SESSION 5

MEAT QUALITY

5-L1

ON-LINE EVALUATION OF MEAT QUALITY USING PROBES AND ROBOTS

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Abstract

Robotic probes can navigate using ultrasonics. But, without navigation or with a high probe resolution, incoming data must be checked for the type of tissue from which they originate. A method for this using a Boolean matrix is described. New methods also are described for exploiting sample heterogeneity, measuring meat softness by vacuum application of fibre optics, combining electrical, optical and rheological probes, using polarised light, and for multichannel probes. It is concluded that vertical integration within the meat industry is a prerequisite for exploiting meat-quality probes.

Introduction

To be applicable in a practical situation, the on-line evaluation of meat quality must be fast enough to keep pace with processing line speeds in major plants, and must be based on objective measurements (Swatland, 1995). Measurements must be non-contaminating and relatively non-destructive. On-line evaluation of meat quality could improve the feed-back of information and financial incentives to producers of high quality carcasses, could improve meat grading to allow reliable quality control procedures, and could enhance profitability by allowing niche marketing and least-cost optimisation of meat processing. At present, meat quality evaluation on-line is at the threshold of being useful: but we still have a long way to go. This presentation of the most recent research findings will examine some current problems and possibilities for future development.

Range of methods

There are numerous methods for on-line evaluation of meat quality, ranging from widely used methods for predicting meat yield from fat depth, to various experimental methods at the prototype stage of development. Some of the methods are listed in Table 1. Many will be familiar to the audience and need no further introduction.

Table 1. Some on-line methods for evaluating meat quality

Property	Methods	Quality attributes
Subcutaneous fat depth	Diode probes, Ultrasonics	Predict meat yield
Acidity, pH	Glass electrode, Solid-state electrode	Paleness-darkness, fluid exudation, softness
Electrical impedance	2 or 4 electrodes, conductivity, capacitance, phase angle	Paleness-darkness, fluid exudation, softness
Muscle internal reflectance	Fibre-optic spectrophotometry	Myoglobin concentration, paleness-darkness
Fat internal reflectance	Fibre-optic spectrophotometry	Carotene yellowness, short-chain translucency
Connective tissue	Depth probe for ultraviolet fluorescence	Amount and distribution of collagen and elastin, pyridinoline cross-linking of collagen
Rheology	Electromechanical probes	Toughness
Surface appearance	Video image analysis	Carcass shape (muscularity), rib-eye area and marbling, subcutaneous fat colour
Near infrared reflectance	Fibre-optic and surface reflectometers	Triglyceride content, collagen content
Emulsification in secondary processing	Electrical impedance, light scattering probe	Emulsifying capacity or state

Navigation, integration and recognition

Hand-held diode probes have been very successful in fat depth measurement for predicting the meat yield of pork. With the high cost of labour and the repetitive nature of the task, however, hand-held probes are a prime candidate for automation. But automation creates new problems. Obviously, cost is a factor when designing an automated probe. A smart, navigating robot is considerably more expensive and complex than a non-navigating machine. Figure 1 shows a navigating robot developed by my colleague, Professor Andrew Goldenberg at the University of Toronto Robotics and Automation laboratory. It navigates ultrasonically, using transducers sliding over the pork carcass on water jets, and is able to steer itself to particular locations relative to the ribcage and split vertebral column. At a particular point, it probes the carcass to make a fat-depth measurement. At which time, meat quality measurements also may be made optically, using optical fibres to assess meat quality in an integrated volume of several cubic centimetres of muscle. Only rarely is the probe likely to stop and measure at an inappropriate location. Thus, with a navigating robot and a measurement made with low spatial resolution (integration through a relatively large volume), there is little need for recognition software to check that the measurement is from an appropriate location.

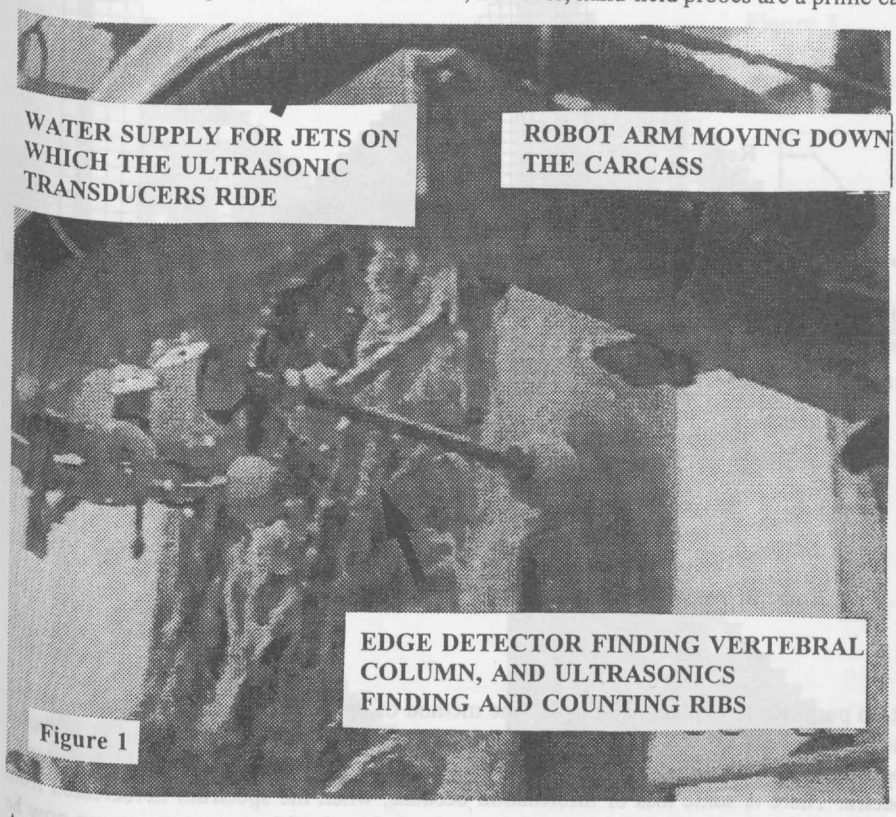


Figure 1

At the other extreme, however, consider a probe operated by a non-navigating robot that simply probes whatever tissue is placed in front of it (hopefully not the human operator). The probe may strike a bone and go nowhere (stopped by a force overload cut-off), or it may got to an inappropriate location, attempting to measure meat quality within a seam of fat or connective tissue. Also, consider what happens if the diameter of the probe is reduced to allow easier penetration of a carcass with a hard, dry rind. Then the optical window in the probe must be reduced as well. This increases the spatial resolution of the probe and decreases the volume of tissue contributing to the integrated measurement. Now even a seam of marbling fat within a muscle at the correct target may yield an inappropriate spectrum for an assessment of meat quality. In other words, if the probe does not navigate, and if the probe diameter is reduced, then it becomes necessary to check that an incoming spectrum is appropriate.

Matrix recognition

Numerous sophisticated methods are available for recognizing images, and a spectrum is really a very simple image, comparable to one raster line of a video image. But commercially available software is expensive and not easily incorporated into a probe system. This problem was solved by using the Boolean interrelationships of the scalars within the vector of the spectrum (Swatland, 1998a).

Consider the spectrum for a blue filter glass in front of white opal glass (Figure 2). Violet to blue light from 400 to 470 nm is more intense than green, yellow, orange and red light from 480 to 700 nm. This spectrum for a number of measurements from wavelength 1 to n was converted to a probability matrix called a **Pmat** and shown on the right of Figure 2. For reflectances from wavelength 1 to n, the **Pmat** is shown as a triangular matrix containing scalars, (n * (n-1)) / 2, to store a comparison of reflectances at each wavelength compared with reflectances at all other wavelengths. For example, column 1 of the blue-filter **Pmat** shown in Figure 2 contains the results of comparing reflectance at wavelength 1 with reflectances at wavelengths 2 to n. As another example, column 2 of the red-filter **Pmat** contains the results for wavelengths 3 to n. Finally, the **Pmat** triangle terminates on the right with comparison of the penultimate with the ultimate wavelength, of wavelength 30 with 31, or 690 with 700 nm in this case. If reflectance at one wavelength is less than reflectance at another wavelength, a value of -1 is assigned to the appropriate position in **Pmat** and illustrated by solid black in Figure 2. Conversely, if reflectance at one wavelength is greater than reflectance at another wavelength, a value of 1 is assigned to the appropriate position in **Pmat**, and this appears as a white area in Figure 2. With numerous decimal places derived from full analogue to digital conversion of the photometric signal, very rarely (if ever) is reflectance at one wavelength exactly equal to reflectance at another wavelength.

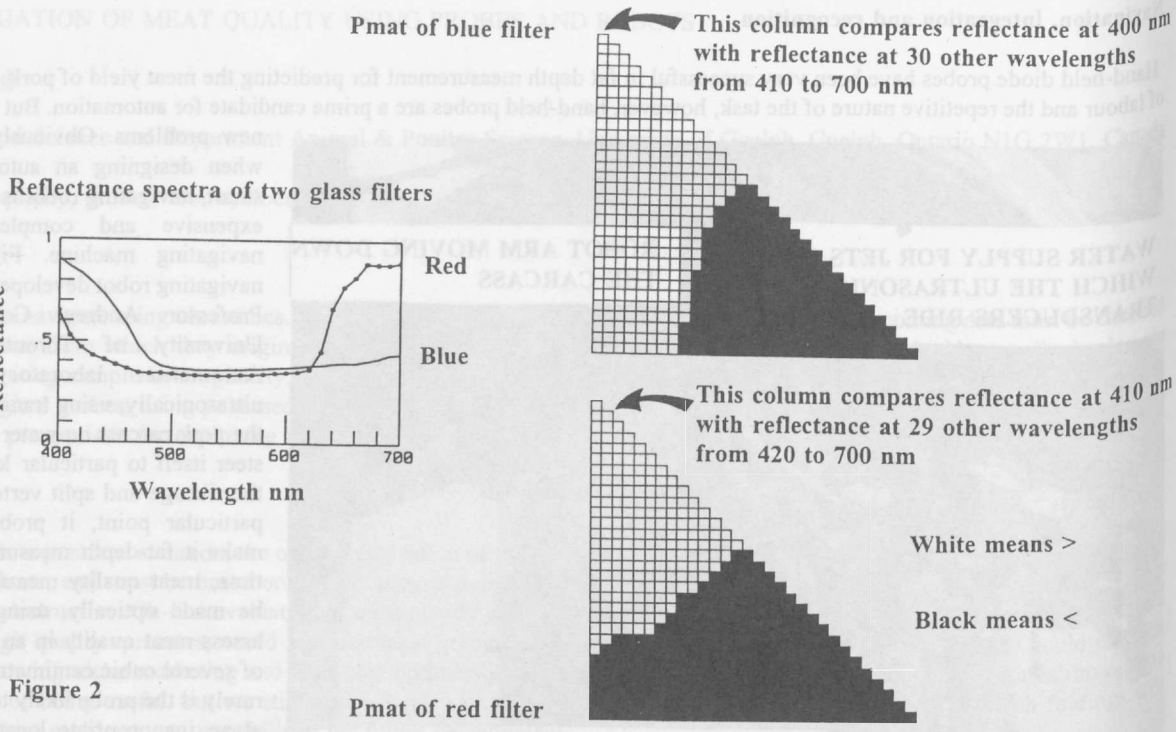


Figure 2

This triangular matrix is used for demonstration purposes to explain and display the method of operation. In practice, the same end result is achieved with a vector. To display the concept for this lecture, a value of +1 is shown by white, while a value of -1 is shown by black. Later on, we will use gray levels between white and black to illustrate intermediate values. Thus, the **Pmats** in Figure 2 are a Boolean representation of the actual spectra. There is some loss of information because, when the spectrum is recreated from the Boolean matrix, there is a loss of grey levels and absolute values. But, a major advantage is gained because spectra can now be easily manipulated. That is, they can be summed, averaged, and compared with other spectra strictly on the basis of the shape of the spectrum - not using absolute values. Sharp-eyed members of the audience may note that reflectance at 670 nm for the red filter is just slightly higher than reflectance at 680 nm, yet there is no corresponding white cell in the bottom right corner of its **Pmat**, which is solid black. This is because the method works best if spectra are smoothed before the Boolean matrix is created. After smoothing, reflectance at 670 was less than at 680 nm.

Having demonstrated the concept, we may now proceed to an application in accepting or rejecting spectra obtained by a probe. The example shown in Figure 3 is for the separation of connective tissue (**CT**) from muscle (**M**) in pork. For each type of tissue, a cumulative probability matrix called a **Cpmat** was trained by adding the **Pmats** of known spectra. The scalars in a **Cpmat** may be called accumulators. Thus, the accumulators in a **Cpmat** become more negative if reflectance at a particular wavelength consistently is less than reflectance at another wavelength, while the accumulators become more positive if reflectance a particular wavelength consistently is higher than reflectance at another wavelength. However, accumulators for comparisons with a random outcome tend towards zero. After a **Cpmat** is trained, the accumulators are divided by the number of spectra used for training. Thus, the maximum range for any accumulator in a completed **Cpmat** is from -1 to 1. In Figure 3, this is illustrated graphically by scaling the grey levels from -1 to +1.

Cpmats from different tissues exhibit many similarities, as may be seen by comparing the **Cpmats** for connective tissue and muscle in Figure 3. Thus, **Cpmats** by themselves do not allow reliable deductions to be made about unknown spectra. But reliability may be greatly increased by subtracting the **Cpmat** of one tissue from the **Cpmat** of another tissue to create a matrix of differences in cumulative probabilities, called a **Dcpmat**. The scalars in a **Dcpmat** may be called weightings. For example, if equivalent accumulators in **Cpmats** for connective tissue and muscle both have a value of 1, then subtraction of one **Cpmat** from the other cancels the weighting of this accumulator (1 - 1 = 0). Thus, features common to both matrices are cancelled and their weightings approach zero, while dissimilar features are enhanced to give stronger weightings as follows: 1 - (-1) = 2, and (-1) - 1 = -2.

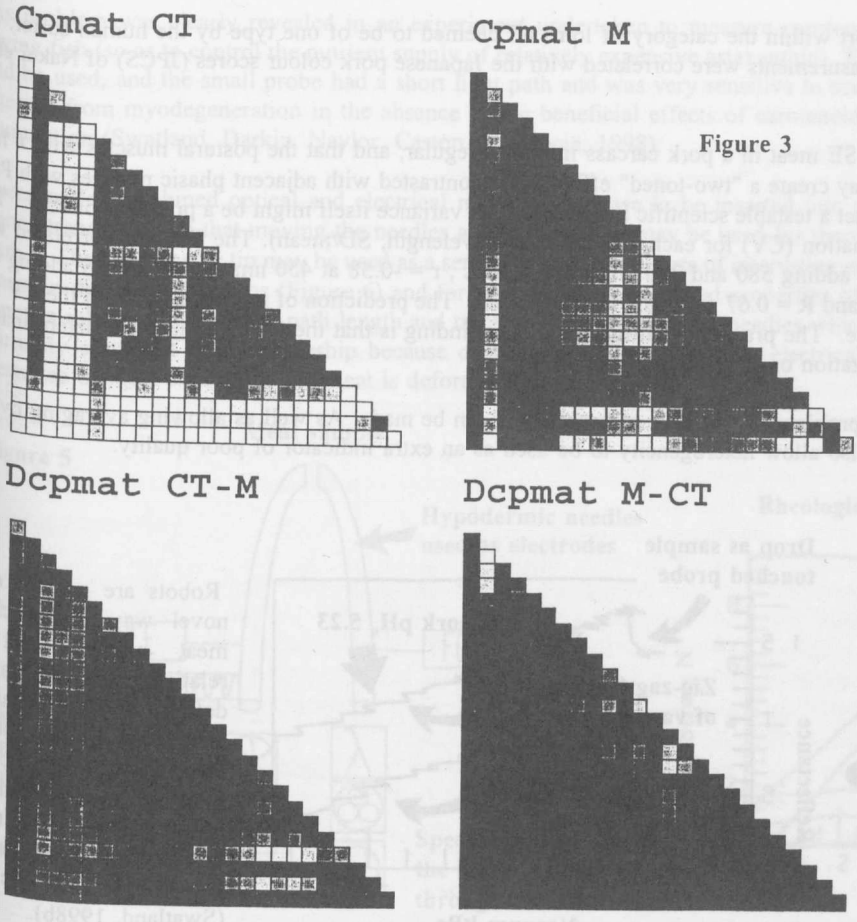


Figure 3

A **Pmat** for a single unknown spectrum collected from a carcass by the robot was evaluated as follows. The **Pmat** of the unknown spectrum was multiplied by the **Dcpmat** for muscle minus connective tissue. The scalars of the **Pmat** were either -1 or 1 (rarely 0). The weightings of the **Dcpmat** ranged from -2 to 2. If the scalar and the weighting were both negative then the product was positive, for example, -1 * -2 = 2. Similarly, if the scalar and the weighting were both positive then the product was positive, for example, 1 * 2 = 2. But the products were negative if the scalar and weighting differed in sign, for example, 1 * -2 = -2. Thus, the sum of **Pmat** scalars multiplied by **Dcpmat** weightings (S_{muscle}) gave a measure of the number and importance of similarities between the unknown **Pmat** and the **Dcpmat**, with non-matching features being subtracted from matching features. This operation was repeated for the inverse case where the **Dcpmat** was derived by subtracting a muscle **Cpmat** from a connective tissue **Cpmat**. Thus, the final probability for an unknown spectrum originating from muscle was S_{muscle} / (S_{muscle} + $S_{non\text{-}muscle}$).

The method gives reasonable but not perfect results when used in a practical application (Swatland, 1998a). Three good examples of white connective tissue and very severe PSE pork were presented to the probe to develop its **Dcpmats**. Then incoming spectra could be sorted with >85% accuracy in a few lines of matrix operations. In other words, this simple example of case-based reasoning can rival the performance of a neural network, which is much more difficult and expensive to incorporate into home-made apparatus and software.

Repeated probing to deal with sample heterogeneity

Variability in meat quality between one location and another within the carcass presents a formidable problem. If meat quality in the whole of the carcass or side is assessed with a measurement at a single site, there is obviously a risk of wrongly rejecting a carcass that has poor meat quality restricted to the probe site, or of wrongly accepting a carcass with overall poor meat quality that happens to have reasonable meat at the probe site. When the probe is launched by a programmable robot, it is possible to repeat the quality measurements until a specified level of certainty is reached regarding the quality of the meat in the whole carcass.

This possibility was investigated in an experiment using 48 pork loins. The robot measured them all repetitively at six sites, moving along the loin at 40 cm per second. For the sake of simplicity, the measurements were very slow, made with a grating monochromator, and taking about 20 seconds at each site. But, in an industrial situation, we could use a photodiode array spectrometer to obtain the spectra almost instantaneously at each site (Swatland, 1998c). Overall, the robotic probe performed about as well as trained sorters in the plant and as well as a laboratory technician with a pH probe measuring ultimate pH.

Table 2. Simple (r) and multiple (R) correlations (P < 0.01) of meat quality traits with predictions made by trained sorters, pH measurements and a robotic probe (from Swatland, Uttaro, Goldenberg and Lu, 1998).

	Sorter	pH	Robotic probe
Fluid loss (bag drip)	r = 0.57	r = -0.61	r = 0.56 (670 nm) R = 0.76 (670, 560 & 540 nm)
Paleness (CIE L*)	r = 0.71	r = -0.74	r = 0.75 (480 nm) R = 0.82 (480, 690 & 520 nm)

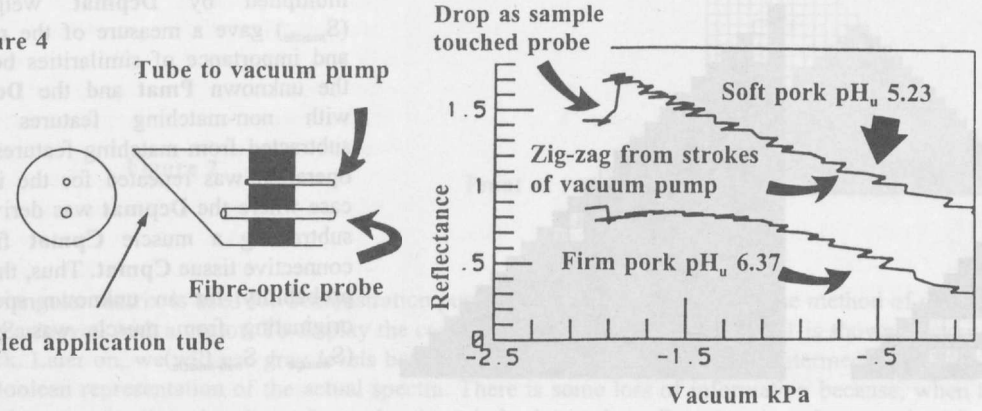
The probe also had a limited capability to sort within the category of loins all deemed to be of one type by the human sorter. For example, within 12 "normal" loins, probe measurements were correlated with the Japanese pork colour scores (JPCS) of Nakai et al. (1975), r = -0.71 ($P < 0.01$ at 700 nm).

It is widely known that the distribution of PSE meat in a pork carcass may be irregular, and that the postural muscles with a high myoglobin content and normal appearance may create a "two-toned" effect when contrasted with adjacent phasic muscles with PSE. From this common knowledge, one may extract a testable scientific hypothesis: that variance itself might be a predictor of PSE. This was tested by calculating a coefficient of variation (CV) for each loin (at each wavelength, SD/mean). The CV was correlated with fluid loss, r = -0.37 at 470 nm, and R = 0.62 adding 580 and 700 nm; with CIE L^*, r = -0.38 at 450 nm, and R = 0.68 adding 670 and 610 nm; and with JPCS, r = 0.40 at 460, and R = 0.67 adding 670 and 640 nm. The prediction of meat quality from the CV was not far short of that obtained using reflectance. The practical significance of this finding is that the CV is a ratio, the determination of which does not require accurate standardization or calibration of apparatus.

Thus, variability may not be such a serious problem if repetitive measurements can be made. As well as allowing averaging over a wide sample base, repetitive measurements also allow heterogeneity to be used as an extra indicator of poor quality.

Vacuum-applied optical probes

Figure 4



Robots are not the only novel way to launch a meat probe. Meat is relatively soft, and may be deformed by a vacuum. Thus, if an optical probe is located within a vacuum tube, the signal from the probe changes as the meat is drawn into the tube, as shown in Figure 4 (Swatland, 1998b).

Combining optical and electrical probes

Electrical probes for PSE detection generally consist of a pair of parallel needles or blades inserted into exposed muscles on the carcass. Optical probes, however, typically have a single spear with optical fibres opening on the side of the shaft. Can both methods be used simultaneously to improve the reliability of PSE predictions? One possibility is to mount optical fibres in parallel hypodermic needle electrodes, thus enabling simultaneous measurements of both optical scattering and electrical impedance in the same sample of pork. Light from a laser or a white source may be used to illuminate the meat through one needle, while scattered light is collected by the other needle and measured with a photomultiplier. Without a sample in position, direct transmittance from one needle to the other is very low, because the receiving fibre is at the edge of the cone of illumination produced by the illuminating fibre.

This unusual method of making the optical measurements was not found to cause any major problems (Swatland and Uttaro, 1998). For example, with 48 pork loins, transmittance of white light was correlated with CIE L^*, r = 0.63, $P < 0.01$. But the method is very sensitive to the anisotropy of muscle tissue. Skeletal muscle is composed of elongated fibres - essentially tubes of electrolytes surrounded by membranes with high dielectric and reflective properties. These function as guides for both electrical currents and light. Thus, when muscle fibres are oriented with their long axes connecting the parallel needles, then electrical impedance is low and optical transmittance is high. Conversely, across the muscle fibre axes, impedance is high and transmittance is low (Swatland, 1997a).

The parallel needle configuration is unattractive from a practical perspective, because the needles may be bent to change the distance between them, but it does offer some useful advantages, as explained next.

Optical path length

One of the major features of a fibre-optic probe used to measure meat quality is that the optical path length through the tissue is unknown. Meat is composed of microstructural sources of scattering, predominantly the highly refractive myofibrils plus any sarcoplasmic proteins that are precipitated by a low pH while the muscle is still near body temperature. Between these sources of scattering, is a variable concentration of myoglobin, depending on the type of meat or muscle being measured. Thus, the two most important factors determining the optical properties of meat are scattering and myoglobin concentration. Unfortunately, scattering thus becomes a problem when we attempt to measure myoglobin concentration, as in veal grading. While myoglobin concentration becomes a problem when we attempt to measure scattering, as in PSE detection. In general, scattering is best measured with a short light path through the tissue, while chromophore concentration is best measured with a long path.

This problem was clearly revealed in an experiment undertaken to measure carotenoid pigment accumulation in the muscles of growing fish (so as to control the nutrient supply of relatively expensive astaxanthin). To avoid damaging the fish, only a small probe could be used, and the small probe had a short light path and was very sensitive to scattering. In fact, it was almost easier to detect scattering from myodegeneration in the absence of the beneficial effects of carotenoids than it was to measure carotenoid pigment accumulation (Swatland, Darkin, Naylor, Caston and Mocia, 1998).

If needles for combined optical and electrical measurements are to be inserted into meat, one may as well incorporate force and distance transducers so that moving the needles apart or together may be used for rheological investigation of the meat, as shown in Figure 5. Thus, the needle tip may be used as a sensitive tool for all sorts of interesting experiments, such as testing the tensile strength of meat in different directions (Figure 6) and for investigating the optical properties of meat. As two needles move apart there is a geometric relationship between path length and transmittance between the needles which obeys the photometric laws. But in meat, it is virtually a straight line relationship because of scattering (Figure 7). The electrical impedance between the needles detects the appearance of meat exudate as the meat is deformed (Figure 8).

Figure 5

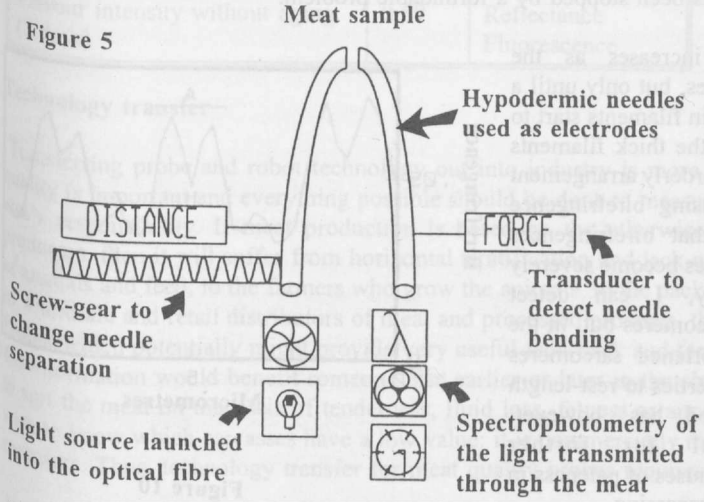


Figure 6

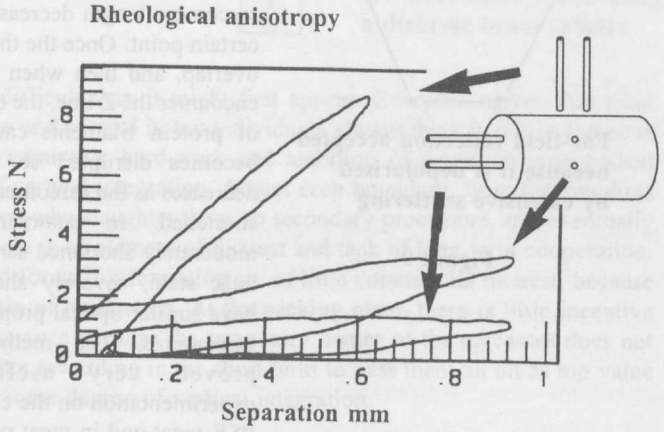


Figure 7

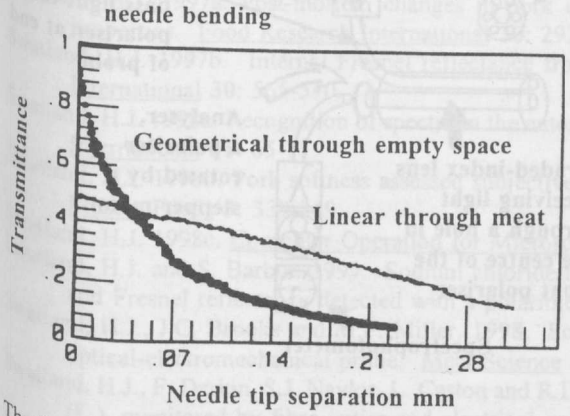
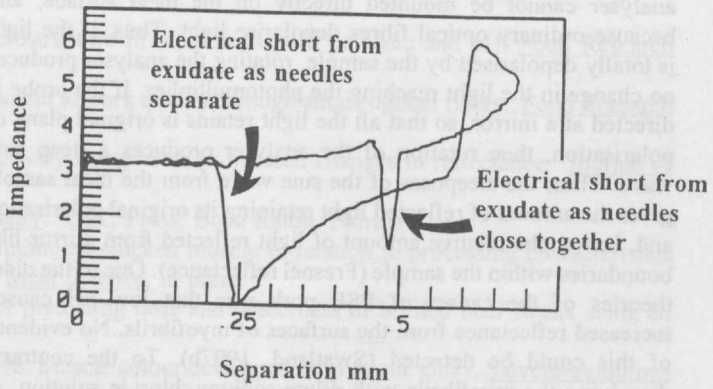


Figure 8



The force and distance transducers connected to the needles allowed the prediction of needle tip separation within the meat, by taking into account and correcting for the bending of the needles as they moved through the meat. But how else can we control the light path without using parallel needles?

Polarised light probes

Controlling the light path through the meat from a single optical window is possible using polarisers. These need not be expensive. In fact, the best ones I have used were obtained from the eye-glasses used for a three-dimensional light show given by a visiting rock-and-roll band in my local hotel. The high-quality polarisers obtained from optical supply companies are thick, rigid and difficult to cut. An inexpensive polarising film is much easier to cut and glue over the optical window of a meat probe. Crossed polarisers over illuminating and receiving windows of a probe force a long light path through the tissue, by rejecting reflected light from the near field in favour of light depolarised by scattering from the far field (Figure 9). This is a useful technique, but it brings us within grasp of something much more important - the detection of sarcomere length in bulk meat.

Briefly, because this is a complex topic, it is well known that the sarcomere is composed of highly birefringent anisotropic or A bands, and less birefringent isotropic bands, or I bands (Swatland, 1995). Note that the difference between A and I bands is one of relative magnitude of birefringence - they are both optically anisotropic and birefringent. The Z line also is birefringent (Figure 10). Sarcomere length is easily measured with a polarising microscope or with a thin strip of muscle illuminated with polarised light from a laser. A major problem with making probe measurements on bulk meat is that we cannot easily rotate a polariser (the analyser) against the surface of the meat. This is why a graded-index lens is necessary. A lens composed of ordinary glass will focus light by refraction. A graded-index lens is cylindrical in shape and focuses light because the refractive index changes across the radius of the cylinder. Thus, the graded index lens gives us a stationary window onto the meat, and allows the analyser to be placed back in the body of the probe where it can be rotated by a stepper motor under computer control. This brings us right up to date. At the moment, my research on sarcomere length detection in bulk meat has been stopped by a formidable problem.

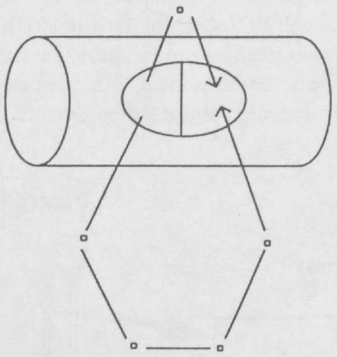


Figure 9

Overall birefringence increases as the sarcomere length decreases, but only until a certain point. Once the thin filaments start to overlap, and then when the thick filaments encounter the Z line, the orderly arrangement of protein filaments causing birefringence becomes disrupted so that birefringences decreases as the sarcomeres become severely shortened. In summary, I can detect moderately shortened sarcomeres but, in the bulk state, severely shortened sarcomeres have similar optical properties to rest-length sarcomeres. The method has, however, proved very useful for further experimentation on the causes of paleness in PSE meat and in meat processing.

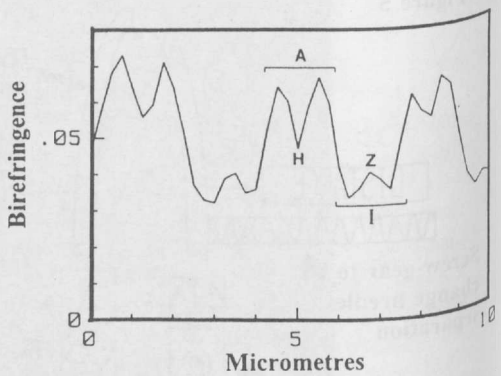


Figure 10

The probe shown in Figure 11 uses a graded index lens to collect the reflectance of initially polarised light and convey it back into the body of the probe where there is a rotary analyser driven by a stepper motor (Swatland, 1997b). This is because the rotary analyser cannot be mounted directly on the meat surface, and because ordinary optical fibres depolarise light. Thus, if the light is totally depolarised by the sample, rotating the analyser produces no change in the light reaching the photomultiplier. If the probe is directed at a mirror, so that all the light retains is original plane of polarisation, then rotation of the analyser produces a steep sine wave. Thus, the steepness of the sine wave from the meat sample gives the amount of reflected light retaining its original polarisation and, hence, the relative amount of light reflected from mirror-like boundaries within the sample (Fresnel reflectance). One of the older theories of the causes of PSE pork was that low pH caused increased reflectance from the surfaces of myofibrils. No evidence of this could be detected (Swatland, 1997b). To the contrary, dissolving the myofibrils with dilute sodium chloride solution, as in meat processing, caused an increase in the relative amount of polarised light reflected (Swatland and Barbut, 1999).

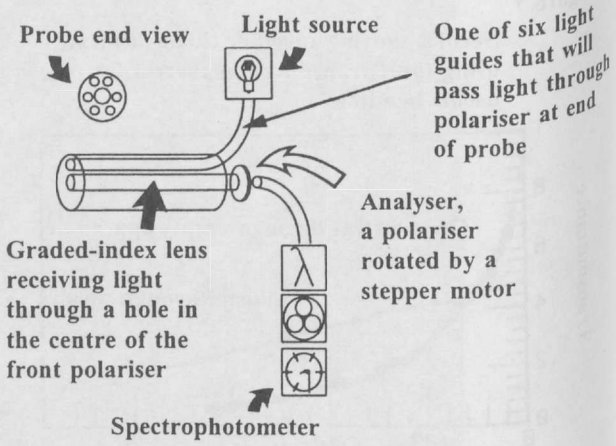


Figure 11

Multi-channel probes

The probe shown in Figure 12 looks at connective tissue abundance and pyridinoline cross-linking from its UV fluorescence, at the reflection of initially polarised light across the spectrum, and at the overall rheology of the meat. Quality traits of beef such as taste and tenderness are interrelated, so it is not surprising to find that measurements aimed at tenderness prediction (such as UV fluorescence for connective tissue) yield predictive information on meat taste (Table 3). For the excitation and detection of connective tissue fluorescence, light must penetrate the meat to some extent and, in doing so, may be secondarily affected by other factors, such as pH, lipid and myoglobin. Different attributes of meat quality often are interrelated, so why not exploit the cross-correlations obtained with a multichannel probe?

Table 3. Prediction of sensory attributes of beef quality from multichannel probe measurements (from Swatland, Brooks and Miller, 1998).

	R	Information
Tenderness without aging (3 days)	0.58	Reflectance Fluorescence Rheology
Tenderness with aging (21 days)	0.58	Rheology Reflectance Fluorescence
Flavour intensity without aging (3 days)	0.59	Reflectance Fluorescence

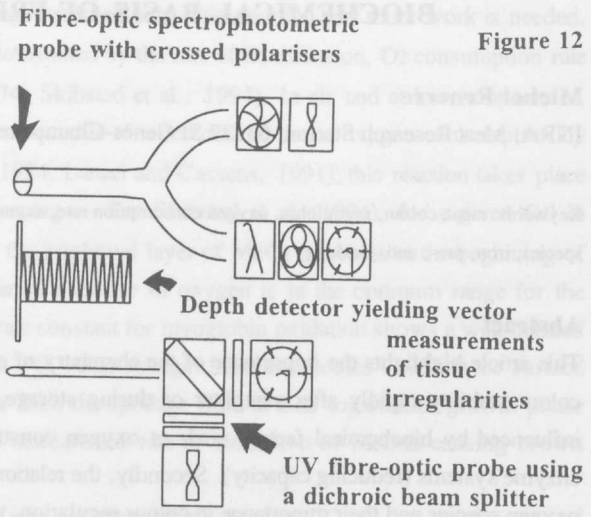


Figure 12

Technology transfer

Transferring probe and robot technology out into industry is more difficult than it might first appear. Everyone agrees that meat quality is important and everything possible should be done to measure and control it, but individuals always think that it is someone else's responsibility. If meat production is based on the otherwise admirable hard-work and ambition of countless independent producers, then it will suffer from horizontal stratification and lack of vertical integration. Across each boundary, from the suppliers of animals and feed, to the farmers who grow the animals, to the packers who slaughter them, to secondary processors, and eventually to wholesale and retail distributors of meat and processed products, there is an element of distrust and lack of long-term cooperation. Probes which potentially might provide very useful feed-back and feed-forward information are of little commercial interest, because the information would benefit someone else earlier or later in the chain of production. At the packing plant, there is little incentive to sort the meat on the basis of tenderness, fluid loss, fatness or appearance because the temporary owner of the carcasses does not wish to know which carcasses have a low value: it is commercially more rewarding in the short-term to pass them all on as top value carcasses. Thus, technology transfer for meat quality probes requires some degree of vertical integration.

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