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Identification of worm-damaged chestnuts using impact acoustics and support vector machine

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Abstract. Chestnut has both economically and nutritional values, and its production in the World is about 2 Mt. Turkey is one of the important chestnut producers with a production amount of about 60,000 t. Worm damage is one of the reasons which may reduce economical value of chestnut. Aim of this study was to reveal possibilities of distinguishing of worm-damaged chestnuts from healthy ones using impact acoustics and sound analysis methods. A Turkish local variety called 'Osmanoglu' was chosen for the study. A sound acquisition station was comprised, and acoustic emissions of worm-damaged and healthy nuts were acquired at a sampling quality of 192 kHz and 16 bit. Each sample was labelled according to worminess situation by shattering the nut after acoustic measurements. A band-pass filter between cutoff frequencies of 70 Hz and 100 kHz was designed and applied to sound samples to alleviate negative effects of unwanted noise. Various signal features such as variance, standard deviation, kurtosis, zero crossing rate, and spectral centroid were calculated. A relevant feature subset was determined using feature selection technics. An identification model was trained using Support Vector Machine and cross-validation rules. Performance of the classification system was measured on a test set. In this study, reporting the preliminary results of an ongoing and comprehensive research project[a], promising results were obtained for identification of worm-damaged chestnuts with proposed system.

Key words: Chestnut classification, Worm Damage, Impact Acoustics, Support Vector Machine.

INTRODUCTION

Chestnut has both economical and nutritional values with about 2 Mt production in the World. Turkey is the second largest chestnut producer with a production about 60,000 t after China (FAO, 2011). Chestnut contains 5% protein, 40–50% carbohydrate, 40–50% moisture, and 1.5–2% clay. Additionally, 100 gr of nut contains 50 gr of vitamin C, some vitamin A, and 100 gr of nut provides 200 cal. Chestnut is also a nutritious source of energy (Gün et al., 2006).

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Determining the quality parameters of chestnut properly is very important for producers and processers. Especially in post-harvest processes, supplying properly classified chestnuts to the consumers increases the reliability of producers and manufacturers allowing buyers to consume their products with confidence. One of the factors highly affecting the chestnut quality is existence of worm (*Cydia splendana* or *Curculio elephas*). These worms cause damage in chestnuts by directly feeding in them resulting a damage between 15% and 40%. During the growing period of a chestnut harmful larvae may dig into the peel of the nut in the hedgehog and start damaging it. In the meantime, both the hedgehog and the nut keep growing when the larvae is still active in the nut. While the growing process is still in progress the inlet hole of the larvae may be closed without leaving any trace. Generally, worms leave the fruit by piercing the nuts after harvest in storage rooms or sale stands. Damaged galleries in the nut occurred due to larvae activities may cover some parts or entire of the nut over time. Conventionally, separation of wormy chestnuts is carried out by expert employees. Chestnuts with worm-damages and closed-holes are difficult to recognize without cutting or deforming the nut. Additionally, human factor may cause errors in detecting wormy products manually. Therefore, it is extremely important to determine economic values of chestnuts effectively in evaluating raw products. Furthermore, it is advantageous to be able to classify the crops correctly and fast for the economy of the producers.

Considering the reasons explained above, auto-classification systems are needed to identify worm-damaged chestnuts by reducing labour and time. Impact acoustics (IA) method has been used for classification of some agricultural products by some researchers. IA methodology relies on both digitizing the sound obtained when a chestnut is dropped on an impact surface from a distance and also analysing it using the signal processing techniques. With this method, it is possible to conduct an identification work without peeling, deforming or damaging agricultural commodities. In an early study by Pearson (2001), an IA system was developed to distinguish uncracked pistachios from open ones. The sound signals which were created when nuts hit to an impact surface were analysed in both time and frequency domains. It was reported that closed-shell pistachios could be classified with an accuracy rate of 97%. In another study, an algorithm was developed for the same purpose using methods of speech recognition (Çetin et al., 2004). Distinguishing features consisting of Mel-Cepstrum coefficients were extracted and principal component analysis (PCA) was performed. It was reported that closed-shell nuts were successfully identified with accuracy rates over 99%. Amoodeh et al. (2006) investigated the possibility of measuring moisture content of wheat kernels based on IA. Calibration of moisture determination system was made by revealing the relation between digital sound signal and wheat moisture content. In the studies by Kalkan & Yardımcı (2006) and Kalkan et al. (2008) facilities of differentiating open-shell nuts from closed-shell nuts using IA techniques were reported. IA method was also used for identification of pistachio varieties (Omid et al. 2009). Characteristic features of sound signals were calculated using fast Fourier transform. PCA was used for reduction of feature space and a classification model was proposed using neural networks. The researchers reported an identification accuracy of 97.5% for their experiments. Another IA-based research was performed to identify walnut varieties (Khalesi et al., 2012). PCA was applied to frequency domain features and neural network was used for the classification model. Walnut varieties could be classified with an accuracy rate of 99%.

Although some studies have been conducted involving the application of IA methods on agricultural materials, there has been a big gap in impact acoustic studies conducted on chestnuts in the literature. Automated classification systems which are able to identify worm-damaged chestnuts may provide many benefits to the producers by reducing labour and time. In this study, it was aimed to develop a prototype, an experimental classification system to identify worm-damaged chestnuts using IA method, digital sound signal processing and support vector machine. Impact acoustic method has been investigated by some researchers for the classification of agricultural crops as relatively new and immature method. In that respect, determining the impact acoustic characteristics of chestnut will also contribute to the literature as an original work.

MATERIALS AND METHODS

Chestnut samples

In this study, a local variety of chestnut (*Castanea Sativa* Mill.), namely 'Osmanoglu' was selected for developing and testing the identification system. A total of 904 chestnut samples were used. Of those chestnut samples, 460 were worm-damaged and 444 were of healthy samples. Some chestnut samples, which were used in this study, are shown in Fig. 1. In sound acquisition experiments, each chestnut sample was sliced and examined carefully after obtaining the sound signal. After examining internal flesh quality of each chestnut its sound signal was categorized into one of the two classes, as healthy or worm-damaged.

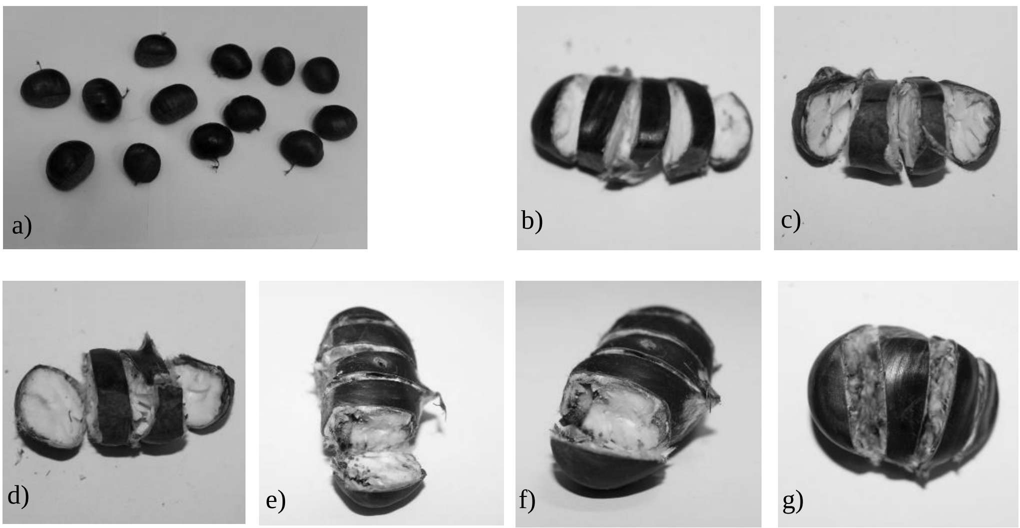

Figure 1. Some chestnut samples used in this study (a), healthy chestnuts (b, c, and d), worm-damaged chestnuts (e, f, and g).

Impact conditions

IA methodology is basically performed based on digitizing of the sound obtained when a chestnut impacts on a surface after releasing from a distance using a microphone and analysing this sound signal using digital signal processing methods. In this study, a sound acquisition station, shown in Fig. 2, was comprised to capture impact signals of chestnut samples. In IA methodology, it is vitally important to convert the majority of the kinetic energy emerged from the impact itself into sound energy and to prevent any possible vibration of the platform. To determine an optimum impact plate size, preliminary tests were performed with steel plates with the dimensions of 80 x 80 x 15, 150 x 150 x15 mm, and 200 x 200 x15 mm. It was found that impact plates of 150 x 150 x15 mm and 200 x 200 x 15 mm caused unwanted vibrations and tinging at the impact moment. On the other hand, the impact plate of 80 x 80 x 15 mm was found suitable and used for impact sound acquisitions of the chestnuts studied.

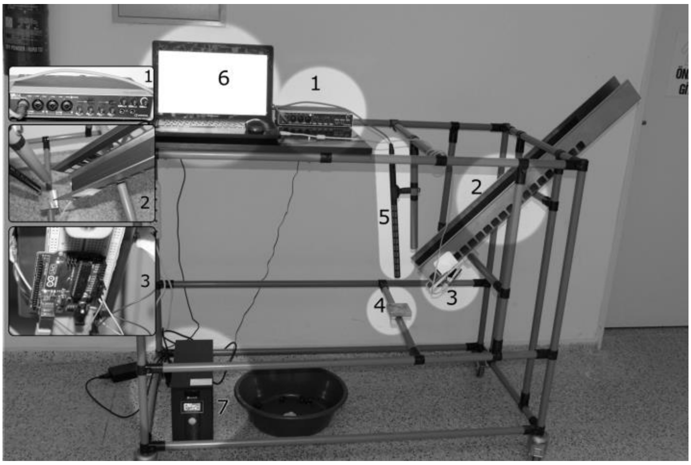

Figure 2. General view of impact signal acquisition station. 1 – sound card, 2 – sliding platform, 3 – triggering system, 4 – impact plate, 5 – shotgun microphone, 6 – computer, 7 – Uninterruptible power supply.

Sliding platform

In the sound acquisition experiments, a sliding platform was used to obtain similar impact conditions for all the samples. As shown in Fig. 2, the sliding platform was made of sheet metal with a smooth surface. In preliminary tests, it was experienced that sliding platform was vibrating when chestnuts was sliding through it. Therefore, inner floor surface of the sliding platform was covered with a smooth surfaced plastic band to prevent the vibration sound to interfere with the impact itself.

Microphone

A shot-gun microphone (ME-67 and K6 power module, Sennheiser Electronics Corporation, Old Lyme, Conn.), commonly used for broadcasting purposes, was used in this study for acquiring chestnut impact sound. This types of microphones are able to gather sound waves from a desired direction and can highly alleviate environmental noise. The microphone was placed in a location where its receiving point is 100 mm far from the impact plate.

Triggering system

A triggering system (Fig. 2) was also designed to avoid interference of unwanted noise with the sound signals of chestnuts. With this system, sound acquisition was triggered right after a chestnut left the sliding platform. The triggering system basically consisted of light dependent resistors, laser emitters, and a microprocessor (ARDUINO, UNO R3) which was responsible for sending a command to the computer to start signal recording.

Another parameter for sound acquisition system was the angle between the sliding platform and the impact surface. It was expected that nuts hit the impact surface only once avoiding multiple impact peaks. On the other hand, it was observed that bigger angle values caused delays in the triggering system and unwanted hits to the microphone. Different angle values were tried to determine an optimum angle degree and the angle degree of 45° was determined and used in the experiments as the optimum one.

Sound device

Most of the computer systems include a sound device with the sampling frequency of 44 kHz. To obtain more information from an impact sound signal, a sound device (UR-44, Steinberg GmbH, Germany) having 192 kHz sampling frequency was used in this study. A computer (Intel® Core™ i7-4700MQ CPU @ 2,40 GHz, 8 GB RAM) was used for signal processing and developing identification algorithms. During sound acquisition experiments, WiFi and Bluetooth devices of the computer were disabled to prevent unpredictable interferences.

Programming environment

In this study, the algorithms of signal processing were programmed in Python 2.7 programming language using the Scipy and Numpy scientific computing libraries (Oliphant, 2007). Classification algorithms and cross-validation approaches were implemented using Scikit-learn machine learning library (Pedregosa et al., 2011). The microprocessor was programmed in C programing language.

Signal processing

In sound acquisition, it is important to include impact signal in an appropriate time frame without skipping any important part of the signal vector. To make sure that the entire impact signal is included, sound recording was started 0.15 s before the impact moment and stopped 0.4 s after the impact moment. Thus, actual impact signal was covered by a comparatively long vector at first. On the other hand, a shorter signal frame consisting 512 peaks (about 2.7 ms for 192 kHz) was enough to represent the actual impact signal as shown in Fig. 3. Based on this approach, each recorded signal was post-processed to obtain an uniform signal length using a simple slicing algorithm. The first big extrema value of the peak values from the beginning was considered for slicing the signal vector.

Considering the signal shown in Fig. 3, a low frequency noise in the silence part before the impact moment is very distinguishable. It is unavoidable that this noise also interferes with the framed actual impact signal. It was necessary to eliminate this noise using a high-pass filter (Buerano et al., 2012). In this study, impact signals were also zoomed in and inspected carefully. So, it was observed that there was also a high frequency noise in signals due to jagged signal vector. Thus, a band-pass filter with cut-off frequencies of 70 Hz and 100 kHz was applied to each signal sample for alleviating negative effects of the noises involved in the sound signals. Fig. 4 shows an example chestnut acoustic signal before and after filtering.

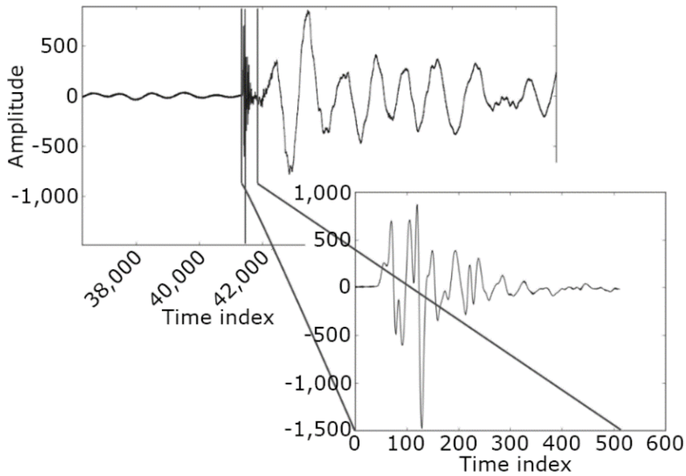

Figure 3. Typical acoustic signal of chestnut.

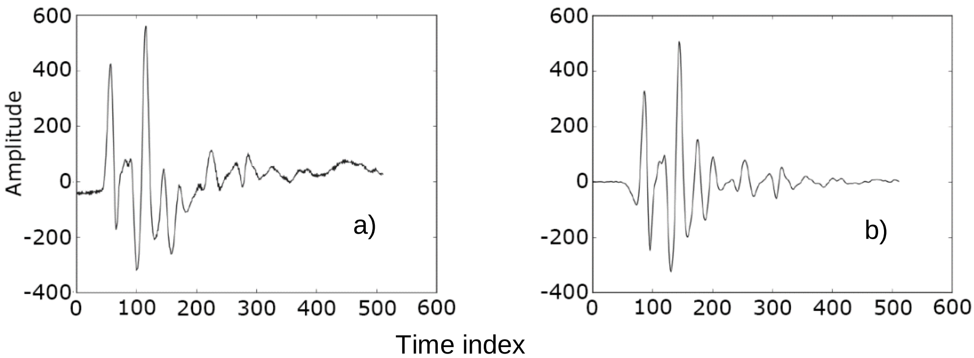

Figure 4. Signal vectors of chestnut sound signal before (a) and after (b) filtering.

Feature extraction and reduction

After obtaining impact signal samples, signal features were calculated over those signals using LibXtract audio feature extraction library (Bullock, 2007). A feature vector including 36 scalar features was extracted as given in Table 1. It is beyond the scope of this paper to give all the mathematical background related with the features computed. So, the equations of those features were not included in the text due to space limitations and more details can be found in (Bullock, 2007).

In pattern classification problems, it is important to use only the features that have a discriminating power over the input samples. An optimum feature model can be defined as a subset of relevant features. Recursive feature elimination (RFE) process, which is based on feature ranking, by Guyon & Elisseeff (2003) was followed in this work to determine the relevant features for chestnut classification. For performing RFE, a complete feature set is taken into consideration at first, and features are included as smaller sets of features recursively. A support vector machine is used as a central classifier. The SVM is trained on the initial set of features and weights are assigned to each one of them. The features are ranked based on their predictive significance at each iteration and the least significant variable is removed from the feature set. The elimination procedure is recursively reiterated on the reduced set until the desired number of features to select is reached (Pedregosa et al., 2011; Ataş et al., 2012). Desired number of features is a given parameter of the RFE and different feature numbers are also tried to reach the highest classification performance. Finally, this process yields a subset of the features used to identify worm-damaged chestnut samples.

Table 1. Features extracted from chestnut acoustic signals

Features		
Mean	Irregularity-k	Tonality
Variance	Irregularity-j	Noisiness
Standard deviation	Tristimulus-1	Root mean square of amplitude
Average deviation	Tristimulus-2	Spectral inharmonicity
Skewness	Tristimulus-3	Spectral crest
Kurtosis	Smoothness	Odd to even ratio
Spectral mean	Spectral spread	Spectral slope
Spectral variance	Zero crossing rate	Lowest value
Spectral standard deviation	Rolloff	Highest value
Spectral skewness	Loudness	Sum of values
Spectral kurtosis	Flatness	Pitch of harmonic product spectrum
Spectral centroid	LOG spectral flatness	Fundamental frequency

Constituting an identification model using SVM

After calculating features and obtaining a relevant feature set, a classification model was needed to identify chestnut signals. A SVM model was utilized to achieve this. The SVM is a maximal margin classifier. Contrary to most of the machine learning approaches SVMs do not model probability distribution of the training vectors, instead they try to separate different classes by directly searching for adequate boundaries between them (Keuchel et al., 2003). To be able to succeed this SVM fits hyper-planes in the feature space between the classes. In this work, SVM was constructed using the training set containing positive and negative classes for classifying chestnut samples. To propose an effective classifier for identification of worm-damaged chestnuts, the parameters of SVM shown in Table 2 were tuned in this study.

Table 2. Tuned parameters of the SVM used in this study

Parameter	Possible inputs
Regularization parameter	1; 10; 100;1,000
Kernel function type	Linear, Polynomial, Radial basis
Kernel coefficient (for polynomial and radial basis)	0.001; 0.0001
Degree of the polynomial kernel function (for only polynomial kernel)	1; 2; 3

RESULTS AND DISCUSSION

In this work, optimum sound acquisition conditions were established as explained in the previous section. Sound acquisition experiments were performed under the same conditions for all the chestnut samples. After pre-processing the chestnut impact signals and composing relevant feature sets, cross-validated experiments were conducted with chestnut acoustic data. In creating classification models, it was desired to find an optimum model having a high generalization ability to avoid overfitting. Cross-validation routines were usually applied when performing training and testing machine learning models. In the experiments, K-fold cross validation procedure was incorporated with grid-search to determine an overfitting-safe identification system. Thus, the signal data was first split into two equal subsets; a development (75% of data) and a dedicated validation (25% of data). Training of SVM was performed on the development set with 5-fold cross validation. The development set was then again split into 5 equal sized subsets randomly. Of the 5 subsets, a single subset was assigned as the test data for testing the model, and the remaining 4 subsets were used as training data. The cross-validation process was then repeated 5 times using each of the 5 subsets once as the test data. By using grid-search with the cross-validation, this process was repeated for each combination of the tuned parameters for SVM to minimize the error and to maximize the score parameter of classification accuracy. After this training process, the model having the highest score was evaluated on the dedicated validation set which included totally unseen chestnut signal samples by the trained model.

Parameters of the SVM were tuned during the experiments using development dataset. To determine the performance of the identification experiments, performance metrics of 'precision' and 'recall', as defined in Eq. 1, were computed over confusion matrix resulted from the experiments on the dedicated validation dataset.

$$precision = \frac{tp}{tp + fp} \quad recall = \frac{tp}{tp + fn} \tag{1}$$

where *tp*, *fp*, and *fn* represent 'true positives', 'false positives', and 'false negatives', respectively.

The recall value was accepted as an indicator in concluding which model parameters were more successful in this study. To determine the optimum number of the features, identification experiments with RFE were conducted using desired feature numbers from 5 to 36 (all features) with the increment value of 5. Table 3 shows performance scores of the experiments.

Table 3. Identification performances of SVM on the dedicated validation data

	Performance scores						
N. of features	5	10	15	20	25	30	36
Precision	0.75	0.76	0.76	0.77	0.77	0.77	0.77
Recall	**0.71**	0.70	0.69	0.68	0.69	0.68	0.68

Having the best identification result using only five features in the experiments was quite promising. These 5 features were 'variance', 'average deviation', 'irregularity-k', 'root mean square of amplitude' and 'highest value'. On the other hand, it was found that scores were close to each other for different number of the features. This was a good finding because a real world application requires less processing time with lower number of the features. Grid-search results showed that the best SVM model parameters were found with linear kernel and a regularization parameter of 10. The cross-validated accuracy score for the development set during k-fold experiments was 0.88 (± 0.008).

A confusion matrix is given in Table 4 to reveal the relations between different classes and to show how errors are distributed between the negative and the positive classes. In Table 4, identification results are also shown for a total of 226 test samples at class level. According to these results, 86 healthy and 74 worm-damaged chestnuts were successfully classified by the proposed system. Within 138 samples of healthy chestnuts, 86 samples were identified correctly while 52 samples were incorrectly identified as worm-damaged. Of 88 worm-damaged samples, 74 samples were successfully identified by the system while 14 worm-damaged samples were misidentified as healthy. Therefore, class-level accuracies for healthy and worm damaged samples were found to be 62.32% and 84.01%, respectively.

Table 4. The confusion matrix of worm-damaged chestnut identification on the dedicated validation data for the best SVM model

		Predicted by the identification system		
		Healthy chestnuts	Worm-damaged chestnuts	Recall in class level (%)
Ground-truth	Healthy chestnuts	86	52	62.32
	Worm-damaged chestnuts	14	74	84.01

In this study, worm-damaged chestnuts could be identified with an accuracy rate of 71% with lower number of the features (only 5 features). This study was the first effort to identify worm-damaged chestnuts using a IA based approach. Alongside of this modest identification score, it should be noted here that chestnuts do not have a hard shell compared to other nuts studied in the literature such as pistachios and hazelnuts. It was concluded that relatively softer shell of chestnut was a challenge for an IA based identification system. Still, the results obtained in this study showed that identification of worm-damaged could be achieved using IA based methods. However, more work is needed to achieve higher identification accuracies.

CONCLUSION

Identification of chestnuts with worm damage was achieved with a promising classification success (71%) using impact acoustics, sound signal processing techniques and feature extraction and classification algorithms. Considering the difficulty in the nature of recognizing a worm defect in a chestnut covered by a perfectly healthy looking shell, these results should encourage further studies on the subject to understand chestnut impact and sound interactions and also to improve sound acquisition systems and finally the classification rates further.

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