Neurocomputing 168 (2015) 1011–1023

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

A local binary pattern based texture descriptors for classification of tea leaves

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ARTICLE INFO

Article history:
Received 24 December 2014
Received in revised form
21 April 2015
Accepted 7 May 2015
Communicated by Huaping Liu
Available online 16 May 2015

Keywords:
Tea classification
Local binary pattern
Gray level co-occurrence matrix
Texture classification

ABSTRACT

For tea processing production lines, different fresh tea leaves require different processing parameters for the control systems of tea machines. Hence, an effective algorithm for classification of tea leaves will be important for automatic tea processing. However, most of tea classification researches were focused on gross tea, instead of fresh tea leaves. In this paper, a texture extraction method combing a non-overlap window local binary pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM) has been proposed for green tea leaves classification. By taking advantages of both LBP and GLCM for texture extraction, this method is able to effectively extract texture of tea leaves for classification at low computational cost to meet automatic tea production line requirements. The experiments have been conducted to prove the effectiveness of the proposed method.

1. Introduction

Tea is one of the most popular beverages consumed by mankind worldwide. Processing quality of tea production plays a pivotal role in determining its market value. It is well-known that in tea production processing different tea leaves require different processing parameters. Traditionally, tea is manually. However, extensive manpower is needed to determine different process parameters according to different types of tea leaves. Nowadays, most massive tea manufacturers have adopted automatic tea processing production lines. To ensure high quality processing of tea leaves, it is essential to be able to classify the tea leaves automatically.

Up to now, there are many different methods for classification of gross tea. Wu et al. [1] adopted a multi-spectral image technique to sort green tea into distinctive categories, entropy values of green tea images captured at diverse wavelengths are used as image texture features. It turns out that a support vector machine (SVM) with radial basis function (RBF) kernel function can successfully determine tea categories with 100% accuracy after the entropy features are trained by SVM, which is much better than SVM with linear kernel, partial least squares and RBF neural networks. Near-infrared (NIR) spectroscopy has been successfully used for rapid identification of green, black and Oolong teas by Chen et al. [2]. The spectral differences due to different types of tea are used as identification features. The SVM is applied to attain differentiation of the three tea categories. The top five latent variables extracted by the principal component analysis (PCA) were used as the input of the SVM classifier. The authors presented a simple, rapid, reliable and low-cost approach for identification of tea categories. Borah et al. [3] proposed a texture feature estimation technique for discriminating images of eight different grades of CTC (cutting, tearing and curling) tea. The primary objective of their work is to estimate tea granules sizes in different images. The size classifier method presented by Borah et al. [3] is based on the surface roughness of CTC tea images. The method adopted the Daubechies' wavelet based decomposed sub-band images and feature vectors for calculating the new set of features. Classification accuracy rates of 74.67% and 80% in two neural networks were obtained. Gagandeep et al. [4]presented a technique of discriminating among four categories of machine-made black tea using texture features based on grey tone spatial dependencies. A grading accuracy of order of 80% was achieved. Borah et al. [5] employed a nondestructive imaging technique to determine tea fermentation status through color information. Palacios-Morillo et al. [6] used the UV–Vis data of tea to discriminate tea varieties. A successful classification model was built by combining the PCA and multilayer perception artificial neural network (ANN). Laddi et al. [7] discussed the role of illumination in discriminating tea samples based upon textural feature of tea granules. Their works show that textural features are feasible to estimate tea quality under Darkfield illumination as a non-destructive and fast technique.

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http://dx.doi.org/10.1016/j.neucom.2015.05.024
0925-2312/

Li et al. [8] proposed an intelligent method for recognizing different types of Chinese famous tea based on multi-spectral imaging technique. Two kinds of feature extraction methods including gray level co-occurrence matrix and wavelet transform (WT) were adopted for mining characteristic of multi-spectral image. Chen et al. [9] used 12 color feature variables and 12 texture feature variables to identify five types of Chinese green tea. The linear discriminant analysis (LDA) was applied to build the identification model based on the PCA. Experimental results demonstrated the effectiveness of their proposed method.

The aforementioned literature reviews presented different image texture analysis approaches for classification of gross tea (e.g. CTC, black tea, green tea, etc.). However, there are no researchers who have addressed classification of fresh tea leaves up to now, to the best of our knowledge. Although the classification issue of gross tea and tea leaves share some common characteristics, classification of tea leaves is more challenging because of wide variations in the sizes and patterns of tea leaves. A new texture analysis approach towards classification of fresh tea leaves is therefore essential and highly desired in tea processing.

There are many texture classification algorithms during the recent decade (Li et al. [10], Fernando et al. [6]), e.g. the scale-invariant feature transform (SIFT) [11], gray level co-occurrence matrix (GLCM), wavelet transform and Gabor filter. For any kind of texture classification methods, feature descriptor is very crucial in texture analysis. In recent years, local binary pattern (LBP) feature descriptor, proposed by Ojala et al. [12], has made a considerable progress in various applications, e.g. face recognition (Yang and Chen [13], Shih and Chuang [14], Ahonen et al. [15], Nanni and Lumini [16], Zhao and Pietikainen [17], Lahdenoja et al. [18]), industrial vision inspection (Paclik et al. [19] and Nanni and Lumini [20]), and biomedical and medical image analysis (Nanni and Lumini [21]). Despite the impressive progress of LBP, conventional LBP comes with some disadvantages and limitations, e.g. long histograms sensitive to image rotation, small spatial support, as well as loss of local textural information, sensitive to noise. To resolve these issues, various improved LBP descriptors have been proposed (Liao et al. [22], Heikkilä et al. [23], Ahonen et al. [24] and Zhao et al. [25]).

In this paper, a new method that combines a non-overlap window LBP and GLCM (LBP–GLCM) for classification of green tea leaves is proposed. Because the non-overlap window LBP can reduce the image matrix significantly without losing texture information, this property can improve the efficiency of image matrix operation. Furthermore, classification accuracy for tea leaves has improved greatly by combining non-overlap window LBP and GLCM.

The rest of this paper is organized as follows. Section 2 presents the significances of automatic process tea classification issue. The LBP operator, GLCM and our proposed texture feature extract approach are given in Section 3. Section 4 presents details of experimental results. Conclusions are drawn in Section 5.

2. Problem formulation

The complete procedure of roasting tea leaves is shown in Fig. 1, which demonstrates every process step in automatic production line of tea processing. The ratio of solid part to the rectangular box stands for moisture content percentage of tea leaves at this step. This production line adopts microwave as the second and third drying processing to ensure tea rapid drying and green color presentation of tea leaves. The tea scent and general quality are ensured by scent enhancing and rolling-roasted technology.

Moisture content is one of key indices for tea processing. There is an exact moisture content requirement for every single tea process step. This index determines the control parameters of tea processing machines, e.g. water removing time and temperature, drying and roasting time, etc. Unfortunately, there are no effective devices to detect tea leaf moisture at the moment. The traditional moisture content devices through drying process take about 1 min to obtain the moisture content [26], which is too time-consuming for on-line moisture detection in the production line. As a result, there are no existing adaptabilities for tea processing machines due to the lack of feedback of tea leaf status. All the control parameters need to be tuned off-line through trials and errors. The well-tuned control parameters for every tea process machine need to be stored in the supervisory control and data acquisition (SCADA). This open-loop control system is less robust than closed-loop system. Furthermore, the open-loop control system requires complete understanding of processing techniques for control engineers [27].

The limitation of the above approach is that a set of control parameters is feasible for only one class of tea leaf i.e. one bud with on leaf, one bud with two leaves, one bud with multiple leaves, etc. The control parameters for different tea leaves are very different and are summarized in Table 1. In actual tea production, fresh tea leaves are a combination of various types of leaves. These different tea leaves arrive at the production line simultaneously or sequentially. Hence, it is very important to identify the content of fresh tea leaves to ensure that the tea processing quality is high. The SCADA can select different sets of control parameters for tea production line based on the content of fresh tea leaves. Besides the moisture content, the size and shape of tea granules are other major factors determining tea quality and content of tea [28].

It is not practical and unnecessary to identify all exact content of fresh tea leaves in the production line. To automatically select control parameters in the control system of a tea production line, the primary content of tea leaf type (e.g. one bud with a leaf or two or more) needs to be identified. Because images of different tea leaves have different texture properties, the primary content of tea leaf type can be obtained by analyzing image texture properties. Based on the content information, the SCADA is able to select appropriate control parameters for the tea processing machines. The system architecture to implement the closed-loop control system is shown in Fig. 2. The tea leaf images are captured from the conveying belt by a vision system. After feature extraction and recognition, the content information of tea leaves is derived for the SCADA. The main contribution of this paper is to propose an effective feature extraction method for indentifying the tea leaves content in real time.

3. Image texture analysis

3.1. Local binary patterns (LBP)

The LBP is a simple and widely used texture analysis method. The LBP operator, first proposed by Ojala et al. [12], encodes the pixel-wise information in texture images. In the LBP approach, a “local pattern” describes the relationships between a pixel and its neighbors. The classic LBP operator is defined by comparing the gray value of central pixels with its 8 local neighborhood pixels. All neighbors that have value higher or equal to the value of central pixels are given a value of 1, while all those lower values given a value of 0. The binary values associated with the neighbors are then acquired sequentially, clockwise, to form a binary number which may be used to characterize the local texture. The LBP