Specification of food colour and appearance using digital cameras

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ABSTRACT

The aim of this study is to develop a method for specifying the appearance of two food products: banana and tomato. It is important to use digital cameras for measuring the appearance of food products because they often have three-dimensional shapes and are of non-uniform colour. It is not possible. These are specifying to make adequate measurements using conventional colour measuring instruments. However, the output values of digital cameras are device-dependent and must be first characterised in terms of CIE tristimulus values. Captured food images can then be analyzed for specifying total appearance. A psychophysical experiment was performed to understand how the ripeness and preference of the selected products are affected by appearance. Finally, a model based on both physical and psychophysical data was developed. This successfully predicts the visual ripeness and preference scores from the colour images.

1. INTRODUCTION

Consumers have a tendency to purchase foods by judging quality by its inherent appearance and colour. So, it is sufficient to regard the initial criteria of purchasing foods as two features: appearance and colour. The colour of materials having uniform flat surfaces can be specified using a conventional spectrophotometric instrumentation. Many foods, such as fruit and vegetables, are irregularly shaped and coloured, and conventional instrumentation can not be used to give an adequate specification of colour and appearance. One solution is to use a digital camera with sufficient colour resolution and versatility. The data can be easily transferred from the digital camera to a PC for analysis. The aim of this study is to develop suitable features to specify the colour and appearance of food using the digital camera. Banana and tomato are chosen specially in this study.

2. METHOD

A digital camera can be used to capture the whole appearance of the product. Unfortunately, a digital camera does not present the standardised colorimetric data such as CIE tristimulus values. The raw red, green and blue signals from the digital camera are device-dependent but, however these RGB signals can be transformed to XYZ values by characterising the digital camera using a polynomial[1] method.

The captured images were analysed so that the colours representing aspects of the total appearance could be abstracted. As, in general, we see a restricted number of colours, it is convenient to cluster the data using. When we see a banana, we only see few colours such as yellow, green, brown, and black. With the tomato, these are red, green and white (gloss part). Therefore, there is no need to use the entire pixel-by-pixel information for representing a food object. Clustering technique comes in handy in this aspect. It can reduce the whole image into few colours to represent the colours we actually perceive. The partitional clustering algorithm named Forgy's algorithm[2] was used in this study in order to analyse the appearance in total and its colours. Images of four tomatoes and bananas were captured over nine days and seven days respectively using a digital camera under D65 illuminant and 0/45 geometry. Each fruit image was cut in half so that the shadowed area was removed. The banana images were clustered into nine groups, three for detecting the black spot feature and six for the background skin colour. Tomato images were clustered in to seven groups for the skin colour information and eight for the gloss aspect. The black spot and gloss are important appearance attributes for banana and tomato respectively.

Psychophysical experiments were performed to find out how colours affected consumer judgements such as 'ripeness' and 'preference'. A CRT monitor was also characterised to display food images in a device-independent way. The experiment was conducted in a darkened room. Each original banana and tomato image was shown to subjects who were asked to give 'ripeness' scores from 1 to 10. For the preference experiment, 20 pairs of tomato or banana images were shown to subjects who were asked to indicate the preferred sample to eat right away. A model was developed to correlate the physical and psychophysical results. Each of fifteen observers was seated approximately 50cm from the screen.

3. RESULTS

3.1 Camera characterisation

Many methods have been developed for characterising digital cameras. The polynomial method used here is probably the most popular method. It requires a test set of target colours. The polynomial model derived using the GretagMacbeth ColorChecker digital chart and the IT8.7/2 (Fujifilm IT8 Color Input Targets) chart did not perform well. An improvement model used a reduced training set for each food product. For bananas, a 3×11 polynomial model using sample close to the banana colours from the GM chart gave the best performance. Thirty additional training colours were selected from the GM chart. These colours were less than 10 ΔE^*_{ab} units colour difference from the 21 banana test samples. The polynomial model using training samples close to few particular colour regions is called local characterisation.

For tomato images, the performance of the initial local characterisation model was poor. This was caused by the gloss aspect due to the curved nature of the fruit. The requirement for flat test surfaces for measurement of gloss is difficult to meet, because an instrument cannot differentiate between the flat surface colour and the curved surface colour. The eye, however, can readily distinguish between these effects. Therefore, when the XYZ values were measured from the sixteen tomato samples, a small portion of a non glossy area was selected. Thirty training colours for tomatoes were also selected from the IT8 chart.

3.2 Image Analysis

Using the local characterisation model as described above RGB values of the banana image were transformed to CIELAB values. The features of the bananas were analysed. The appropriate number of clusters to represent the banana skin colour was selected by varying the cluster numbers to compare with colours that were visually selected from the original images. It was found that the chroma of the yellow skin did not change greatly but reduced slightly over time, while the hue angle shifts about 12° to become redder. Overall the skin colour changes from bright yellow to a brownish yellow colour. After about five days, neither the hue angle nor the chroma changed. It can be seen that when the black spots developed, the background skin colour becomes uniform at the same time. Therefore, different numbers of clusters are used to indicate the skin colour after development of the black spots.

A model was developed to determine the number of clusters required at different stages. We first examined whether the black spots were present. For detecting the black spot aspect for bananas the whole image was clustered into three groups. Black spot existence was determined by checking the L* value of the group with the darkest colour. If the group has L* value less than 20, it indicates the presence of black spots. Subsequently, the entire image was clustered into four groups and the group having the highest L* value represented the yellow skin colour. Alternatively, banana having no black spots is clustered into six groups; that having the highest L* value represented the yellow skin colour and the group having a* value under –5 represented the green skin colour.

The tomato images were clustered into eight groups. Among the eight groups, the red skin colour is represented by the group having the highest chroma value from the four groups having the highest L* values. The b* value of the gloss part does not change but the a* value changes with time. Only the colour of the gloss part changes as the red skin colour changes. This explains that the amount of gloss does not change with skin colour but with the shape of the tomato. In the image the glossy part is seen as a whiteish colour which the camera captures as high L* values. The red skin colour was the cluster with the greatest chroma among the four clusters with the largest L* values.

3.3 Psychophysics

The above results clearly showed the change of fruit colour and gloss with time. The psychophysical experiment showed that time and ripeness have a positive relationship for both foods. For the bananas, the black spot precentage obtained using the clustering techniques as explained in the last section was used to predict the ripeness score. If there are no black spots the chroma and hue angle of the yellow skins were used. Equations (1) and (2) are the formulae to calculate ripeness.

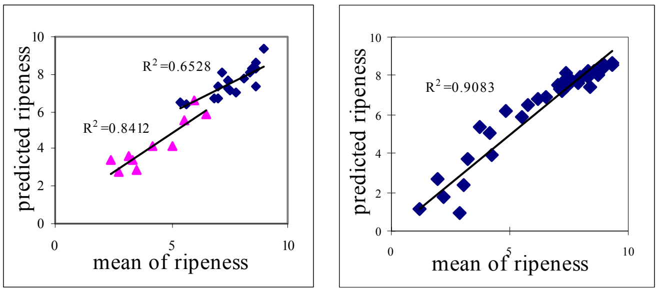
Therefore, the results from both experiments could be linked as a function of time and a. model that predicts ripeness score using the food colour can be established.

$$\text{Ripeness score} = 5.6B^{0.18} \quad \text{(Black spots exists)} \tag{1}$$

$$\text{Ripeness score} = 40.39 - 0.09C^*_{ab} - 0.36h_{ab} \quad \text{(No black spots exist)} \tag{2}$$

The above equations were developed by fitting the psychophysical data where $\mathbf{C^*_{ab}}$, $\mathbf{h_{ab}}$ are the bananas yellow skin colours and **B** the black spot percentage corresponding to the clustering method mentioned above.

$$\text{Ripeness score} = -0.085L^* - 0.0063C^{*2}_{ab} + 0.67C^*_{ab} + 0.002h_{ab}^2 - 0.26h_{ab} - 1.36 \tag{3}$$



(a) **(b)**

Figure 1: The visual and predicted ripeness scores for (a) bananas and (b) tomatoes

Similarly, the ripeness score for tomatoes can be predicted using the red skin chroma and hue angle.

The model preformance is shown in Figure 1. The two graphs show the predicted and visual 'ripeness' scores. The triangles and the diamonds in Figure 1(a) show the performance of the models using the skin colour equation (2) and the using the black areas equation (1). The model reasonably predicted visual results with an error of 0.4 root-mean-square units. Figure 1(b) shows a good agreement between the visual and predicted results using equation (3). The tomato model gave an error of 0.1 root-mean-square units. Finally, using the results of the psychophysical experiment a model to correlate 'ripeness' score and the 'preference' score was also established.

Figures 2 (a) and (b) shows the relationship between the 'preference' and 'ripeness' scores for the tomatoes and bananas. It can be seen from the data points from the psychophysical experiment are reasonably fitted by the smooth curve calculated by the following polynomial equations.

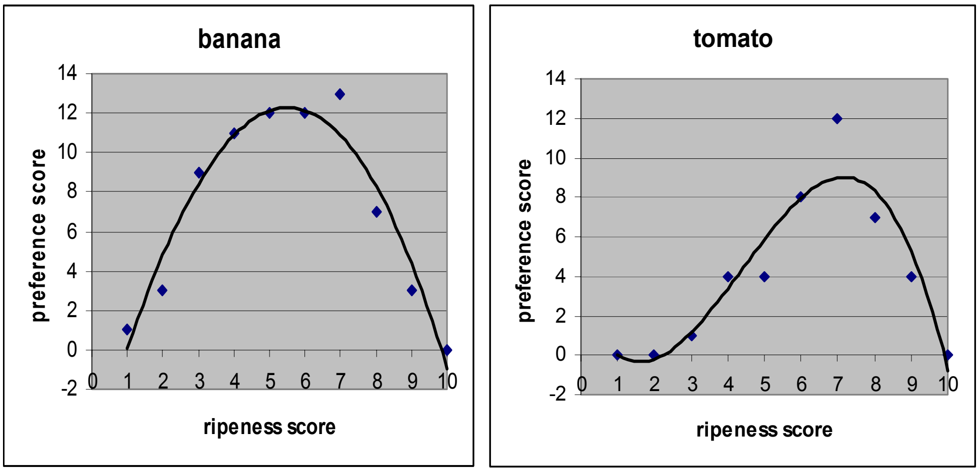
Equation (4) can be used to predict the preference score for bananas where **R** is the ripeness score calculated by equation (1) and (2).

$$\text{Preference score} = -0.12R^3 + 1.6R^2 - 4.26R + 2.8 \tag{4}$$

Equation (5) can be used to predict the preference score for tomatoes where **R** is the ripeness score calculated by equation (3).

$$\text{Preference score} = -0.041R^3 + 0.201R^2 + 1.932R \tag{5}$$

The equation for the preference score of tomatoes.



(a) **(b)**

Figure 2: Graphs plotted of (a) bananas and (b) tomatoes ripeness score against preference score that is fitted by polynomial equations,

4. CONCLUSIONS

Psychometric models were developed to explain the ripeness and the preference from the images of banana and tomato. The food colours were captured using a characterised digital camera, which is valuable for measuring food objects that are three dimensional and multi-coloured. It was found that the polynomial models using localised training colours gave the most accurate performance to transform camera's RGB values to CIE tristimulus values. Using the characterised digital image, the clusters produced by calculation were comparable with results obtained using the visual method. The psychophysical experiment was conducted to scale bananas and tomato images in term of ripeness and preference. The results showed that the ripeness had a positive correlation with the time and that the preference had a correlation with the ripeness. Models that predict the ripeness score and the preference score were developed using the clustered colorimetric results and the experimental visual results. The models derived in this study gave a reasonable prediction to the visual results. This study demonstrates a promising way forward to understand and integrate ripeness and preference terms giving industry the ability to understand and thus possibly control their fruit products using a scientific methodology.

References

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