperspectral observations to classify pork meat into four quality classes was investigated. The impact of the place of spectral measurement along the loin was evaluated. Classification models were developed using the stepwise and discriminant analysis method for five different location sites along the chunk of meat. The classification accuracies obtained by the leave-one-out cross-validation method were as high as 99%. Results suggest the possibility of using this study for the development of an on-line sensor system.

5.7 Acknowledgments

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CHAPTER 6
SUMMARY AND CONCLUSIONS

6.1 Summary

This study investigated the applicability of hyperspectral observations from both visible and near infrared region for classifying pork meat into four quality classes: RFN, RSE, PFN, and PSE. In addition, four classification methods, (DA, k-NN, DTs, and ANNs), were tested. Finally, the potential for the industrial applicability of the technique was evaluated by measuring hyperspectral reflectance at five different location sites along the meat sample.

The objectives were met by collecting a total of 280 samples of fresh pork loin samples in a span of 6 months. Samples were regrouped into pale and red classes. A further split of samples into SE and FN within the pale and red classes was also evaluated.

6.2 Conclusions

The conclusions reached in this study are presented in the order in which they were presented in the thesis.

(1) Hyperspectral observations from both visible and near infrared region were analyzed for their applicability in classifying pork meat into four quality classes. Sixty samples per class (PFN, RFN, PSE and RSE) were collected. The ability of a stepwise approach in the selection of important wavebands was examined. Classification models were developed using the stepwise and discriminant analysis methods. Two different cross-validation procedures were used to evaluate the predictive ability of the model. For the leave-one-out method, a classification accuracy of 80% was obtained, while with the five-fold cross-validation method; an accuracy of 79% was obtained for the unseen data. The study revealed that discriminant functions based on a restricted set of wavebands can show a better performance and suggests the possibility of its use in the development of a faster on-line sensor system. Our results clearly show the potential of using hyper-spectral observations in pork meat quality classification.

(2) The performance of four classification methods in the analysis of hyperspectral data for pork meat quality class evaluation was compared. Artificial Neural Networks, Decision Trees, k-Nearest Neighbors, and multivariate Discriminant Analysis models were trained and tested using a hyperspectral dataset of 240 spectral observations within the VIS/NIR region. For the sorting of meat into four quality classes, DA resulted in an overall classification accuracy of 76% on unseen data. Since DA gave the best results, this method was investigated further. Aiming to improve the classification accuracy of the DA method, the samples were regrouped into pale and red meat classes. The data analysis suggested the possibility of separating pale meat from red meat samples. The classification accuracy attained for the discrimination of red and pale meat samples by DA increased positively to 89%. Samples were then regrouped into Soft and Exudative (SE) or Firm and Non-exudative (FN), given that they were Pale or Red. Regrouping of samples resulted in higher classification accuracies; however, the classification accuracy of DA method could not be increased from regrouping the samples, and an overall classification accuracy of 76% was attained for the classification of pork meat into four quality classes.

(3) Aiming to develop an automated and reliable technique for pork meat quality class evaluation, the industrial applicability of the proposed technique was assessed. Reflectance measurements were obtained from fresh pork samples from different quality classes, at five different location sites along the loin. The importance of the place of spectral measurement along the loin was investigated. A Stepwise approach was used for the selection of important wavebands. Further selection of wavebands resulted in smaller subset of discriminant wavebands which reinforced its potential use in the development of sensors for industrial applications. Discriminant Analysis was used to assess the usefulness of the selected wavebands and to develop predictive models for the classification of meat samples. The classification accuracies obtained by the leave-one-out cross-validation method were as high as 99%. Results suggest the possibility of using this study for the development of an on-line adaptation system. Based on the results presented, further research work is recommended to move forward to standardization of the technique and in future, for the development of a sensor that can be used in industrial applications for meat quality evaluation.

APPENDIX A

Remaining classification matrices from the five-fold cross-validation by Discriminant Analysis for the sorting of meat into four quality classes.

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	15 (75%)	1	3	1	20
	RSE	0	7 (88%)	0	1	8
	PFN	3	1	5 (56%)	0	9
	PSE	0	0	2	9 (81%)	11
	Total	18	9	10	11	48

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	7 (70%)	2	1	0	10
	RSE	2	8 (73%)	1	0	11
	PFN	2	0	12 (80%)	1	15
	PSE	0	0	2	10 (83%)	12
	Total	11	10	16	11	48

		Predicted				
		RFN	RSE	PFN	PSE	Total
Actual	RFN	6 (75%)	0	2	0	8
	RSE	2	12 (80%)	1	0	15
	PFN	2	0	10 (83%)	0	12
	PSE	2	0	3	8 (62%)	13
	Total	12	12	16	8	48

Remaining classification matrices from the five-fold Cross-validation by Artificial Neural Network for the sorting of meat into four quality classes.

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**5** (50%)	**4**	**1**	**0**	**10**
	RSE	**5**	**7** (58%)	**0**	**0**	**12**
	PFN	**1**	**1**	**8** (53%)	**5**	**15**
	PSE	**0**	**0**	**4**	**7** (64%)	**11**
	Total	**11**	**12**	**9**	**16**	**48**

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**11** (92%)	**1**	**0**	**0**	**12**
	RSE	**2**	**11** (79%)	**1**	**0**	**14**
	PFN	**4**	**0**	**4** (44%)	**1**	**9**
	PSE	**2**	**1**	**3**	**7** (54%)	**13**
	Total	**19**	**13**	**8**	**8**	**48**

		Predicted				
		RFN	**RSE**	**PFN**	**PSE**	**Total**
Actual	**RFN**	**4** (50%)	**1**	**3**	**0**	**8**
	RSE	**1**	**13** (87%)	**1**	**0**	**15**
	PFN	**2**	**1**	**9** (75%)	**0**	**12**
	PSE	**1**	**0**	**5**	**7** (54%)	**13**
	Total	**8**	**15**	**18**	**7**	**48**

APPENDIX B

Remaining classification matrices from the five-fold cross-validation by Discriminant Analysis for the discrimination between pale and red classes.

		Predicted		
		Pale	**Red**	**Total**
Actual	**Pale**	**24** (96%)	**1**	**25**
	Red	**3**	**20** (87%)	**23**
	Total	**27**	**21**	**48**

		Predicted		
		Pale	**Red**	**Total**
Actual	**Pale**	**18** (72%)	**7**	**25**
	Red	**0**	**23** (100%)	**23**
	Total	**18**	**30**	**48**

		Predicted		
		Pale	**Red**	**Total**
Actual	**Pale**	**23** (79%)	**6**	**29**
	Red	**0**	**19** (100%)	**19**
	Total	**23**	**25**	**48**

APPENDIX C

Classification matrices from the three-fold Cross-validation method of DA for the classification of Pale meat into SE and FN classes:

			Predicted		
			PALE MEAT		
			SE	FN	Total
Actual	PALE MEAT	SE	17 (94%)	1	18
		FN	1	21 (96%)	22
		Total	18	22	40

			Predicted		
			PALE MEAT		
			SE	FN	Total
Actual	PALE MEAT	SE	17 (74%)	6	23
		FN	0	17 (100%)	17
		Total	17	23	40

			Predicted		
			PALE MEAT		
			SE	FN	Total
Actual	PALE MEAT	SE	17 (74%)	6	23
		FN	0	17 (100%)	17
		Total	17	23	40

Classification matrices from the three-fold Cross-validation method of DA for the classification of Red meat into: SE and FN classes:

			Predicted		
			RED MEAT		
			SE	FN	Total
Actual	RED MEAT	SE	16 (94%)	1	17
		FN	3	20 (87%)	23
		Total	19	21	40

			Predicted		
			RED MEAT		
			SE	FN	Total
Actual	RED MEAT	SE	17 (77%)	5	22
		FN	3	15 (83%)	18
		Total	20	20	40

			Predicted		
			RED MEAT		
			SE	**FN**	**Total**
Actual	**RED MEAT**	**SE**	**13** (62%)	**8**	**21**
		FN	**0**	**19** (100%)	**19**
		Total	**13**	**27**	**40**