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System for removing shell pieces from hazelnut kernels using impact vibration analysis

A. Enis Cetin [a], Tom C. Pearson [b], R. Akin Sevimli [a,*]

[a] Electrical and Electronics Engineering Department, Bilkent University, Ankara 06800, Turkey
[b] USDA-ARS-CGAHR, 1515 College Avenue, Manhattan, KS 66502, USA

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ABSTRACT

A system for removing shell pieces from hazelnut kernels using impact vibration analysis was developed in which nuts are dropped onto a steel plate and the vibration signals are captured and analyzed. The mel-cepstral feature parameters, line spectral frequency values, and Fourier-domain Lebesgue features were extracted from the vibration signals. The best experimental results were obtained using the mel-cepstral feature parameters. The feature parameters were classified using a support vector machine (SVM), which was trained a priori using a manually classified dataset. An average recognition rate of 98.2% was achieved. An important feature of the method is that it is easily trainable, enabling it to be applicable to other nuts, including walnuts and pistachio nuts. In addition, the system can be implemented in real time.

1. Introduction

Dried nuts are commonly used in processed food industry. The presence of shell fragments and pieces inside foods containing dried nuts are undesirable and can pose a safety concern. In this article, a system for removing shell pieces from hazelnut kernels using impact vibration analysis is described.

Hazelnuts (Fig. 1) are softer and less dense than the shell pieces, so vibration signals, or acoustic emissions, produced by the moment of the impact with a steel plate are different between hazelnuts and the shell pieces, as shown in Fig. 2. As a result, it is possible to design a system for removing shell fragments and pieces from hazelnuts by analyzing the impact signals. Impact sound and vibration analysis systems have been widely used in practice Haff and Pearson (2007), Yorulmaz et al. (2012, 2011), Pearson et al. (2007b), Cetin et al. (2004), Onaran et al. (2005), Pearson et al. (2005, 2007a), Cataltepe et al. (2005, 2004b,a), Cetin et al. (2005), Ince et al. (2008), Buerano et al. (2012), Omid et al. (2010), Chen et al. (2011) and Michihiro and Takahisa (2012). Haff and Pearson developed a sorting system to separate pistachio kernels from in-shell nuts using vibration analysis of a small steel plate after a shell or nut piece impacted it Haff and Pearson (2007). For this system, at the lowest throughput rate, classification accuracies were 96% for in-shell nuts and 99% for kernels. For throughput rates between 10 and 40 nuts/s, correct classification ranged from 84% to 90% for in-shell nuts. For kernels, the accuracy was 95% at 10 and 20 nuts/s and 89% at 40 nuts/s. The authors based the classification on the cumulative histogram of the signal gradients and did not use the other feature extraction methods, such as those used in acoustic signal processing.

Hazelnut kernels do not stick to the shell in dried hazelnuts. When a hazelnut is cracked the kernel comes out as a separate entity. However large shell pieces may cause problems. They cannot be sieved because some shell pieces may be as large as a kernel. In this article a vibration acoustics based system that is capable of separating large shell pieces from kernels is described.

2. Materials and methods

2.1. Description of system hardware and experiment

A vibratory feeder (FT00, FMC Corp. Homer City, PA) forces the hazelnuts in a single file from a hopper onto an 90-cm-long slide made from stainless steel sheet metal. The slide, inclined at 60° above the horizontal, terminated above a steel plate, onto which the hazelnuts impacted. The steel plate has dimensions of $8 \times 8 \times 2$ cm. Schematic of sorting system is shown in Fig. 3. A vibration sensor (GS-20DX, Geophone, Geospace Technologies) is mounted onto the steel plate. A laser is used to detect the sliding hazelnuts in the system. When the shell fragments of the hazelnuts pass from the end of the chute, the laser light is blocked, initiating data collection from the vibration sensor. The analog signal is digitized by using chipKIT Uno32. The sensor signal is sampled at 4 KHz for 2048 samples.

* Corresponding author. Mobile: +90 312 290 1477; fax: +90 312 266 4192.
E-mail address: sevimli@ee.bilkent.edu.tr (R. Akin Sevimli).

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Fig. 1. Hazelnut and shell fragments.

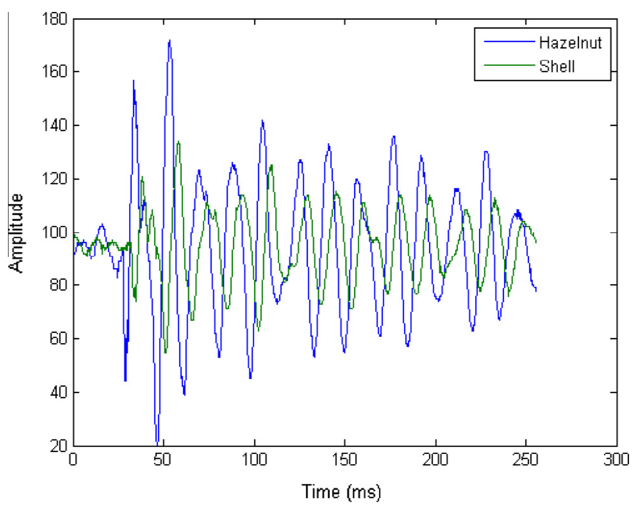

Fig. 2. Vibration signal example for hazelnuts and shell pieces.

Vibration impact signals were collected for 130 hazelnuts and 152 shell pieces from the Akcakoca region of Turkey. After data collection, the vibration signals are processed off-line. The average of the sampled signals is removed by mean-centering before calculating the feature vectors. The cumulative histogram of gradients used by Pearson and Haff, the mel-cepstrum, the line spectrum frequencies, the frequency amplitude bins, and the Lebesgue features are computed as described in Sections 2.1, 2.2, 2.3, 2.4, 2.5 and 2.6, respectively. After all of the features are extracted, classification is

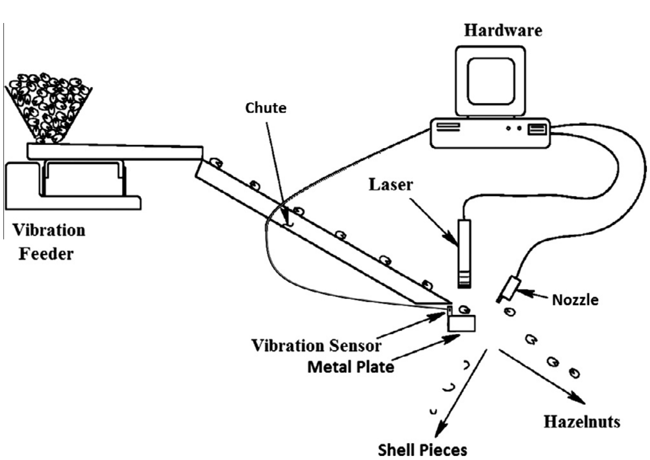

Fig. 3. Schematic of sorting system.

performed using a support vector machine (SVM), as described in Section 2.7.

2.2. Cumulative histogram of gradients (CHOG)

Haff and Pearson (2007) used cumulative histogram of gradients as a feature vector to separate pistachio kernels from in-shell nuts.

Let $x[n]$ be the zero mean vibration signal and x_m represent a normalized version of x, calculated as follows:

$$x_m[n] = x[n]/max(|x|) \tag{1}$$

Then, the gradient $g[n]$ is calculated as follows:

$$g[n] = |x_m[n-1] - x_m[n+1]| \tag{2}$$

Then, a histogram of this gradient signal is calculated. In Haff and Pearson (2007), the authors observed that most of these gradient signals do not contain any values larger than 0.5; to reduce the number of bins of the histogram, they clamped gradient signals with a threshold of 0.5 as follows:

$$g_c[n] = min(g[n], 0.5) \tag{3}$$

Then, the histogram $h[n]$ of $g_c[n]$ is calculated. The bins of this histogram covers the range from 0 to 0.5. Finally, a cumulative histogram of gradients $b[k]$ is calculated as follows:

$$b[k] = \sum_{j=0}^{k} h[j], \quad k = 0, 1, \ldots, K \tag{4}$$

where K is the number of feature parameters. The vector $b[k]$ is used to train a SVM with two classes. The first class consists of the vibration signals of the shell pieces, and the second class contains the hazelnut signals.

2.3. Mel-Cepstrum

The mel-cepstrum or mel-frequency cepstral coefficient (MFCC) vector is the most widely used feature vector in speech and sound recognition. Cetin et al. (2004) also used the mel-cepstrum to classify the impact sounds of open and closed shell pistachio nuts. Let $X[k]$ represent the N-point discrete Fourier transform (DFT) of $x[k]$.

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j\frac{2\pi kn}{N}}, \quad k = 0, 1, \ldots, N-1 \tag{5}$$

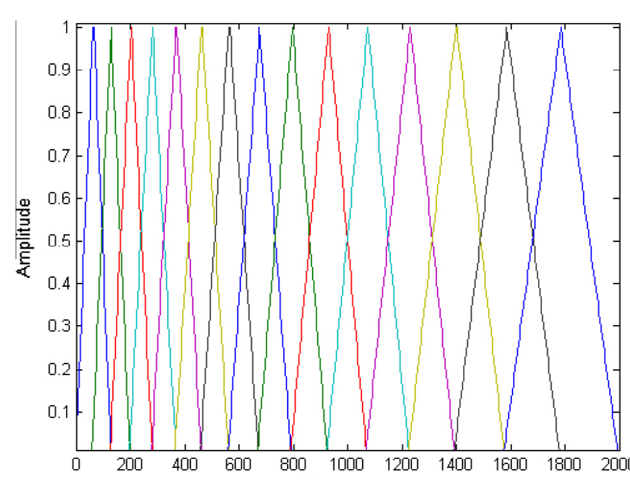

Fig. 4. Filter Bank with Mel-scale.