

1 Introduction

Customers are hugely influenced by factors such as the colour and presentation of food products. The fact remains that the core colour of poultry can be misleading in that it varies with meat quality. Holownia et al. (2003) [1] outlined some of the other causes of discolouration in poultry meat. In this paper it was highlighted how factors such as pigments present in the meat, pre-slaughter factors such as genetics, feed, hauling and handling, the presence of nitrate/nitrite and other factors have an impact on the colour of cooked chicken meat. The discolouration does not affect the safety of the product but it is entirely undesirable from a consumer viewpoint as consumers assume pink means undercooked meat. It would therefore be of huge benefit to any food preparation industry to have a sensor that measures core and surface colour, combined with temperature in order to keep track of aesthetics, doneness and meat quality. This would allow control of a full scale oven so that the rate at which food cooks would ensure even colouring, (e.g. it is not favourable to allow the surface to darken before the core is cooked), while also recording temperature data for food safety reasons and concurrently checking meat quality by detecting meat pinking. This could also be applied to beef, particularly ground beef, which also displays pinking [2] as well as what is called 'premature browning' [3]. Both of these occur due to poor quality in meat and as a result of factors such as storage time, muscle pH, nitrates and nitrites in the muscle.

The food preparation industry makes use of large-scale, conveyor belt ovens to pre-cook large quantities of food in as short duration of time as possible. Previous work conducted by the authors has resulted in two colour probes for online measurement of food as it cooks in conventional large-scale convection ovens, one for external surface readings and another for core readings of the product [4,5]. The colour classification was performed by cooking the products to various stages, (e.g. under cooked, rare, optimal, overcooked), taking measurements based on the visual appearance of the food and then performing classification techniques on this data.

An alternative approach is proposed in this paper based on a method of collecting data to train the Neural Network. This would involve recording the temperature of the meat where each spectral reading is taken and then using the temperature data to help build the training files. The principal reason for this is to attempt to simplify and eventually automate the
training process. At present the training process is manual and this could prove unattractive in industry as it complicates the addition of new food products to the oven. The method proposed in this paper allows the probe to collect data throughout the cooking process by inserting it in the product with a temperature probe rather than manually probing the meat based on its visual appearance. This allows the first segregation to be performed by using the corresponding temperature data, which in turn simplifies the building of training files for the Neural Network.

Tests have been carried out on high quality chicken breast meat from five different vendors and including organic chicken. Chicken was chosen, as it is one of the more difficult products to classify. This is because it does not undergo significant colour changes during the cooking process – it starts as a pale-pink when raw and gradually transforms to a creamy-white colour when fully cooked.

2 System Set-up

Cooking causes colour changes to occur in the visible region of the electromagnetic spectrum. To examine the changes in the spectra at each cooking stage an Ocean Optics S2000 spectrometer was employed. This was controlled by a host PC running a LabVIEW™ Virtual Instrument (VI) software on Windows 2000 and communicating with it using USB.

The spectrum of each food sample represents the distribution of reflected light across a wide spectrum of wavelengths in the visible region in the wavelength range 440nm to 750nm. The food is illuminated through six 400µm core diameter fibres coupled to a tungsten halogen white light source, which emits light in the wavelength range 360nm to 2µm. One other fibre, located centrally within the same probe, guides the reflected light to the spectrometer (Figure 1).

A K-type thermocouple with a USB 8-channel thermocouple DAQ system from Superlogics was used to measure and record the temperature. All thermocouple temperature readings are logged over time with WINVIEW software. The temperature and colour probes were secured together and inserted simultaneously and at the same depth into the meat. Figure 2 shows chicken breasts obtained from five different vendors to test the classifier. Figure. 3 shows the temperature and the colour probe inserted into chicken meat.

Figure 2: Examples of the Chicken Breasts used to train and test the ANNs. Each fillet shown is from a different vendor

Figure 3 : Temperature and colour probes inserted into a chicken breast at the same point as it cooks.

3 Results

3.1 Spectroscopic Results

Spectra and temperature readings were recorded every five seconds so that each spectrum was saved with its corresponding temperature. The spectra were then divided into 3 groups; group 1 < x, x < group 2 < y and group 3 > y, where x and y represent temperature values in degrees Celsius. It was found that the optimal values for x and y for...
chicken were 68 °C and 76°C. The spectral plots of group 1 and group 3 are shown in Figure 4. Group 1 and group 3 make up the training set, with 2 classifications; pink and white, while group 2 is considered a safety gap to ensure that no pink spectra end up in the white training set and vice versa. There are 150 spectra for each class; pink and white so that the full training set comprised 300 training patterns.

3.2 Principal Component Analysis

The S2000 spectrometer from Oceanoptics has a high resolution due to its 2048-element linear silicon CCD array (also described as 2048 pixels). This means that the data in the spectra is highly correlated and that there is undesirable redundant information for the neural network to use in training. The region of interest for signal changes occurs in the visible spectrum between 440nm and 750nm. By confining the spectral range to this, the data set is reduced to 945 pixel intensity values, which is still relatively high number. Principal Component Analysis (PCA) makes it possible to reduce the dimensions of this solution to a smaller subspace by only including significant data and thus eliminating the redundant information. It was found that 2 Principal Components maintained enough variance to represent each spectrum. Plots of the two Principal Components, which are representative of the colour are presented in Figure 5. The red plots in this diagram represent pink colour (< 68°C) and the green plots represent white colour (> 76°C).

3.3 Training the Neural Network

The two Principal Components (PCs) were used as the input to the feed-forward neural network. Backpropagation with momentum was chosen as the learning function and the parameters used were as follows: a learning rate, \( \eta \), of 0.8 and a momentum term, \( \alpha \), of 0.3. The neural network was trained using spectra from below 68°C and above 76°C, corresponding to pink and white respectively.

3.4 Testing the Neural Network

After the neural network was trained it was essential to test it using previously unseen data. For this purpose a test set of three groups was compiled, with 200 test patterns per group. The three groups were: test group 1 < 68°C, 68°C < test group 2 < 76°C and group 3 > 76°C. While there are only two classifications pink and white, the three test groups were used to demonstrate the transition region where the chicken breast gradually changes from pink to white. Figure 6 shows a Principal Component plot of this test set. As expected groups 1 and 3 have a clearly defined boundary (plots red and green, respectively) The blue plots indicate colour readings taken in the transition region between 68°C and 76°C where the colour changes from white to pink and where it is acceptable that either pink or white is present. This is evident here since the blue plot spans across both the red and green plots.

This data was then processed through the trained Neural Network. The results are shown in Table 1.
3.5 Discussion of Results

Table 1 shows the classification of the 600 test patterns. Of the 200 test patterns in test group 1, 2% classified as white, which is acceptable as the spectra could be moving into the transition region if very close to 68°C. As expected the transition region, between 68°C and 76°C contain both classifications. All of the test spectra over 76°C classified correctly as white.

4 Conclusion

The method discussed in this paper has greatly simplified the training process for the neural network. This simplification is an essential part of the system, as industry will require that new products can be added with ease by decreasing the amount of manual work required. It also greatly reduces the likelihood of subjectivity, as the training spectra are now divided by their temperature and not by the visual appearance of the food at the time they were recorded. The accuracy of this method is demonstrated in Table 1, which is further proof that this method was successful in its simplification.

By combining online colour readings with online temperature readings it will also assist in the detection of pinking in poultry of beef and premature browning in beef.

Future work would involve applying this method to further meat products and also the surface of the product.

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6 References


![Figure 6: PCs used to test the ANN. As can be seen, the PCs generated from data in the temperature range between 68°C and above 76°C straddle the other two groupings](image)

Table 1: Results obtained by the ANN classifier tested using the PCs in Figure 6

<table>
<thead>
<tr>
<th>Colour</th>
<th>Test Group 1 &lt;68°C</th>
<th>Test Group 2 &gt;68°C &amp; &lt;76°C</th>
<th>Test Group 3 &gt;76°C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pink</td>
<td>96%</td>
<td>30%</td>
<td>0%</td>
</tr>
<tr>
<td>White</td>
<td>2%</td>
<td>62%</td>
<td>100%</td>
</tr>
</tbody>
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