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Review

Recent advances in image processing using image texture features for food quality assessment

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The use of computer vision technology has been highly successful in food classification problems in the past and it has continued this success in recent times. There does however exist a number of opportunities to progress computer vision technology further, these opportunities are critically examined based on cost and feasibility. A range of hardware options are considered along with a range of software options. The economic cost of implementing new hardware continues to prove a major impediment. Thus future efforts need to be focused on maximising the potential benefits of the existing hardware framework and instead concentrate on developing improved software. Of the improved software available the aspect that offers the greatest promise is more efficient analysis of food surface texture attributes which will lead to more powerful understanding of the relationships between quality factors and experimentally measured food quality.

Introduction

Computer vision systems are a very popular choice for delivering fast, reliable and robust food classification as the grading of foodstuffs by human graders has essential weaknesses of subjectivity, inconsistency and unreliability (Du & Sun, 2004, 2006a; Jackman & Sun, 2011a, 2011b, 2011c; Jackman, Sun, Du, Allen, & Downey, 2008; Sun, 2008). The rules applied for food classification are those published by the United States Department of Agriculture (USDA Agricultural Marketing Service, 2011) or some other national or regional rulebooks that are based on the same principles. Conveniently these rulebooks depend primarily on food features that are suitable for automatic measurement *via* digital cameras, personal computer and other low cost equipment e.g. colour, size, shape and texture (Jackman & Sun, 2011b). There have been many successful years and decades of implementing computer vision systems (Sun, 2000; Brosnan & Sun, 2002, 2004; Sun & Brosnan, 2003; Zheng, Sun, & Zheng, 2006a, 2006b), however some of the grading problems remain elusive (Jackman & Sun, 2011a). Hence new approaches need to be devised, involving better hardware capable of better data generation or better software capable of better data processing or some improvement in both aspects.

The main barrier to better data generation has been the cost (Jackman & Sun, 2011c). A very basic system consisting of a charged coupled device (CCD) digital camera, frame grabber and personal computer can be built for at most few thousand dollars (Edmund Optics Online Catalogue, 2011). However to move outside that realm requires increases in hardware cost in the orders of magnitude. Specialist cameras exist that are able to tackle awkward imaging environments by suppressing fringe effects or cope with badly light conditions such as the "PIXIS". However their costs will be substantially higher (Princeton Instruments Online Catalogue, 2011). A cost effective alternative option is a standard scanner. If moving outside the visible light range to see more objects or to illuminate alternative texture patterns is anticipated to provide stronger image features then there is potentially even greater costs as a spectrograph such as the "ImSpector range" (Specim Imaging Online Catalogue, 2011) will be needed to isolate the different wavelengths.

Any foray into three dimensional imaging will result in vastly increased hardware costs of possibly multiple orders of magnitude (Jackman & Sun, 2011c). The well established three dimensional imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) etc. can easily elevate the cost of hardware into the order

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of a many hundreds of thousands of dollars or more (Absolute Medical Equipment, 2012). Added to that is the very slow imaging time. While it can be reasonably expected that over time hardware costs will reduce, it is clear that moving into three dimensional image acquisitions will be unrealistic except for the most well funded research centres.

Where the problem of additional cost proves impossible or where previous results show the necessary information is in the visible range then efforts should be directed at maximising the usefulness of the existing imaging equipment. This opens up a main option for improvement; a better image processing regime that finds more powerful grading information by expressing the features more efficiently or by identifying image features previously missed.

Fortunately the existing grading rules such as those of the USDA (USDA, 2011) are built around measuring some type of colour, texture, shape or size features of a food product and then estimating how a paying consumer is likely to judge it, i.e., what they are willing to pay for said food product. There is a great multitude of methods for estimating likely consumer judgements ranging from the true test of a consumer taste panel to alternatives such as chemical and mechanical tests (Instron Inc., 2008; Jackman & Sun, 2011a, 2011b, 2011c; Jackman, Sun, Allen, Brandon, & White, 2010). Therefore, what needed is some sort of model that can give a robust and accurate prediction of likely consumer judgement. As images recorded are expected to reveal the food product features such as colour, texture, shape and size, it is these features that can be used to create a model, which can then be calibrated and validated against an independent quality test. Thus there is a requirement to find more useful image features of colour, texture, shape and size and to identify better mechanisms of tying them to measured independent quality data.

This paper will review the prospects for substantial advancements in image processing that are possible both with existing technology and some emerging ones. This will involve analysing step by step what is required in constructing an image processing solution to a practical food quality assessment problem; followed by an analysis of how each of these steps might be improved leading to an overall higher performance. A strong emphasis will be placed on the extraction of quality indicators such as colour, morphology and texture.

Steps in image processing

Image acquisition when carried out in the visible light range will yield three greyscales in red, green and blue. Within the image there is a region of interest (ROI) that requires removing the non-interesting parts of the image, i.e., segmenting the image into ROI and non-ROI (Du & Sun, 2004). The task of segmentation might be straightforward or so difficult that manual intervention is required to finish the extraction as found by Jackman *et al.* (2008) and Jackman, Sun, Du, and Allen (2009) when trying to isolate the ribeye muscle in beef cuts.

Irrespective of the level of difficulty algorithms are available to successfully derive the ROI even if it is highly inefficient (Jackman & Sun, 2011a) and even if manual intervention was required. A whole host of image segmentation algorithms are discussed by Du and Sun (2004). Some segmentation algorithms that stand out with distinction are the graceful degradation algorithm of Borggaard, Madsen, and Thodberg (1996) which built its thresholds for isolating beef carcasses with multiple criteria ensuring that failure of one criterion did not cause the thresholding process to collapse, the active contour algorithm of Antequera, Caro, Rodriguez, and Perez (2007) that monitored the ripening of ham muscle by creating contours with Variational Calculus, Dynamic Programming and Greedy Algorithms, the B-spline algorithm of Goni, Purlis, and Salvadori (2008) which used a lofting technique to generate the muscle boundaries, the region growing algorithm of Blasco, Aleixos, and Molto (2007) that grew the defected and non-defected regions of oranges to identify the flawed fruits, the shadow elimination algorithm of Du and Sun (2009) which solved the problem of shadows confounding the segmentation of confocal microscopy images by combining partial differential equation based diffusion and thresholding segmentation, the gradient and spline algorithm of Du and Sun (2006b) which identified the boundaries of a cooked ham by obtaining radii, applying a wavelet transform, locating protrusion and applying spline interpolation and the clustering and thresholding algorithm of Jackman, Sun, and Allen (2009a) that combined simple thresholding with a crisp *K*-means clustering algorithm and a clipping step to isolate the muscle of a beef cut. If it is absolutely required segmentation can be sidestepped by keeping only the ROI inside the field of view.

After the image has been successfully segmented into the ROI and non-ROI, the useful parts should be characterised in meaningful ways that reflect the food grading rules such as those issued by the USDA or another competent authority and also condense predictive power into as few variables as possible to avoid the curse of dimensionality. Once these variables are found they should be linked by a trained and tested model to independent experimental verification of the food quality (Jackman & Sun, 2011a). This will allow the qualities of any future sample to be safely estimated.

The kind of grading procedures that are envisaged by the USDA rules can be divided into four essential categories of features: colour, texture, shape and size (Jackman & Sun, 2011b). All of these have been proven to be highly suitable to a computer vision system. The types of predictive models typically applied in computer vision processes are classical statistical methods and neural networks (Jackman & Sun, 2011a). This points to two principal avenues for improving the image processing; extracting better colour, texture, size and shape features or create stronger predictive models that can better condense the useful image information as it is by exploring these avenues that additional hardware cost will be avoided and the area of predictive modelling has already been widely explored in the mathematical and statistical sciences.

Finding improved image features

There are a multiple of approaches that can be initially considered; firstly a better image acquisition method that reveals more information or is less confounded by background noise, illumination irregularities, greater pixel precision or reduced blurring might produce superior experimental data; secondly better sample preparation to ensure minimum data corruption. While these are possibilities there are also areas that should have already been dealt with during the preparation of the experimental protocols.

As pre-processing methods are well established, searching for a better image segmentation algorithm that will give a more accurate region of interest should be a focus at this stage. However as already stated effective segmentation can always be found even if it requires very complex algorithms such as the graceful degradation algorithm of Borggaard *et al.* (1996) or even if manual segmentation has to be used as the last resort. Thus improved segmentation should be deemed to be a lower priority for advancing the application of computer vision systems.

The latest image segmentation methods should still be monitored closely as automatic algorithms are far more desirable than any manual segmentation and less complex algorithms are more computationally efficient and can also be expected to be more robust. In particular disciplines such as medicine should be monitored very closely as some exceptionally difficult segmentation problems exist such as cell microscopy (Russell *et al.*, 2009).

Considering the above option are not likely to provide easy and cost effective means of improving a computer vision system this leaves the options of superior feature characterisation and superior model building as the leading candidates for improving image processing. In particular these option lead to the hypotheses that more efficient data extraction algorithms might find stronger quality indicators and might filter out the redundant and non-useful features and also that superior model building would better cope with non-linearities in the relationship between the quality indicators and measured quality and help screen out weak features.

It must be noted that great care should be taken when implementing powerful image processing techniques as there is a danger that chance correlations might be mistaken for meaningful correlations. To protect against this only features described by a competent food grading authority such as those of the USDA should be used.

Extracting better colour features

As discussed previously the USDA grading rules are based on colour, texture, shape and size. Of these properties colour is the simplest to measure but is also the property that requires the greatest care if absolute rather than relative colour measurement is sought. After segmentation the food colour can be simply expressed with histograms of red, green and blue. If absolute colour measurement is required, transformations to the $L^*a^*b^*$ such as that detailed by the Commission Internationale d'Eclairage (CIE) in 1976 (HunterLab, 2008) are possible without significant loss of colour information. Alternatively the system can be calibrated to a standard colourspace such as the sRGB proposed by Hewlett Packard© and Microsoft© (Stokes, Anderson, Chandrasekar, & Motta, 1996). Colour standards are often expressed as $L^*a^*b^*$, thus transformation to absolute colour measurement may be needed (Quevedo, Diaz, Caqueo, Ronceros, & Aguilera, 2009; Quevedo, Diaz, Ronceros, Pedreschi, & Aguilera, 2009; Quevedo, Mendoza, Aguilera, Chanona, & Gutierrez-Lopez, 2008; Zenoozian & Devahastin, 2009).

Transformations can also be performed to other colourspaces such as the YCbCr colourspace (Jackman, Sun, & Allen, 2009d) or the HSI colourspace (Li, Tan, & Shatadal, 2001). Some novel variations on colour features are purple LED properties of pork (Wakamatsu, Odagiri, Nishimura, & Hattori, 2006) and the customised colour channel of Lee, Archibald, Chang, and Greco (2008) for analysing dates.

The measured colour can be used as a feature for a predictive model (Li, Tan, Martz, & Heymann, 1999) or for comparison against a standard (Quevedo *et al.*, 2008) or even against a threshold (Blasco, Cubero, Gomez-Sanchis, Mira, & Molto, 2009). Simple summary properties such as mean, standard deviation, skewness, kurtosis and interquartile range are easily calculated (Jackman, Sun, Du, & Allen, 2009; Jackman *et al.*, 2008). Local variations in food colour can be vital as they can indicate the onset of ripening or a malaise. For example most of the product flaws described by the USDA standards for peaches (USDA, 2004) could be observed as local colour variations. These local variations can be found by noting peaks and troughs in the colour channels across the image. There is however little if any scope for determining additional colour features that are not already devised.

Additional and comprehensive discussion of this utilisation of colour features in image analysis is described in detail by Jackman and Sun (2011a, 2011b). The most obvious successes have been in quantifying food colour in terms of red, green and blue (Jackman, Sun, Du, & Allen, 2009; Jackman *et al.*, 2008, 2009a, 2009b, 2009c, 2009d). Other ways of using colour features are in terms of Hue, Saturation and Intensity (Zion, Alchanatis, Ostrovsky, Barki, & Karplus, 2008) or the device independent $L^*a^*b^*$ format (Quevedo, Aguilera, & Pedreschi, 2010; Quevedo, Diaz, Caqueo, *et al.*, 2009; Quevedo, Diaz, Ronceros, *et al.*, 2009).

Extracting better shape and size features

To measure shape and size, it first requires an object outline to be found with image segmentation. With a clear object outline a selection of features can be calculated. This can be a feature that indicates desirable qualities or a feature that indicates the presence of some kind of undesirable quality such as infestation or rotting. Important shape and size features are detailed by Du and Sun (2004). While the exact size and shape may not always be critical to classification the approximate size and shape should still be. For example classes of fruit are expected to lie within particular size ranges (Moreda, Ortiz-Canavate, Garcia-Ramos, & Ruiz-Altisent, 2009). Further discussion of important size parameters is detailed by Moreda *et al.* (2009). The USDA (2011) lists a selection of important size and shape features for foods. Some novel shape and size features that have been used would be the curvature of a depression induced by a standard weight (Quevedo & Aguilera, 2010).

Further analysis of the application of size and shape features in image analysis is detailed in Jackman and Sun (2011b). Notable successful applications have been characterising the area and density of ham porosity (Du & Sun, 2006c). Similarly the morphology of muscles (Antequera *et al.*, 2007; Goni *et al.*, 2008), whole fish (Zion, Alchanatis, Ostrovsky, Barki, & Karplus, 2007; Zion *et al.*, 2008), fruit segments (Blasco, Aleixos, Cubero, Gomez-Sanchis, & Molto, 2009), whole fruits (Riquelme, Barreiro, Altisent, & Valero, 2008) and rice kernels (Yadav & Jindal, 2007).

Extracting better texture features

In reality the best opportunities for better data extraction lie in surface texture as computer vision systems have the ability to analyse texture in many ways that cannot be perceived by the human eye, thus providing for more powerful texture analysis. Unlike with colour, shape and size condensing texture information into a few simple summary properties is not possible as the patterns of these spatial variations can be highly elaborate and convoluted. Previous research has opted to express food surface texture with the classical features of co-occurrence, difference histograms and run lengths (Jackman & Sun, 2011b). Whichever texture analysis approach is employed the precision of pixel data should be sufficient to retain meaningful texture patterns but not too sensitive to non-meaningful fluctuations.

The classical approaches for surface texture is as already mentioned the pixel co-occurrence, run length and difference histogram methods. The co-occurrence method records the values of neighbouring pixels a fixed distance apart in a matrix and the matrix features reflect the image texture. This works by cyclically picking a pixel, measuring its value and then moving a fixed number of pixels in a particular direction and measuring the value of the second pixel. This results in a pair of values which are treated as co-ordinates in a two-dimensional matrix and the value at that co-ordinate is increased by one. When all available pixels have been processed the matrix can be interpreted. Typical co-occurrence features are listed in Table 1.

Table 1. Typical co-occurrence matrix features (Jackman, 2009).

Feature	Definition
Angular second moment	$\sum_i \sum_j p(i,j)^2$
Contrast	$\sum_{n=0}^{N-1} n^2 \{ \sum_{i=1}^{N} \sum_{j=1}^{N} p(i,j) \}, \quad \lvert i-j \rvert = n$
Correlation	$\dfrac{\sum_i \sum_j (ij) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
Sum of squares: variance	$\sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse difference moment	$\sum_i \sum_j \dfrac{p(i,j)}{1+(i-j)^2}$
Sum average	$\sum_{i=2}^{2N} i p_{x+y}(i)$
Sum entropy	$-\sum_{i=2}^{2N} p_{x+y}(i) \log\{p_{x+y}(i)\}$
Sum variance	$\sum_{i=2}^{2N} (i - \text{Sum Entropy})^2 p_{x+y}(i)$
Entropy	$-\sum_i \sum_j p(i,j) \log(p(i,j))$
Difference variance	$\sum_{i=0}^{N-1} i^2 p_{x-y}(i)$
Difference entropy	$-\sum_{i=0}^{N-1} p_{x-y}(i) \log\{p_{x-y}(i)\}$
Information measure of correlation 1	$\dfrac{\text{Entropy} - HXY_1}{\max(HX, HY)}$
Information measure of correlation 2	$(1 - \exp[-2(HXY_2 - \text{Entropy})])^{0.5}$
Maximum correlation coefficient	$\sqrt{\max(\text{eigenvalue})}$ of Q
Maximum probability	$\max(\max(p_{ij}))$

Notes: $HX = \text{Entropy}(p_x)$, $HY = \text{Entropy}(p_y)$, $HXY_1 = -\sum_i \sum_j p(i,j) \log\{p_x(i) p_y(j)\}$, $HXY_2 = p_x(i) p_y(j) \log\{p_x(i) p_y(j)\}$, $Q = \sum_k p(i,k) p(j,k) / p_x(i) p_y(k)$.

The run length algorithm records the distance travelled before meeting an abrupt change in pixel value. This works by cyclically picking a pixel and moving in a particular direction until a pixel is encountered that is substantially different from the first one. The length of the chain of pixels is treated as an entry on a histogram of recorded lengths and the value at that length is increased by one. When all available pixels have been processed the histogram can be interpreted.

A difference histogram merely records the difference between the values of pixels that are a set distance apart. This is a limited hybrid of the co-occurrence and run length which cyclically picks a pixel and compares it to another pixel a fixed number of pixels away in a particular direction. The measured difference is treated as an entry on a histogram of differences and the value at that difference is increased by one. When all available pixels have been processed the histogram can be interpreted.

These algorithms are described in many literatures (Chandraratne, Kulasiri, & Samarasinghe, 2007; Haralick, Shanmugam, & Dinstein, 1973; Li *et al.*, 1999). While

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these classical algorithms have their uses they are inefficient and create too many duplicate features. The classical approaches however need to be retained for comparison as they continue to be successful (Gonzales-Barron & Butler, 2008). Even simpler texture features have been used to characterise cooked bread structure (Rosales-Juarez *et al.*, 2008). Figs. 1 and 2 illustrate the classic texture algorithms. In Fig. 1 the red line illustrates a path taken across the texture image, the blue box shows the change encountered over a run length of a certain number of pixels and the green bar shows whether the change is outside the acceptable limits. In Fig. 2 the red box shows a portion of the texture image with the individual pixel values (from 0 to 15 shown) and above the red box is a co-occurrence matrix populated with entries using the pixels inside the red box.

Another option is the Fourier transform which perceives a texture pattern as a convolution of sinusoidal waves (Stein & Shakarchi, 2003). This can model the fine detail that can occur in food surface texture. However many frequencies might be needed to accurately approximate the waveform which defeats the purpose of replacing the classical algorithms in the first place. Thus the Fourier transform should only be considered where a small number of frequencies can reproduce the surface image (Jackman & Sun, 2011c).

Wavelet transform

Of the alternatives to the classical approaches in characterisation of surface texture the wavelet transform is an excellent option. The Wavelet transform can simulate the greyscale images with building blocks called wavelets. These can then be brought together to bring back the original signal. One of the great advantages is that a small subset of wavelets is enough to very closely reproduce the original signal.

This wavelet transform is perfectly suited to image texture analysis as it can approximate a texture image by conceiving it as a two-dimensional wave with lighter pixels for the peaks and the darker pixels for the troughs. In practical application this means that images will need to be cropped to their nearest Dyadic scale, typically 1024, 512, 256 or 128.

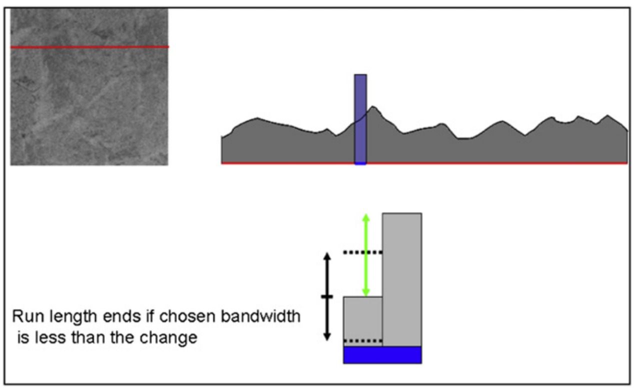

Fig. 1. Illustration of run lengths (Jackman, 2009).

Thus if a wavelet transform is fully applied on an image each chosen decomposition level will produce a horizontal, vertical and diagonal detail as well as an image approximation. Thus there are $4k + 1$ possible details available. The resulting details can be used to simulate the source image quite accurately *via* the inverse transform.

Important choices in applying wavelet transforms are the type of wavelet or wavelet "family" to be used, the number of orders of the wavelet to be applied and the decomposition level. Each of these has a number of strengths and weaknesses for analysing a particular image. The Matlab version user guide (The Mathworks, 2011) discusses this in considerable detail. The Matlab user guide, and the work of Randen and Husoy (1999), Kaiser (1994) and Singh, Choudhary, Jayas, and Paliwal (2008), further explain the wavelet transform and its possible applications.

Some notably successful applications of the wavelet transform for food texture analysis are those of Jackman, Sun, and Allen (2009b, 2009c, 2009d) and Jackman (2009), Jackman, Sun, Allen, Brandon, *et al*. (2010), which have shown the superiority of the wavelet transform over classical algorithms for beef muscle. Pumpkin flesh texture was also successfully characterised with a wavelet transform by Zenoozian and Devahastin (2009) as was ham surface texture by Jackman, Sun, Allen, Valous, *et al.* (2010). In summary the wavelet transform is an extremely powerful tool for characterising image texture if it is applied correctly.

Fractal dimensions

Another promising alternative to the classical approaches at characterising image texture that seeks to compress image information efficiently and effectively is fractal dimensions. Recurring patterns identified at various modalities in the image texture will allow the image to be broken down into a series of self-similar building blocks. These building blocks can be succinctly expressed by a characteristic dimension. These characteristic dimensions are fractal dimensions. Examples of patterns suited to fractal analysis are shown in Fig. 3. A comprehensive discussion on the utility of fractal dimensions in expressing food surface texture is given by Quevedo, Lopez, Aguilera, and Cadoche (2002). Some of the fractal patterns they encountered in their analysis of the surface texture of popular foodstuffs such as chocolate, apples, potatoes and pumpkins are shown in Fig. 4.

This is quite an ambitious form of texture analysis but it can be highly effective if these repeating patterns are at least closely approximated by reality. As might be expected such a simple approach can often fail to reflect reality and a more realistic approach of multifractal dimensions is needed. In the case of multifractals a spectrum of exponents is used instead of a single exponent. Fractal dimensions have been very successfully applied recently by Quevedo *et al*. (2008) and Quevedo, Diaz, Ronceros, *et al*. (2009).

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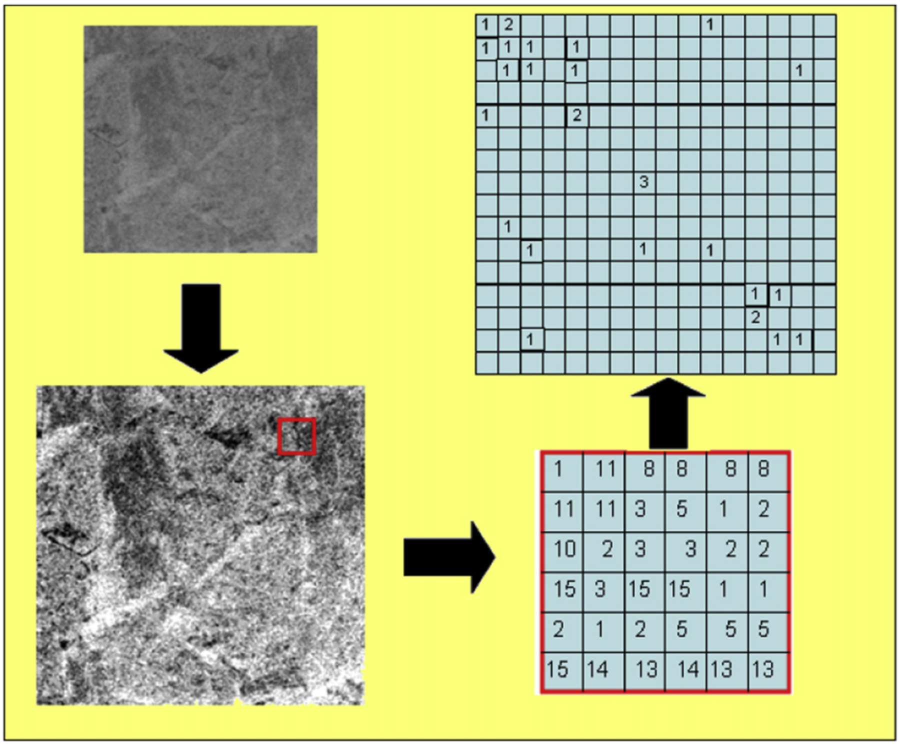

Fig. 2. Pixel co-occurrence calculation at a distance of 1 pixel (Jackman, 2009).

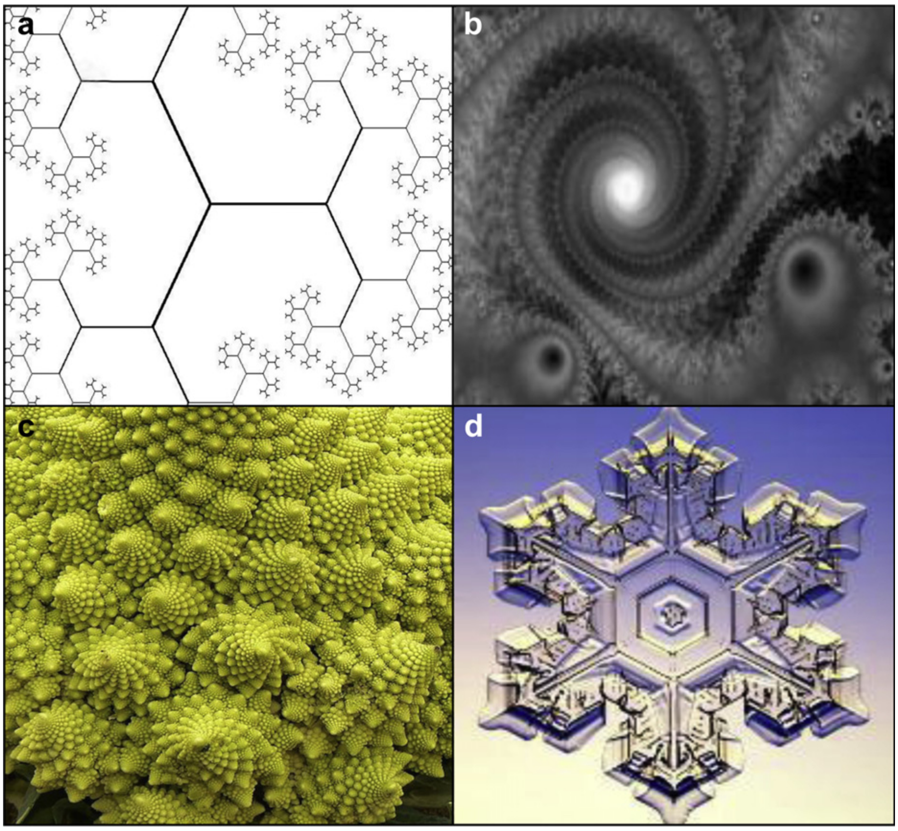

Fig. 3. Fractal patterns: (a) basic shape; (b) complex repeating pattern; (c) natural fractal patterns in vegetation; (d) natural fractal patterns in snowflakes (Jackman, 2009).

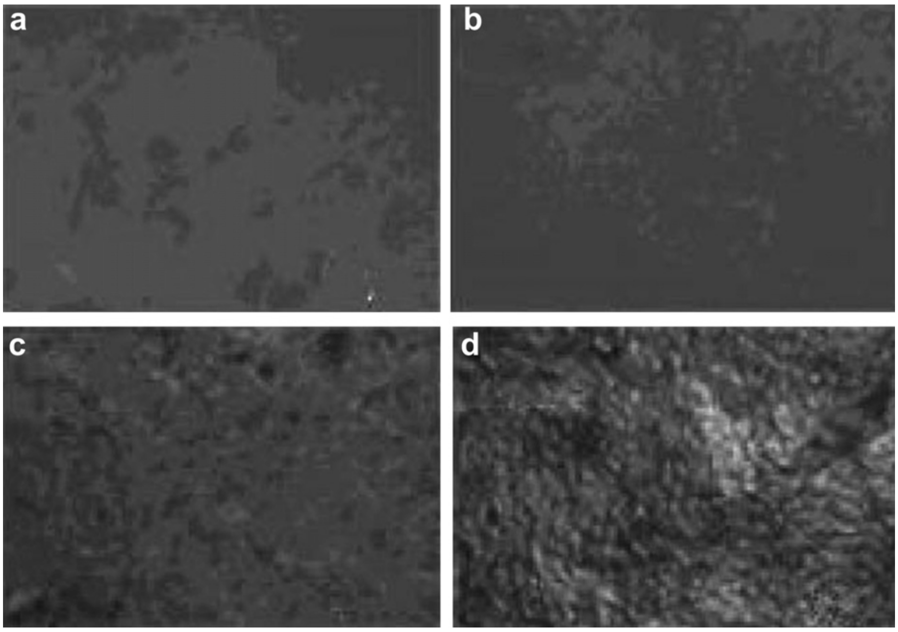

Fig. 4. Fractal patterns in food texture: (a) chocolate; (b) apple; (c) potato; (d) pumpkin (Quevedo *et al.*, 2002).

Not all foods have such self-similar recurring patterns. For example this is not expected to be found in foods such as fresh meat as there are fundamental changes in the nature of the muscle when the modality changes. The nature of the muscle will change from fibre bundles surrounded by connective tissue to individual fibres and all the way to individual sarcomeres. Thus attempting to apply fractal dimensions to all food texture problems is erroneous.

Applications

A comprehensive discussion of the texture features commonly used in image processing is detailed in Jackman and Sun (2011b). Meat has been a research area where texture characterisation is vitally important and the texture of beef was comprehensively analysed by Jackman *et al.* (2008, 2009b, 2009c, 2009d) and Jackman, Sun, Du, and Allen (2009) with the wavelet transform. The key result of which was that beef overall acceptability could be accurately predicted from image features ($r^2 = 0.95$) similarly comprehensive analyses were performed by Chandraratne, Samarasinghe, Kulasiri, and Bickerstaffe (2006), Chandraratne, Kulasiri, Frampton, Samarasinghe, and Bickerstaffe (2006), and Chandraratne *et al.* (2007) for Lamb using classical techniques with some good results as lamb tenderness was predicted quite well ($r^2 = 0.75$).

Characterisation of texture for fruit and vegetables have also attracted considerable research interest with Quevedo *et al.* (2008), Quevedo, Diaz, Ronceros, *et al.* (2009), and Quevedo, Diaz, Caqueo, *et al.* (2009) using fractal dimensions to monitor the progress of browning in bananas and pears although the predicted enzymatic browning rate was not very close to the independently measured one, the wavelet transform was used very successfully by Zenoozian and Devahastin (2009) to quantify dried pumpkin flesh with moisture, shape and colour features very accurately predicted ($r^2 = 0.99$). Classic texture features were used by Pydipati, Burks, and Lee (2006) to measure diseases and malaises 95% of the time. The classic texture characterisation algorithms also were used successfully by Gonzales-Barron and Butler (2008) and others for expressing the texture created during baking.

Future trends

The application of computer vision to food classification problems has been widely successful but there is scope for improving the implementation of computer vision without having to incur additional hardware costs. Furthermore there would not be a need to incur additional costs in upgrading skill levels as the improvements to image processing envisaged in this review are all achievable within existing skill sets. This will have the effect of limiting computer vision to visible wavelength examination of product surfaces, non-visible illumination of product surfaces or some kind of bulk assessment of the inner regions of a food product. Fortunately this will be sufficient for very many food grading challenges. A true three dimensional imaging of a food product is presently impractical; where such information would be required alternative technologies will need to be employed.

The emergence of more efficient algorithms for characterising image texture offers the strongest possibilities for extracting more useful or more efficient image features and as such there should be a strong emphasis on attempting to advance texture characterisation in the coming years with the maximisation of the power of the wavelet transform being the main focus unless a completely novel procedure for

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the extraction of texture features emerges that is more useful. There is no substantial scope for extracting more efficient colour, shape and size features without improving imaging equipment or imaging protocols, which should already be maximised with proper planning.

The possible emergence of more powerful and robust artificial intelligence modelling should be closely monitored over the coming years as it too might give an opportunity to build better models that can be used to deal with the potential non-linearities in food quality variability, which are beyond the reach of the existing methods. However caution should be maintained that robustness is not sacrificed in the same move.

It would be very useful to monitor how improved image processing techniques could synergise with improved hardware to see whether the net effect of both is substantially better than the effect of improved image processing alone. This could allow considerable expense to be saved in image processing centres and industrial settings.

Conclusions

Considering the above, it is clear that computer vision technology continues to be a very powerful means of tackling a great number of food classification and quality prediction tasks and that scope has been identified to improve the application of computer vision technology without incurring substantial new costs of hardware or expertise. As in the absence of a large budget such as a public healthcare budget the best must be made of the existing equipment.

The best of these opportunities lies in developing a superior characterisation of image texture to produce more accurate classifications and predictions as there is little if any scope for deriving better colour or morphology features without radical hardware upgrades and there is an abundance of algorithms that offer more powerful modelling of the variability between samples.

References

Absolute Medical Equipment. (2012). *Online catalogue*. Garnerville, NY, USA.

Antequera, T., Caro, A., Rodriguez, P. G., & Perez, T. (2007). Monitoring the ripening process of Iberian ham by computer vision on magnetic resonance imaging. *Meat Science, 76*(3), 561–567.

Blasco, J., Aleixos, N., Cubero, S., Gomez-Sanchis, J., & Molto, E. (2009). Automatic sorting of satsuma (*Citrus unshiu*) segments using computer vision and morphological features. *Computers and Electronics in Agriculture, 66*(1), 1–8.

Blasco, J., Aleixos, N., & Molto, E. (2007). Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. *Journal of Food Engineering, 81*(3), 535–543.

Blasco, J., Cubero, S., Gomez-Sanchis, J., Mira, P., & Molto, E. (2009). Development of a machine for the automatic sorting of pomegranate (*Punica granatum*) arils based on computer vision. *Journal of Food Engineering, 90*(1), 27–34.

Borggaard, C., Madsen, N. T., & Thodberg, H. H. (1996). In-line image analysis in the slaughter industry, illustrated by beef carcass classification. *Meat Science, 43*(S1), 151–163.

Brosnan, T., & Sun, D.-W. (2002). Inspection and grading of agricultural and food products by computer vision systems – a review. *Computers and Electronics in Agriculture, 36*(2–3), 193–213.

Brosnan, T., & Sun, D.-W. (2004). Improving quality inspection of food products by computer vision – a review. *Journal of Food Engineering, 61*(1), 3–16.

Chandraratne, M. R., Kulasiri, D., Frampton, C., Samarasinghe, S., & Bickerstaffe, R. (2006). Prediction of lamb carcass grades using features extracted from lamb chop images. *Journal of Food Engineering, 74*(1), 116–124.

Chandraratne, M. R., Kulasiri, D., & Samarasinghe, S. (2007). Classification of lamb carcass using machine vision: comparison of statistical and neural network analyses. *Journal of Food Engineering, 82*(1), 26–34.

Chandraratne, M. R., Samarasinghe, S., Kulasiri, D., & Bickerstaffe, R. (2006). Prediction of lamb tenderness using image surface texture features. *Journal of Food Engineering, 77*(3), 492–499.

Du, C.-J., & Sun, D.-W. (2004). Recent developments in the applications of image processing techniques for food quality evaluation. *Trends in Food Science & Technology, 15*(5), 230–249.

Du, C.-J., & Sun, D.-W. (2006a). Learning techniques used in computer vision for food quality evaluation: a review. *Journal of Food Engineering, 72*(1), 39–55.

Du, C.-J., & Sun, D.-W. (2006b). Estimating the surface area and volume of ellipsoidal ham using computer vision. *Journal of Food Engineering, 73*(2), 260–268.

Du, C.-J., & Sun, D.-W. (2006c). Automatic measurement of pores and porosity in pork ham and their correlations with processing time, water content and texture. *Meat Science, 72*(2), 294–302.

Du, C.-J., & Sun, D.-W. (2009). Retrospective shading correction of confocal laser scanning microscopy beef images for three-dimensional visualization. *Food and Bioprocess Technology, 2*(2), 167–176.

Edmund Optics. (2011). *Online catalogue*. Barrington, NJ, USA.

Goni, S. M., Purlis, E., & Salvadori, V. O. (2008). Geometry modelling of food materials from magnetic resonance imaging. *Journal of Food Engineering, 88*(4), 561–567.

Gonzales-Barron, U., & Butler, F. (2008). Discrimination of crumb grain visual appearance of organic and non-organic bread loaves by image texture analysis. *Journal of Food Engineering, 84*(3), 480–488.

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Texture features for image classification. *IEEE Transactions on Systems, Man and Cybernetics, 3*(6), 610–621.

HunterLab. (2008). *Insight on color: CIE L*a*b* color scale*. Reston, VA, USA.

Instron Inc.. (2008). *5500 Series advanced materials testing systems*. Norwood, MA, USA: Instron Inc.

Jackman, P. (2009). *Development of a novel image analysis system for the prediction of beef palatability*. Dublin, Ireland: National University of Ireland.

Jackman, P., & Sun, D.-W. (2011a). Recent advances in the use of computer vision technology in the quality assessment of fresh meats. *Trends in Food Science and Technology, 22*(4), 185–197.

Jackman, P., & Sun, D.-W. (2011b). Application of computer vision systems for objective assessment of food qualities. In Y.-J. Cho (Ed.), *Emerging technologies for evaluating food quality & food safety*. Boca Raton, Florida, USA: Taylor & Francis.

Jackman, P., & Sun, D.-W. (2011c). Computer vision in the meat industry (fresh and processed). In In D.-W. Sun (Ed.), *Computer vision technology in the food and beverage industries*. Cambridge, UK: Woodhead.

Jackman, P., Sun, D.-W., & Allen, P. (2009a). Automatic segmentation of beef *longissimus dorsi* muscle and marbling by an adaptable algorithm. *Meat Science, 83*(2), 187–194.

Jackman, P., Sun, D.-W., & Allen, P. (2009b). Comparison of various wavelet texture features to predict beef palatability. *Meat Science, 83*(1), 82–87.

Jackman, P., Sun, D.-W., & Allen, P. (2009c). Comparison of the predictive power of beef surface wavelet texture features at high and low magnification. *Meat Science, 82*(3), 353–356.

Jackman, P., Sun, D.-W., & Allen, P. (2009d). Prediction of beef palatability from colour, marbling and surface texture features of longissimus dorsi. *Journal of Food Engineering, 96*(1), 151–165.

Jackman, P., Sun, D.-W., Allen, P., Brandon, K., & White, A. M. (2010). Correlation of consumer assessment of longissimus dorsi beef palatability with image colour, marbling and surface texture features. *Meat Science, 84*(3), 564–568.

Jackman, P., Sun, D.-W., Allen, P., Valous, N. A., Mendoza, F., & Ward, P. (2010). Identification of important image features for pork and turkey ham classification using colour and wavelet texture features and genetic selection. *Meat Science, 84*(4), 711–717.

Jackman, P., Sun, D.-W., Du, C.-J., & Allen, P. (2009). Prediction of beef eating qualities from colour, marbling and wavelet surface texture features using homogenous carcass treatment. *Pattern Recognition, 42*(5), 751–763.

Jackman, P., Sun, D.-W., Du, C.-J., Allen, P., & Downey, G. (2008). Prediction of beef eating quality from colour, marbling and wavelet texture features. *Meat Science, 80*(4), 1273–1281.

Kaiser, G. (1994). *A friendly guide to wavelets*. Boston, MA, USA: Birkhauser.

Lee, D.-J., Archibald, J. K., Chang, Y.-C., & Greco, C. R. (2008). Robust color space conversion and color distribution analysis techniques for date maturity evaluation. *Journal of Food Engineering, 88*(3), 364–372.

Li, J., Tan, J., Martz, F. A., & Heymann, H. (1999). Image texture features as indicators of beef tenderness. *Meat Science, 53*(1), 17–22.

Li, J., Tan, J., & Shatadal, P. (2001). Classification of tough and tender beef by image texture analysis. *Meat Science, 57*(4), 341–346.

Moreda, G. P., Ortiz-Canavate, J., Garcia-Ramos, F. J., & Ruiz-Altisent, M. (2009). Non-destructive technologies for fruit and vegetable size determination – a review. *Journal of Food Engineering, 92*(1), 119–136.

Princeton Instruments. (2011). *Princeton instruments online catalogue*. Trenton, NJ, USA: Princeton Instruments.

Pydipati, R., Burks, T. F., & Lee, W. S. (2006). Identification of citrus disease using color texture features and discriminant analysis. *Computers and Electronics in Agriculture, 52*(1).

Quevedo, R. A., & Aguilera, J. M. (2010). Computer vision and stereoscopy for estimating firmness in the salmon (*Salmon salar*) fillets. *Food and Bioprocess Technology, 3*(4), 561–567.

Quevedo, R. A., Aguilera, J. M., & Pedreschi, F. (2010). Color of salmon fillets by computer vision and sensory panel. *Food and Bioprocess Technology, 3*(5), 637–643.

Quevedo, R. A., Diaz, O., Caqueo, A., Ronceros, B., & Aguilera, J. M. (2009). Quantification of enzymatic browning kinetics in pear slices using non-homogenous *L** color information from digital images. *LWT – Food Science and Technology, 42*(8), 1367–1373.

Quevedo, R. A., Diaz, O., Ronceros, B., Pedreschi, F., & Aguilera, J. M. (2009). Description of the kinetic enzymatic browning in banana (*Musa cavendish*) slices using non-uniform color information from digital images. *Food Research International, 42*(9), 1309–1314.

Quevedo, R. A., Lopez, C. G., Aguilera, J. M., & Cadoche, L. (2002). Description of food surfaces and microstructural changes using fractal image texture analysis. *Journal of Food Engineering, 53*(4), 361–371.

Quevedo, R. A., Mendoza, F., Aguilera, J. M., Chanona, J., & Gutierrez-Lopez, G. (2008). Determination of senescent spotting in banana (*Musa cavendish*) using fractal texture Fourier image. *Journal of Food Engineering, 84*(4), 509–515.

Randen, T., & Husoy, J. H. (1999). Filtering for texture classification: a comparative study. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 21*(4), 291–310.

Riquelme, M. T., Barreiro, P., Altisent, M. R., & Valero, C. (2008). Olive classification according to external damage using image analysis. *Journal of Food Engineering, 87*(3), 371–379.

Rosales-Juarez, M., Gonzalez-Mendoza, B., Lopez-Guel, E. C., Lauzano-Bautista, F., Chanona-Perez, J., Gutierrez-Lopez, G., et al. (2008). Changes on dough rheological characteristics and bread quality as a result of the addition of germinated and non-germinated soybean flour. *Food and Bioprocess Technology, 1*(2), 152–160.

Russell, R. A., Adams, N. M., Stevens, D. A., Batty, E., Jensen, K., & Freemont, P. S. (2009). Segmentation of fluorescence microscopy images for quantitative analysis of cell nuclear architecture. *Biophysics Journal, 96*(8), 3379–3389.

Singh, C. B., Choudhary, R., Jayas, D. S., & Paliwal, J. (2008). Wavelet analysis of signals in agriculture and food quality inspection. *Food and Bioprocess Technology*, http://dx.doi.org/10.1007/s11947-008-0093-7.

Specim Imaging. (2011). *Specim imaging online catalogue*. Oulu, Finland: Specim Imaging.

Stein, E. M., & Shakarchi, R. (2003). *Fourier analysis: An introduction*. Princeton, NJ, USA: Princeton University Press.

Stokes, M., Anderson, M., Chandrasekar, S., & Motta, R. (1996). *A standard default color space for the internet: sRGB*. Reston, VA, USA: International Color Consortium.

Sun, D.-W. (2000). Inspecting pizza topping percentage and distribution by a computer vision method. *Journal of Food Engineering, 44*(4), 245–249.

Sun D.-W. (Ed.), (2008). *Computer vision technology for food quality evaluation*. San Diego, California, USA: Academic Press/Elsevier, (583 pp.).

Sun, D.-W., & Brosnan, T. (2003). Pizza quality evaluation using computer vision – part 1 – Pizza base and sauce spread. *Journal of Food Engineering, 57*(1), 81–89.

The Mathworks. (2011). *Matlab user guide R2011b*. Massachusetts, USA: Natick.

USDA. (2004). *United States standards for grades of peaches*. Washington, DC: USDA.

USDA Agricultural Marketing Service. (2011). *Grading, certification and verification: USDA quality standards*. Washington, DC: USDA.

Wakamatsu, J., Odagiri, H., Nishimura, T., & Hattori, A. (2006). Observation of the distribution of Zn protoporphyrin IX (ZPP) in Parma ham by using purple LED and image analysis. *Meat Science, 74*(4), 594–599.

Yadav, B. K., & Jindal, V. K. (2007). Dimensional changes in milled rice (*Oryza sativa* L.) kernel during cooking in relation to its physicochemical properties by image analysis. *Journal of Food Engineering, 81*(4), 710–720.

Zenoozian, M. S., & Devahastin, S. (2009). Application of wavelet transform coupled with artificial neural network for predicting physicochemical properties of osmotically dehydrated pumpkin. *Journal of Food Engineering, 90*(2), 219–227.

Zheng, C. X., Sun, D.-W., & Zheng, L. Y. (2006a). Recent developments and applications of image features for food quality evaluation and inspection – a review. *Trends in Food Science & Technology, 17*(12), 642–655.

Zheng, C. X., Sun, D.-W., & Zheng, L. Y. (2006b). Recent applications of image texture for evaluation of food qualities – a review. *Trends in Food Science & Technology, 17*(3), 113–128.

Zion, B., Alchanatis, V., Ostrovsky, V., Barki, A., & Karplus, I. (2007). Real-time underwater sorting of edible fish species. *Computers and Electronics in Agriculture, 56*(1), 34–45.

Zion, B., Alchanatis, V., Ostrovsky, V., Barki, A., & Karplus, I. (2008). Classification of guppies' (*Poecilia reticulata*) gender by computer vision. *Aquacultural Engineering, 38*(2), 97–104.