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Pizza sauce spread classification using colour vision and support vector machines

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Abstract

An automated classification system of pizza sauce spread using colour vision and support vector machine (SVM) was developed. To characterise pizza sauce spread with low dimensional colour features, a sequence of image processing algorithms was developed. After image segmentation from the background, the segmented image was transformed from red, green, and blue (RGB) colour space to hue, saturation, and value (HSV) colour space. Then a vector quantifier was designed to quantify the HS (hue and saturation) space to 256-dimension, and the quantified colour features of pizza sauce spread were represented by colour histogram. Finally, principal component analysis (PCA) was applied to reduce the 256-dimensional vectors to 30-dimensional vectors. With the 30-dimensional vectors as the input, SVM classifiers were used for classification of pizza sauce spread. It was found that the polynomial SVM classifiers resulted in the best classification accuracy with 96.67% on the test experiments.

Keywords: Classification; Colour; Computer vision; Image processing; Machine vision; Principal component analysis; PCA; Pizza; Pizza sauce; Pizza topping; Support vector machine, SVM; Vector quantification

1. Introduction

The sauce is everything and can be a signature part of the pizza (Burg, 1998). Therefore, the quality of pizza sauce spread is an influential factor while evaluating the whole quality of a pizza. In the pizza industry, the quality evaluation of pizza sauce spread is still performed manually by trained inspectors, which is tedious, laborious, and costly, and is easily influenced by physiological factors, thus inducing subjective and inconsistent evaluation results. Increased popularity and consumption of pizzas have necessitated the automated quality evaluation of pizza sauce spread. Sun and Brosnan (2003a) analysed images of pizza sauce spread based on simple thresholding segmentation that included three steps. Firstly the whole pizza image was segmented from the white background using the red, green, and blue (RGB) model. Then by setting the hue, saturation, and intensity (HSI) values in the following ranges [220, 14], [0, 125] and [0, 200], respectively, segmentation of pizza sauce from pizza base was achieved. Finally, segmentation of the light zones of pizza sauce was accomplished by setting the HSI values as follows: [2, 14], [53, 125] and [106, 200], respectively. The most disadvantage of the method is that it is likely to become tuned to one type of image (e.g., a specific sensor, scene setting, illumination, and so on), which limited its applicability. The performance of the algorithm degrades significantly when the colour and the intensity of the illuminant are changed.

Image analysis techniques have been used increasingly for food quality evaluation over the past decades (Brosnan & Sun, 2004; Kavdir & Guyer, 2002; Park & Chen, 2000; Sun, 2000, 2004; Sun & Brosnan, 2003b; Sun & Du, 2004; Wang & Sun, 2001). In image analysis for food products, colour is an influential attribute of visual information and powerful descriptor for measurement. Colour vision offers a tremendous amount of spatial resolution that can be used to quantify the colour distribution of ingredients. Colour features of an object can be extracted by examining every pixel within the object boundaries and have proven successful for the objective measurement of many types of food products with applications ranging from fruit, grain, meat, to vegetable

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Nomenclature

$\vec{v}$	assumed vector of two-dimensional HS colour space
$\vec{u}_i$	eigenvector of the covariance matrix
$\overrightarrow{cy}_i$	new colour feature vector
$\vec{\varphi}(\cdot)$	non-linear transformation
$\vec{w}$	normal to the hyperplane
$\overrightarrow{cx}_i$	quantified colour feature vectors
$\vec{c}$	two-dimensional code-vector
σ	sigma term of Gaussian radial basis function kernels
ξ_i	nonnegative slack variable
α_i	coefficient obtained by solving a convex quadratic programming problem
λ_i	eigenvalue of the covariance matrix
$\vec{x}$, $\vec{x}_i$, $\vec{x}_j$	input vector
b	bias term
C	parameter used to penalise variables ξ_i
CM	covariance matrix
CS	set of 256 colours as the codebook
d	degree of polynomial kernels
f	classification function
H	high dimensional feature space
h	hue component of HSV colour space
i, m, n	index variable
k	kernel function
l	number of pizza sauce spread samples
M	assumed number of colours
nb	normalised blue component of RGB colour space
ng	normalised green component of RGB colour space
nr	normalised red component of RGB colour space
P	probability distribution function
Q	vector quantifier
R	partitioned region of the HS space
RS	set of 256 regions
s	saturation component of HSV colour space
T	transformation matrix
v	value component of HSV colour space
VS	assumed vector set of two-dimensional HS colour space
y_i	class of acceptable or unacceptable quality level

(Daley & Thompson, 1992; Jahns, Nielsen, & Paul, 2001; Leemans, Magein, & Destain, 1998; Ruan et al., 2001). Among the applications, one would expect most applications to be based on RGB colour space (Ahmad, Reid, Paulsen, & Sinclair, 1999; Lu, Tan, Shatadal, & Gerrard, 2000) and HSI colour space (Sun & Brosnan, 2003a; Tao, Heinemann, Vargheses, Morrow, & Sommer, 1995). However, $L^*a^*b^*$ colour space has also been used for colour features extraction (Vizhanyo & Felfoldi, 2000).

Classification identifies objects by classifying them into one of the finite sets of classes, which involves comparing the measured features of a new object with those of a known object or other known criteria and determining whether the new object belongs to a particular category of objects. A wide variety of approaches have been taken towards this task in the food quality evaluation. They have a common objective that is to simulate a human decision-maker's behaviour. Support vector machine (SVM) is a state-of-the-art classification technique, which has a good theoretical foundation in statistical learning theory (Vapnik, 1998). SVM fixes the classification decision function based on structural risk minimisation instead of the minimisation of the misclassification on the training set to avoid overfitting problem. It performs binary classification problem by finding maximal margin hyperplanes in terms of a subset of the input data (support vectors) between different classes. If the input data are not linearly separable, SVM firstly maps the data into a high dimensional feature space, and then classifies the data by the maximal margin hyperplanes. Moreover, SVM is capable of learning in high-dimensional feature space with fewer training data. Recently, SVM has been successfully applied to numerous classification problems, such as electronic nose data (Pardo & Sberveglieri, 2002; Trihaas & Bothe, 2002) and bakery process data (Rousu et al., 2003).

In this paper, a hybrid image processing algorithm was firstly developed to segment the pizza sauce spread from the background. Then the RGB colour space was transformed to hue, saturation and value (HSV) colour space, and the image was represented by hue and saturation (HS) colour components to ensure illumination independence. An efficient colour quantification method was presented to characterise the colour contents in the images of pizza sauce spread, which were represented by colour histogram. After that, principal component analysis (PCA) was applied to reduce the dimensionality of the colour feature vectors, and finally, the SVM classification techniques were employed for grading pizza sauce spread.

2. Materials and methods

2.1. Computer vision system

The samples of pizza sauce spread were provided by Green Isle Foods (Naas, Ireland), which were categorised into five quality levels by the qualified inspection personnel in the company, i.e., reject underwipe, acceptable underwipe, even spread, acceptable overwipe and reject overwipe. The image acquisition system used in this study consists of a Dell Workstation 400 equipped with an IC-RGB frame grabber (Imaging Technology, US), and a high quality 3-CCD Sony XC-003P camera. The images of pizza sauce spread were captured under two fluorescent lamps with plastic light diffusers. The overall sequence of digital image processing algorithms for classification of pizza sauce spread was presented in Fig. 1.

2.2. Image segmentation

To partition the image of pizza sauce spread from the background, a gradient-based segmentation approach was developed, which includes five steps, i.e., edge detection, morphological dilation, flood filling, image smoothing and mask operation. For the pizza image that differs greatly in contrast from the background, the Sobel operator (Sobel, 1970) was applied to detect the edge of pizza. The threshold value employed by Sobel operator for edge detection was determined using Otsu's method (Otsu, 1979). To eliminate the gaps in the edges, morphological dilation was implemented to the edge image. Then a flood filling operation (Soille, 1999) was performed to fill the holes in the image and a disk structure element was used to smooth the object by eroding the image twice. Finally, mask operation was applied to the original image to obtain the region of interest, i.e., the pizza sauce spread. The block diagram of image segmentation algorithm sequences was shown in Fig. 2.

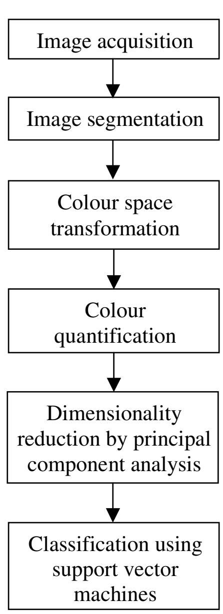

Fig. 1. The overall sequence of digital image processing algorithms for classification of pizza sauce spread.

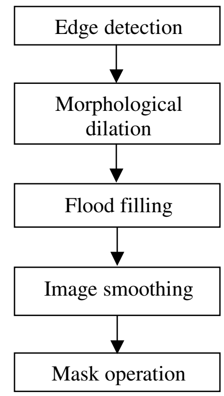

Fig. 2. The block diagram of image segmentation algorithm.

2.3. Colour space transformation

Since colour is invariant with respect to camera position and pizza orientation, it is one of the most significant features for pizza measurement. The images of pizza sauce spread were taken by the CCD camera and saved in the three-dimensional RGB colour space. Unfortunately, the RGB colour space used in computer graphics is device dependent, which is designed for specific devices, e.g. cathode-ray tube (CRT) display. Therefore, the RGB space has no accurate definition for a human observer, where the proximity of colours in the space does not indicate colour similarity in perception.

Colour space transformations are effective means for distinguishing colour images, which is an operation on the original colour space to produce a new transformed space. Linear transformation is the simplest method for colour conversion from the RGB space to others. Several linear transformations are used for transmitting videos and representing colour images. For example, YUV (standard colour space used in European TVs, where Y is linked to the component of luminance, and U and V are linked to the components of chrominance) and $i1i2i3$ (Ohta, Kanade, & Sakai, 1980) are obtained by linear transformation through simple matrix multiplications. Other colour space transformations are more complex, such as HSV and $L^*a^*b^*$, which are generated by non-linear transformations.

Compared to the other colour spaces, HSV is an intuitive colour space, which is a user-oriented colour system based on the artist's idea of tint, shade and tone. HSV separates colour into three components, i.e., hue (H), saturation (S) and value (V). H distinguishes among the perceived colours, such as red, yellow, green and blue. S refers to how far a colour is from a grey of equal intensity, and V represents the brightness of a reflecting object. For efficient classification of pizza sauce spread, the RGB colour space was transformed to HSV space. Given the normalised $r, g, b \in [0, \ldots, 1]$, the transformation to HSV is achieved by the following equations:

$$v = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \tag{1}$$

$$s = \frac{v - \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb})}{v} \tag{2}$$

Let

$$\mathrm{tr} = \frac{v - \mathrm{nr}}{v - \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb})},$$

$$\mathrm{tg} = \frac{v - \mathrm{ng}}{v - \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb})},$$

$$\mathrm{tb} = \frac{v - \mathrm{nb}}{v - \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb})},$$

then

$$6h = \begin{cases} 5 + \mathrm{tb} \text{ if } \mathrm{nr} = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \text{ and } \mathrm{ng} = \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \\ 1 - \mathrm{tg} \text{ if } \mathrm{nr} = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \text{ and } \mathrm{ng} \neq \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \\ 1 + \mathrm{tr} \text{ if } \mathrm{ng} = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \text{ and } \mathrm{nb} = \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \\ 3 - \mathrm{tb} \text{ if } \mathrm{ng} = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \text{ and } \mathrm{nb} \neq \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \\ 3 + \mathrm{tg} \text{ if } \mathrm{nb} = \max(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \text{ and } \mathrm{nr} = \min(\mathrm{nr}, \mathrm{ng}, \mathrm{nb}) \\ 5 - \mathrm{tr} \text{ otherwise} \end{cases} \tag{3}$$

where $h, s, v \in [0, \ldots, 1]$.

2.4. Colour quantification

Generally, the HSV colour space is discretised to 256 levels at each channel, which yields a very large number of colours ($256 \times 256 \times 256$). In order to limit the dimensionality of the colour features of the pizza sauce spread, the colour space must be reduced and quantified into a smaller number of colours, which was realised by the following three steps. Firstly, to reduce the effect of illumination on the system, the value component (V) was not used for colour features extraction of pizza sauce spread. Then, a vector quantifier (Gray, 1984) was designed to quantify the remaining two-dimensional space, i.e., hue and saturation. Finally, colour histogram was employed to represent the distribution of colour features in the image of pizza sauce spread.

After ignoring the value component, the two-dimensional HS space was assumed to consist of $M (M \gg 256)$ colours: $\mathrm{VS} = \{\vec{v}_1, \vec{v}_2, \ldots, \vec{v}_M\}$, where the vectors were two-dimensional, i.e., $\vec{v}_m = (v_{m,1}, v_{m,2})$, $m = 1, 2, \ldots, M$. The hue and saturation components were quantified into 16 intervals respectively to produce a set of 256 colours as the codebook: $\mathrm{CS} = \{\vec{c}_1, \vec{c}_2, \ldots, \vec{c}_{256}\}$, where the code-vectors were two-dimensional, i.e., $\vec{c}_n = (c_{n,1}, c_{n,2})$, $n = 1, 2, \ldots, 256$. In this way, the HS space was partitioned into 256 regions: $\mathrm{RS} = \{R_1, R_2, \ldots, R_{256}\}$. Thus, a vector quantifier (Q) was generated, which mapped the vector set VS containing M inputs into a finite set CS containing 256 outputs: $Q(\vec{v}_m) = \vec{c}_n$, if $\vec{v}_m \in R_n$. The aforementioned quantification yielded a collection of 256 distinct colours in HS space.

The colour histogram method is one of the simplest and most popular approaches to characterise colour information in the images. Using the 256-colour quantified HS space, the distribution of colour content in the image of pizza sauce spread was represented by a colour histogram. Column III in Fig. 3 showed five examples of quantified colour histogram of pizza sauce spread. The abscissa is the index of code-vector n and the ordinate is the frequency of occurrence.

2.5. Dimensionality reduction by principal component analysis

In real implementation, the quantified 256-dimensional vectors are still too large to allow fast and accurate classification. The large feature vectors will increase the complexity of the classifier and the classification error. PCA is one of the powerful techniques for dimensionality reduction (Calvo, Partridge, & Jabri, 1998), which transforms original feature vectors from large space to a small subspace with lower dimensions.

The basic approach of PCA is first to compute the covariance matrix (CM) of the quantified 256-dimensional vectors. The eigenvalue λ_i and eigenvector $\vec{u}_i$ of the covariance matrix (CM) can be obtained by solving the eigenstructure decomposition $\mathrm{CM}\vec{u}_i = \lambda_i \vec{u}_i$. In practice, there are two ways to compute the eigenvalues and eigenvectors: singular value decomposition (SVD) and regular eigen-computation (Zhao, Chellappa, & Krishnaswamy, 1998). Taken the eigenvectors $\vec{u}_i$ as its rows, a transformation matrix (T) is formed. The new colour feature vectors $\overrightarrow{cy}_i$ are obtained by $\overrightarrow{cy}_i = T\overrightarrow{cx}_i$, which maps the quantified 256-dimensional vectors to a smaller vectors.

The first principal component accounts for the most significant characteristic of the original data with the maximum variance. Each succeeding component accounts for less significant characteristic with as much of the remaining variability as possible. Practically, the last few principal components can be truncated from the back of the transformation matrix. These principal components correspond to useless characteristics that are essentially noise.

2.6. Classification using SVM

The classification of pizza sauce spread into acceptable and unacceptable quality levels can be considered as a binary categorisation problem. Suppose there are l samples of pizza sauce spread in the training data, and each sample is denoted by a vector $\vec{x}_i$, which represents the colour features of the pizza sauce spread. The classification of pizza sauce spread can be described as the task of finding a classification function $f : \vec{x}_i \to y_i, y_i \in \{-1, +1\}$ using training data. Subsequently, the classification function f is used to classify the unseen test

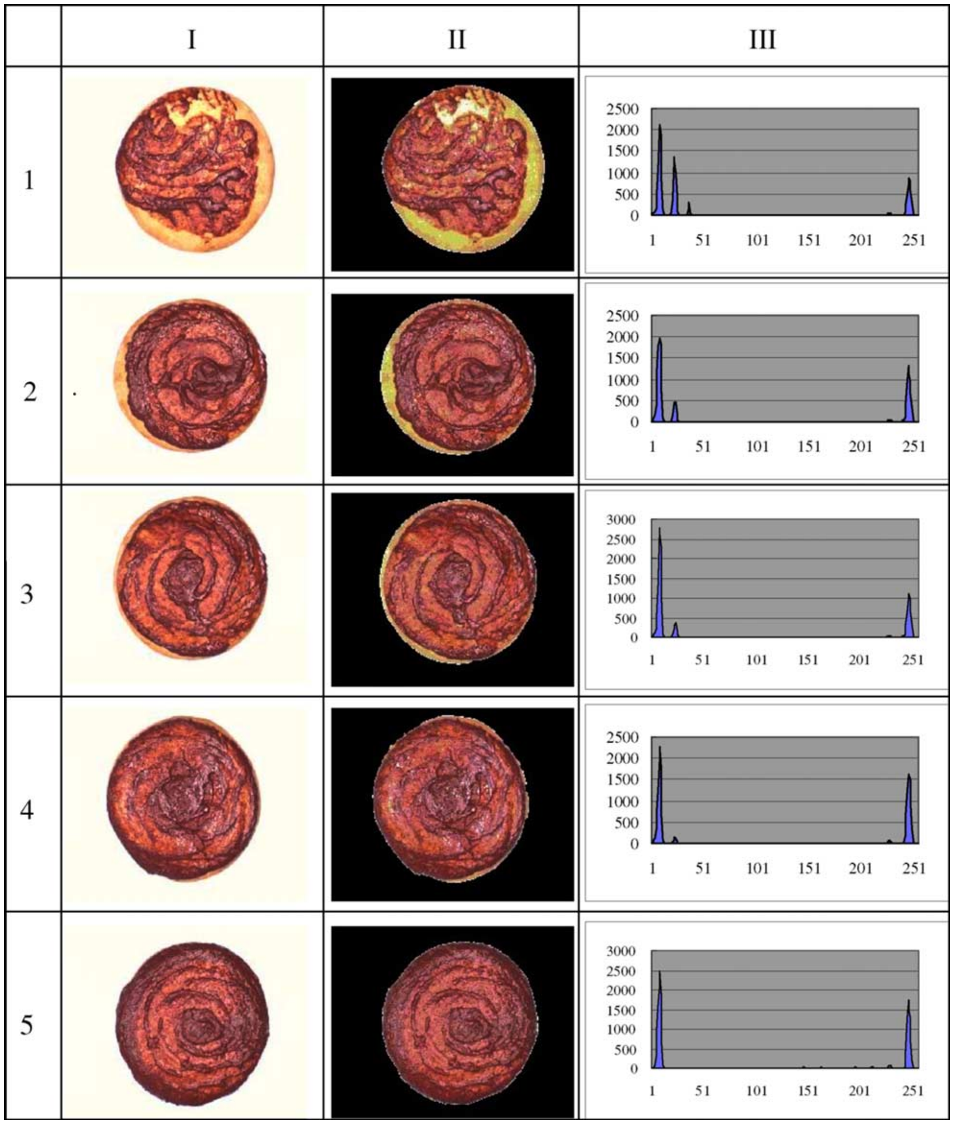

Fig. 3. Results of the image segmentation and colour features extraction algorithms. Column I: original images of the pizza sauces; column II: segmentation results; column III: colour histograms of the segmented images. Row 1: reject underwipe; row 2: acceptable underwipe; row 3: even spread; row 4: acceptable overwipe; row 5: reject overwipe.

data. If $f(\vec{x}_i) > 0$, the input vector $\vec{x}_i$ is assigned to the class $y_i = +1$, i.e., the acceptable quality level, otherwise to the class $y_i = -1$, i.e., the unacceptable quality level.

For the linearly separable training vectors, the classification function f has the following form:

$$f(\vec{x}) = \mathrm{sgn}(\vec{w}^{\mathrm{T}}\vec{x} + b) \tag{4}$$

where $\vec{w}$ is the normal to the hyperplane and b is a bias term, which should satisfy the following conditions:

$$y_i(\vec{w}^{\mathrm{T}}\vec{x}_i + b) \geqslant 1 \quad i = 1, 2, \ldots, l \tag{5}$$

The SVM is trying to find the optimal separating hyperplane that maximises the margin between positive and negative samples. The margin is $2/\|\vec{w}\|$, thus the optimal separating hyperplane is the one minimising $\frac{1}{2}\vec{w}^{\mathrm{T}}\vec{w}$, subject to constraints (5), which is a convex quadratic programming problem.

For the linearly non-separable case, constraints (5) are relaxed by introducing a new set of nonnegative slack variables $\{\xi_i | i = 1, 2, \ldots, l\}$ as the measurement of violation of the constraints (Vapnik, 1998) as follows:

$$y_i(\vec{w}^{\mathrm{T}}\vec{x}_i + b) \geqslant 1 - \xi_i \quad i = 1, 2, \ldots, l \tag{6}$$

The optimal hyperplane is the one that minimises the following formula:

$$\frac{1}{2}\vec{w}^{\mathrm{T}}\vec{w} + C\sum_{i=1}^{l}\xi_i \tag{7}$$

where C is a parameter used to penalise variables ξ_i, subject to constraints (6).

For nonlinearly separable case, the training vectors $\vec{x}_i$ can be mapped into a high dimensional feature space H by a non-linear transformation $\vec{\varphi}(\cdot)$. The training vectors become linearly separable in the feature space H and then separated by the optimal hyperplane described as before. In many cases, the dimension of H is infinite, which makes it difficult to work with $\vec{\varphi}(\cdot)$ explicitly. Since the training algorithm only involves inner products in H, a kernel function $k(\vec{x},\vec{y})$ is used to solve the problem, which defines the inner product in H:

$$k(\vec{x},\vec{y}) = \langle \vec{\varphi}(\vec{x}), \vec{\varphi}(\vec{y}) \rangle \tag{8}$$

Polynomial kernels and Gaussian radial basis function (RBF) kernels are usually applied in practice and are defined as:

$$k(\vec{x},\vec{y}) = (\vec{x}\vec{y} + b)^d \tag{9}$$

$$k(\vec{x},\vec{y}) = \exp(-\|\vec{x}-\vec{y}\|^2/2\sigma^2) \tag{10}$$

where b is the bias term and d is the degree of polynomial kernels.

The classification function then has the following form in terms of kernels:

$$f(\vec{x}) = \operatorname{sgn}\left[\sum_{i=1}^{l} y_i \alpha_i k(\vec{x}_i,\vec{x}) + b\right] \tag{11}$$

where α_i can be obtained by solving a convex quadratic programming problem subject to linear constraints. The support vectors are those $\vec{x}_i$ with $\alpha_i > 0$ in Eq. (11).

3. Results and discussion

In this study, 120 images of pizza sauce spread were captured for classification, including 60 acceptable levels (15 acceptable underwipe, 25 even spread and 20 acceptable overwipe) and 60 unacceptable levels (30 reject underwipe and 30 reject overwipe). The image segmentation algorithm of pizza sauce spread described above was implemented by using Matlab (Mathworks, 1992) under Windows NT 4.0 on a Dell Workstation 400. Five images of pizza sauce spread were chosen to demonstrate the performance of the algorithm as shown in Fig. 3. The first column (I in Fig. 3) shows five original images including two unacceptable quality levels, i.e., reject underwipe (Fig. 3-I1) and reject overwipe (Fig. 3-I5), and three acceptable quality levels, i.e., acceptable underwipe (Fig. 3-I2), even spread (Fig. 3-I3), and acceptable overwipe (Fig. 3-I4). The segmentation results of the five original images were shown in the second column (II in Fig. 3), where the regions of pizza sauce spread were preserved well and the background regions were set with black colour. Based on visual judgement, it can be seen that the segmentation is satisfactory.

After that, the segmented image was converted from RGB colour space to HSV colour space by Eqs. (1)–(3). Then, the vector quantifier described in Section 2.4 was applied to extract the colour features of the pizza sauce spread. The quantified colour histogram of the five segmented images in the second column of Fig. 3 were shown in the third column of Fig. 3. It can be observed that the histograms differ sequentially from Fig. 3-III1 (reject underwipe) to Fig. 3-III5 (reject overwipe) with the sauce spread on the pizza base increasing. In Fig. 3-III1, there are four big peaks (greater than 100), which are located in the following ranges $[1, 13]$, $[17, 27]$, $[33, 39]$ and $[241, 251]$, respectively. However, in Fig. 3-III5, there are only two big peaks located in the ranges $[1, 13]$ and $[242, 251]$, respectively. Fig. 3-III1 (reject underwipe) and Fig. 3-III5 (reject overwipe) are unacceptable levels for too little sauce or too much sauce. Contrastively, there are three big peaks in Fig. 3-III2, III3 and III4, respectively, which are all acceptable levels, namely acceptable underwipe, even spread, and acceptable overwipe. The big peak located in the range $[33, 39]$ disappears in the three acceptable levels, and the big peak located in $[17, 27]$ decreases gradually from the acceptable underwipe to the acceptable overwipe. Based on the colour histogram, it is not difficult to classify the five images into acceptable and unacceptable levels. The three images of acceptable levels have three big peaks, while the other two images of unacceptable levels have four or two big peaks. The illustrational results indicate that the colour contents in the images of pizza sauce spread can be characterised efficiently by the algorithm developed.

256-dimensional vectors are still too large to classify accurately with small sample sizes. Meanwhile, it is easy to find that there are a number of portions of the quantified colour histogram with zero value. PCA was applied to reduce the dimensionality of the colour features. The analysis showed that 99.98% of the total variation is explained by the first 30 principal components. The results were visualised by a scatter plot (shown in Fig. 4), where the abscissa corresponds to the first principal component explained 51.76% of the total variation and the ordinate corresponds to the second principal component explained 17.46% of the total variation. The samples of pizza sauce spread of the unacceptable levels, i.e., reject underwipe and reject overwipe, were mostly located in the right and left part of the plot, respectively. And the samples of pizza sauce spread of the acceptable levels were mostly located in the middle part of the plot.

Sixty images of pizza sauce spread were randomly selected for training and the remaining 60 images for test. The first 30 principal components of each sample were used as input to the classifiers. The SvmFu (Ryan, 2002) implementation of SVMs was used for classification of pizza sauces in all experiments. Besides a linear SVM classifier, polynomial classifiers and RBF classifiers were trained and tested using the kernels defined in Eqs. (9)

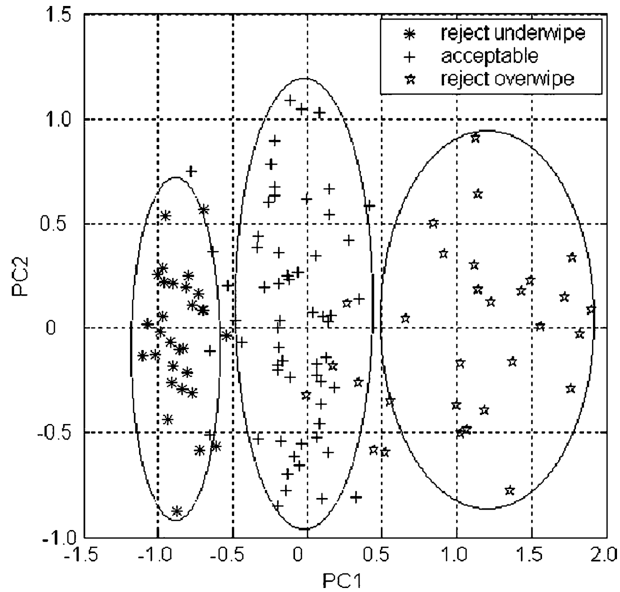

Fig. 4. PCA plot of the first two principal components.

and (10), respectively. A range of parameters for the polynomial and RBF SVM classifiers were selected to eliminate any biased performance of the SVMs that may be caused by inappropriate choice of parameters. The parameters of polynomial SVM were the combinations of bias b and degree d, with $b \in \{0, 1, 2, 3, 4, 5, 6\}$, and $d \in \{1, 2, 3, 4, 5\}$. The values $\sigma \in \{0.2, 0.5, 0.8, 1.0, 1.2, 1.5, 2.0, 2.5\}$ were selected for the RBF SVM classifiers. The penalty parameter C in Eq. (7) was set as the default value 1.0 by the SvmFu algorithm (Ryan, 2002).

The classification results with linear SVM and RBF SVM classifiers are listed in Table 1. On the test experiments, the RBF kernel with $\sigma = 0.5$ resulted in the best classification rate of 95.00%. Table 2 shows the classification results of the polynomial SVM with different combinations of bias b and degree d. The polynomial SVM classifiers (1, 3), (1, 4), (2, 2), (2, 3), (2, 4), (2, 5), and (2, 6) achieved the best classification accuracy of 96.67% on the test experiments. In fact, the polynomial SVM classifiers with $d = 1$ are linear SVM classifiers, which performed worse than any other classifiers with only 60.00% accuracy. Fig. 5 illustrates visually the use of three SVM classifiers for classification of samples of pizza sauce spread characterised by the first two principal components. The decision boundaries of a RBF, a polynomial and a linear SVM classifier were demonstrated by the contours plotted in different type of line. As shown in Fig. 5, it was impossible to separate the data set linearly, which was the reason why only 60.00% accuracy was achieved by the linear SVM classifier.

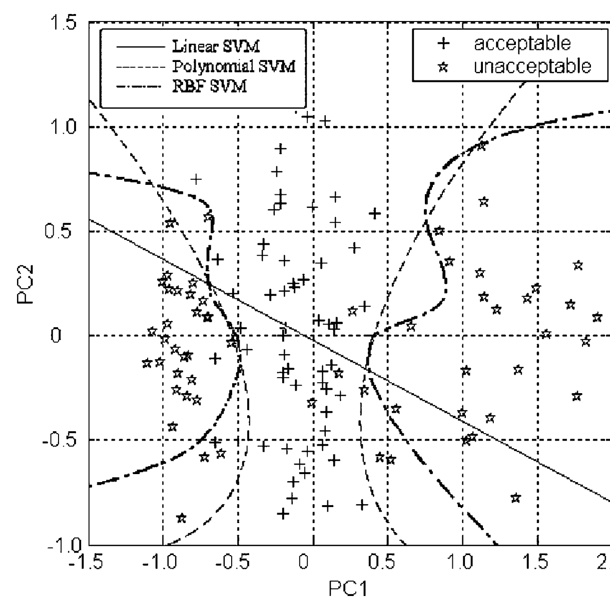

Fig. 5. The illustration of three SVM classifiers.

Table 1
The classification results with linear SVM and RBF SVM classifiers

Classifiers	Linear SVM	RBF SVM							
		0.2	0.5	0.8	1.0	1.2	1.5	2.0	2.5
Rate (%)	60.00	70.00	95.00	91.67	90.00	91.67	85.00	66.67	68.33

Table 2
The classification results (%) of polynomial SVM with different combinations of bias b and degree d

Bias b	Degree d					
	1	2	3	4	5	6
0	60.00	91.67	63.33	88.33	61.67	68.33
1	60.00	93.33	96.67	96.67	95.00	68.33
2	60.00	96.67	93.33	95.00	95.00	68.33
3	60.00	96.67	93.33	95.00	95.00	68.33
4	60.00	96.67	93.33	95.00	95.00	68.33
5	60.00	96.67	91.67	95.00	95.00	68.33
6	60.00	96.67	91.67	95.00	95.00	68.33

The decision boundaries of the RBF SVM classifier and the polynomial SVM classifier can separate the data set with comparative error. Therefore, the performance of the RBF SVM classifier was comparable with the polynomial SVM classifier as shown in Tables 1 and 2.

Although the component V was eliminated to reduce the effect of illumination on the developed computer vision system, the lighting system is still an important prerequisite of image acquisition for quality evaluation of pizza sauce spread. Fortunately, the lighting hardware used is common and readily available for application. In a real inspection task where the illumination is changeable, the new classifier can be obtained by training with samples captured under new lighting conditions.

In practice, binary classification of the pizza sauce spread can satisfy the general requirement of industrial applications. However, it seems a little arbitrary and still cannot satisfy the requirement of multi-classification. Although SVM is originally developed for binary classification, several SVM algorithms have been developed for handling multi-classification problem. One approach is by using a combination of several binary SVM classifiers, such as one-versus-all (Vapnik, 1998), one-versus-one (Kreßel, 1999), and Directed Acyclic Graph (DAG) SVM (Platt, Cristianini, & Shawe-Taylor, 2000), while the other is by directly using a single optimisation formulation (Crammer & Singer, 2001). Our future research will involve in dealing with the multi-classification problem of pizza sauce spread using SVM in details.

4. Conclusions

The results presented here have demonstrated the ability of the approach based on colour vision and support vector machine to classify pizza sauce spread. Being a user-oriented colour space, HSV was employed and the component V was eliminated to reduce the effect of illumination. The vector quantification and PCA techniques successfully reduced the dimensionality of colour features of pizza sauce spread obtained from the remaining HS space. With the first 30 principal components as the input, an overall accuracy of 96.67% was achieved by the polynomial SVM classifiers $(1,3)$, $(1,4)$, $(2,2)$, $(2,3)$, $(2,4)$, $(2,5)$, and $(2,6)$, and 95.00% accuracy was obtained using the RBF SVM classifier with $\sigma = 0.5$.

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