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Journal of Food Engineering 68 (2005) 277–287
JOURNAL OF FOOD ENGINEERING
www.elsevier.com/locate/jfoodeng

Comparison of three methods for classification of pizza topping using different colour space transformations

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Received 8 December 2003; accepted 31 May 2004

Abstract

Five transformations of RGB (red, green, and blue) colour space were evaluated for their performance in classifying pizza toppings, i.e., NRGB (normalised RGB), HSV (hue, saturation, and value), I1I2I3, L*a*b*, and YCbCr. Using these five colour space transformations, the performance of three SVM (support vector machine) classifiers (linear, polynomial, and RBF) on pizza topping classification was compared with two classical classification approaches, i.e., C4.5 classifier and an RBF_NN (radial basis function neural network) classifier. The C4.5 classifier obtained the best classification accuracy of 93.3% with L*a*b* or I1I2I3 colour space transformation, and the RBF_NN classifier achieved the best classification accuracy of 86.7% with YCbCr, HSV or L*a*b* colour space transformation. For the SVM classifiers, the polynomial SVM classifier had the best classification accuracy of 96.7% with HSV colour space transformation, while the radial basis function (RBF) SVM classifier obtained the best classification accuracy of 90.0% with YCbCr, L*a*b* or HSV colour space transformation. Among the SVM classifiers, the polynomial SVM classifier combined with HSV colour space transformation proved to be a good approach for the classification of pizza toppings using computer vision.

Keywords: Classification; Colour; Computer vision; Decision tree; Machine learning; Neural network; Pizza topping; Support vector machine; SVM

1. Introduction

As one of the most popular consumer foods, pizzas have a big market in the world. In this highly competitive market, the topping of pizzas is an influential component in their visual quality because the toppings would greatly affect the psychological orientation of consumers and their subsequent purchases (Sun & Brosnan, 2003b). The general visual features of an acceptable pizza should include a regular overall colour histogram, uniform colour of each individual topping, pre-defined area percentage of topping objects, even distribution of each individual topping, etc. (Sun, 2000). Among these visual features, topping percentage and distribution have been studied to evaluate and classify pizza toppings for the automatic and objective assessment of the visual quality of pizzas using computer vision, which is a rapid, economic, consistent and even more accurate quality inspection tool (Sun, 2000, 2004; Sun & Brosnan, 2003a, 2003b).

Recently, image processing techniques have been applied increasingly for food quality evaluation (Brosnan & Sun, 2004; Sun & Du, 2004; Wang & Sun, 2003). The lowering cost of colour cameras has made colour image processing to become a reality. Colour features can be used to quantify the distribution of ingredients for quality classification using computer vision. Research shows that colour has been successful in classifying a variety of food products (Sun, 2004), such as

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0260-8774/$ - see front matter
doi:10.1016/j.jfoodeng.2004.05.044

Nomenclature

ϕ_j	basis function
$\vec{c}_j$	centre of Gaussian function
$\vec{\varphi}(\cdot)$	nonlinear transformation
$\vec{w}$	normal to the hyperplane
σ_j^2	variance of Gaussian function
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
$\vec{x}, \vec{x}_i, \vec{x}_j$	input vector
A	acceptable level subset
b	bias term
B	blue component of RGB colour space
C	parameter used to penalise variables ξ_i
cb	Cb component of YCbCr colour space
cr	Cr component of YCbCr colour space
cy	Y component of YCbCr colour space
d	degree of polynomial kernels
f	classification decision function
G	green component of RGB colour space
gain	information gained on a given attribute
gain ratio	information ratio gained on a given attribute
H	high-dimensional feature space
h	hue component of HSV colour space
I	information needed to identify the class
i, j, n, k	index variable
I1	I1 component of I1I2I3 colour space
I2	I2 component of I1I2I3 colour space
I3	I3 component of I1I2I3 colour space
k	kernel function
l	number of pizza topping samples
n_b	normalised blue component of RGB colour space
n_g	normalised green component of RGB colour space
n_r	normalised red component of RGB colour space
PC1	first component of PCA
R	red component of RGB colour space
s	saturation component of HSV colour space
split	information due to the split of T
T	training set
T_i	subset of training set T
U	unacceptable level subset
v	value component of HSV colour space
w_j	weight coefficient of RBF_NN
y	output of RBF_NN
y_i	class of acceptable or unacceptable quality level

apple (Nakano, 1997), bell pepper (Shearer & Payne, 1990), peach (Miller & Delwiche, 1989), muffin (Abdullah, Aziz, & Mohamed, 2000), mushroom (Vizhanyo & Felfoldi, 2000), pizza (Sun & Brosnan, 2003a, 2003b), and soybean seed (Ahmad, Reid, Paulsen, & Sinclair, 1999; Casady, Paulsen, Reid, & Sinclair, 1992). Generally speaking, colour images are captured by a colour camera and saved in the three-dimensional RGB (red, green and blue) colour space. Colour space transformation is a powerful tool for colour feature extraction. Among the applications of colour spaces for food product classification, most of them are based on RGB space (Ahmad et al., 1999), HSI (hue, saturation and intensity) space (Sun & Brosnan, 2003a, 2003b), and L*a*b* space (Vizhanyo & Felfoldi, 2000).

Classification is a procedure for sorting each element of a data set into two or more sets of classes utilising a decision criterion, i.e., classifier. It normally consists of a training phase and an application phase. In the training phase, the classifier is induced by learning the training set, which is a collection of objects of known observations from each type. In the application phase, the classifier is applied to the test set, which is a collection of unknown classes, to make a decision on what their classes are likely to be. At the present time, there exist a number of approaches developed for the classification of agricultural and food products. These approaches include the classical methods such as C4.5 and artificial neural networks, and the emerging methods such as support vector machine (SVM). The C4.5 (Quinlan, 1993) algorithm of machine learning is a well-known classification technique, which has been used for determining oestrus in cows (Mitchell, Sherlock, & Smith, 1996), and culling management of dairy herds (McQueen, Garner, Nevill-Manning, & Witten, 1995). The artificial neural networks have been applied to classify many types of food products, such as apple (Kavdir & Guyer, 2002), barley seed (Romaniuk, Sokhansanj, & Wood, 1993), poultry carcass (Park & Chen, 2000), and sweet onion (Shahin, Tollner, Gitaitis, Sumner, & Maw, 2002). Besides the above classical classification approaches, SVM is a currently emerging classification technique, which has a good theoretical foundation in statistical learning theory (Vapnik, 1995). SVM performs binary classification problem by finding maximal margin hyperplanes in terms of a subset of the input data (support vectors) between different classes. SVM has been successfully applied to some classification problems, such as electronic nose data (Pardo & Sberveglieri, 2002) and bakery process data (Rousu et al., 2003).