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Identification and classification of damaged corn kernels with impact acoustics multi-domain patterns

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ABSTRACT

An impact acoustic signal device was tested with undamaged, insect-damaged, and mildew-damaged corn kernels, and the different signals were compared using ensemble empirical mode decomposition methods. These methods were adopted based on their known superiority in processing of non-stationary signals and in suppressing of mode mixing. Time domain, frequency domain, and Hilbert domain features were extracted from an ensemble empirical mode decomposition of the impact acoustic signals. Four features were extracted from the time domain: the average amplitude change, Wilson amplitude, average absolute value, and peak-to-peak value. Three features were extracted from the frequency domain: the mean square frequency, the root mean square of the power spectrum, and the frequency band variance. The energy of the high-frequency and low-frequency bands and the average values of the envelopes were extracted from the Hilbert domain. Subsequently, these features were used as inputs to a support vector machine which was optimized by particle swarm optimization. The use of hybrid features enabled higher classification accuracy than usage of features in each domain separately. In this study, achieving the classification accuracies were 99.2% for undamaged kernels, 99.6% for insect-damaged kernels and 99.3% for mildew-damaged kernels. These results, based on ensemble empirical mode decomposition and integration of multi-domain features, are encouraging for the potential of an automated inspection system.

1. Introduction

Insects and mildew often damage grain during storage. These damages reduce grain quality and are a threat to human health. Therefore, prevention of insects and fungal infection has become a serious concern to managers of stored products. Corn is an important stored grain that is easily damaged by insects and mildew. It is necessary to protect the stored corn from any pest and mildew before it is purchased by consumers. With advances in technology, there are more approaches to detect and identify corn kernels, such as machine vision, X-ray imaging and near-infrared (NIR) spectroscopy etc. The X-ray and NIR spectroscopy methods are cost prohibitive and current NIR instrumentation requires complex operating procedures and calibrations (Neethirajan et al., 2007). Moreover, these methods are costly for many commercial applications. Currently, because of its efficiency and convenience, the detection technology using impact acoustics has attracted research attention.

The impact acoustics method was first developed by Pearson and applied to separate pistachio nuts with closed shells from those with open shells. Four features were extracted from each impact acoustic signal in time domain and spectrum analysis (Pearson, 2001). An exhaustive search algorithm was used to select the optimal feature combination, and linear discriminant analysis was used to classify nuts. The identification accuracy of this system was approximately 97%. Later on, analysis of impact acoustic signal characteristics became strong research interest. Onaran et al. (2006) used the same device as Pearson tested to distinguish underdeveloped hazelnuts from fully developed nuts, by calculating and analyzing time domain signal variances and maximum values within short-time windows. In addition, through analysis of the frequency spectra magnitudes and line spectral frequencies, 98.0% of fully developed nuts and 97.0% of underdeveloped hazelnuts were correctly classified. The acoustic signal was processed using four different methods: modeling of the signal in the time-domain, computing time domain signal variances in short time windows, analysis of the frequency spectra magnitudes, and analysis of a derivative spectrum. Features were used as inputs to a neural network.

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Pearson et al. (2007) reported that 87% of insect damaged kernels and 98% of the undamaged kernels were correctly classified. Zhongli Pan of United States Department of Agriculture (USDA) developed a system for production of high quality processed beans by applying impact acoustics detection and density separations methods (Pan et al., 2010). Hosainpour et al. (2011) designed an intelligent system used for detection and separation of potatoes from clods. By analyzing the impact acoustic signals in time and frequency domain, 31 different combinations of principle component were selected as input to a back propagation neural network. The network model was determined by evaluation of the mean square error, correct detection rate and correlation coefficient. Detection accuracy of the presented system was about 97.3% and 97.6% for potatoes and clods respectively. Omid (2011) developed a classifier based on expert system for sorting open and closed shell pistachio nuts, which selected the best statistical features with the J48 decision tree (DT). The output of J48 DT algorithm was then converted into crisp IF-THEN rules and membership function sets of the fuzzy classifier. For this model, 99.52% of correct classification on the training set and 95.56% of correct classification on the test set could be achieved. Cetin et al. (2014) designed a system for removing shell pieces from hazelnut kernels. The Mel-cepstral feature parameters, line spectral frequency values, and Fourier-domain Lebesgue features were extracted from the impact acoustic signals. The feature parameters were classified using a support vector machine (SVM), whereby an average recognition rate of 98.2% was achieved. However, it was not studied in-depth how to effectively interpret the impact acoustic signal.

It should be pointed out that through previous literatures had made many efforts in obtaining satisfactory accuracy. Summarized the previous research methods of signal processing, found that features extracted by the traditional methods were relatively single. Thus it cannot fully reflect the essential characteristics of the signal, result in lower separability of signals. Almost no literature extracted features by applying multi-domain method which can be used to obtain additional information and maximum separability. This motivated us to exploit the integration of multi-domain to analyse the impact acoustic signals. Features which were extracted from the original impact acoustic signals mainly reflect the general characteristics of signals rather than the local characteristics. Ensemble empirical mode decomposition (EEMD), which was based on the local characteristic time scale of a signal, can self-adaptively process non-stationary signals and suppress mode mixing. After using EEMD for the impact acoustic signals, it can decompose the signals into different frequency bands and will be helpful for further analysing the signals. In addition, the detection system was easy to acquire and low-cost. Therefore, the system was suitable for which the high precision was indeed required (Weaver et al., 1997).

This paper had the following main contributions. First, based on its capability to process non-stationary signals and its suppression of mode mixing, EEMD algorithm was used in this paper. Second, in order to extract the essential features of impact acoustic signals and has a higher separability of signals, integration of multi-domain method was proposed to deal with the impact acoustic signals. Third, to find the optimal parameters so as to overcome the flaws of conventional methods of SVM, the particle swarm optimization-support vector machine (PSO-SVM) was used.

2. Experimental apparatus and materials

2.1. Hardware

The experimental apparatus included a vibration feeder, a microphone, an impact plate and a computer equipped with a sound card (Fig. 1). Its main functions are: (1) the vibration feeder conveys the corn kernels from the bulk hopper into a single-flow by the time they reached the end of the feeder; (2) the Shure BG4.1 cardioid condenser microphone detects the impact signals using a pickup with a broadband frequency response. The frequency response of Shure BG4.1 is from 40 Hz to 18 kHz; and (3) the impact plate provides a high-mass impact point that maximizes the amplitude of grain vibrations and minimizes vibration from the plate itself. Through trial and error, the impact plate is optimized to be a block of stainless steel approximately 24 cm × 12 cm × 0.05 cm. The drop distance from the feeder to the impact plate is set at 40 cm and the plate is inclined at 60° above the horizontal. A MAYA44 sound card equipped with 4 output channels and 4 input channels is used to interface to the signal processing computer. The frequency range of the sound card is 20 Hz–20 KHz, and the microphone signals are digitized at a sampling frequency of 48 KHz with 16bit resolution.

2.2. Experiment material

Three types of corn samples were from the same batches, including undamaged kernels (UDK), insect-damaged kernels (IDK) and mildew-damaged kernels (MDK), as shown in Fig. 2. The corn kernels (UDK, IDK, MDK) were 280 each and 840 in total. The corn samples dropped onto the impact plate, and then the acoustic signals were collected by the microphone. The impact acoustic signals were acquired and stored in WAV format, which were used later for processing.

3. Method

3.1. Signal processing method

3.1.1. Ensemble empirical mode decomposition

The empirical mode decomposition (EMD) method (Huang et al., 1998) was compared with traditional time-frequency analysis methods, such as short-time Fourier transform, wavelet analysis. EMD is based on the local characteristics time scale of the signal and can adaptively decompose a complicated signal into a sum of intrinsic mode functions (IMF). EMD method has been applied widely to signal processing (Li et al., 2014; Li et al., 2015). However, a major drawback to general usage of EMD is mode mixing, in which signals of similar scale reside in different IMF components or a single IMF consists of signals of disparate scale (Huang and Wu, 2008). To alleviate the mode mixing in EMD, EEMD was presented by Wu and Huang (2009). EEMD is a noise-assisted data analysis method, which adds finite white noise to the investigated signal and then decomposes the complicated signal into a set of complete and almost orthogonal components. Because this method suppresses mode mixing effectively, the EEMD has been applied widely for signal detection and fault diagnosis (e.g., Amirat et al., 2013; Wang et al., 2014).

The EEMD algorithm can be given as follows:

(1) Add a white noise series to the investigated signal,

$$X_m(t) = x(t) + n_m(t), \quad m = 1, 2, \cdots, M \tag{1}$$

where $x(t)$ represents the investigated signal, $n_m(t)$ indicates the mth added white noise series, and $X_m(t)$ represents the noise-added signal of the mth trial.

(2) Decompose the noise-added signal $X_m(t)$ into IMF component $c_{i,m}$, using the EMD method. where $c_{i,m}$ represents the i th IMF component of the mth trial.
(3) Add different white noise series to the investigated signal, repeat step (1) and step (2) again for M trials.
(4) Calculate the ensemble mean $\bar{c}_i(t)$ of the M trials for each IMF.

$$\bar{c}_i(t) = \frac{1}{M}\sum_{m=1}^{M} c_{i,m}(t), \; i = 1, 2, \cdots I, \quad m = 1, 2, \cdots, M \tag{2}$$

where I is the number of IMF components.

(5) Eventually, the investigated signal can be represented as follows: