Vol. 56, No. 3 / 2018 INMATEH - Agricultural Engineering

DETECTION AND CLASSIFICATION OF BRUISES IN "RED DELICIOUS" APPLE FRUITS BY APPLYING PIEZOELECTRIC TRANSDUCERS

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تشخیص و طبقه‌بندی کوفتگی سیب "رد دلیشز" با استفاده از ترانسدیوسرهای پیزوالکتریک

Ph.D. Stud. Mehrdad Foj Laley[1], Assoc. Prof. Parviz Ahmadi Moghadam[*1], As Prof. Ali Hasanpour[1], As prof. Vahid Rostampour[1]

[1] Department of Mechanical Engineering of Biosystems, Urmia University, Urmia, Iran

Tel: 0984432779558; E-mail: P.ahmadi@urmia.ac.ir

Keywords: *apple, bruises, piezoelectric transducers, vibration, wavelet*

ABSTRACT

Bruising is one of the most important factors of apple wastes. In this study, the performance of both stimulator and receptor piezoelectric transducers in the diagnosis of Red Delicious apple bruising was evaluated. The evaluations were conducted on damaged apples at level 1 (depth of 0.3 cm and 1.58 cm in diameter), level 2 (depth of 0.4 cm and 2.22 cm in diameter) and level 3 (depth of 0.6 cm and 3.4 cm in diameter). The signal processing was carried out in both time and time-frequency domains and two properties of Root Mean Square (RMS) and Kurtosis were calculated. To transmit signals in time-frequency domain, wavelet transform with 4 levels of decomposition including approximate a1 to a4 and details d1 to d4 were used. Results showed that in the time domain, the value of RMS of level 1 damaged apples was 22% less than safe apples (P <0.05), but there was neither significant difference between damage levels, nor in the value of kurtosis. In the time-frequency domain, the RMS values of safe apples in a1, a2 approximates and d2 and d3 details were significantly higher than level 1 damage (P <0.01), but no significant difference was found between damage levels. In this domain, the value of kurtosis of damaged apples in level 1 in details d4 was 86% higher than safe apples and in the a4 approximate, the difference between the levels of kurtosis was significant in levels of damage 1, 2 and 3 (P <0.01). Therefore, piezoelectric transducers are able to detect apple bruising.

چکیده

کوفتگی از مهمترین عوامل ضایعات سیب می باشد. در این تحقیق کارایی دو مبدل پیزوالکتریک تحریک کننده و دریافت کننده ارتعاش در تشخیص کوفتگی سیب رد دلیشز مورد ارزیابی قرار گرفت. ارزیابی ها روی سیب های آسیب دیده سطح یک (عمق 0/3 سانتی متر و قطر 1/58 سانتی متر)، سطح دو (عمق 0/4 سانتی متر و قطر 2/22 سانتی متر) و سطح سه (عمق 0/6 سانتی متر و قطر 3/4 سانتی متر) انجام شد. پردازش سیگنالها در دو حوزه زمان و زمان- فرکانس انجام شد و دو ویژگی ریشه میانگین مربعات و کورتوسیس محاسبه شد. برای انتقال سیگنال‌ها به حوزه زمان - فرکانس از تبدیل موجک با 4 سطح تجزیه شامل اپروکسیمیت‌های a1 تا a4 و دیتیلزهای d1 تا d4 استفاده شد. نتایج نشان داد که در حوزه زمان مقدار ریشه میانگین مربعات سیب های آسیب دیده سطح 1، 22% کمتر از سیب های سالم بود (P < 0.05) ولی بین سطوح آسیب 1، 2 و 3 اختلاف معنی داری وجود نداشت. در این حوزه اختلاف مقدار کورتوسیس ها معنی‌دار نبود. در حوزه زمان- فرکانس مقدار ریشه میانگین مربعات سیب های سالم در اپروکسیمیت های a1 و a2 و دیتیلزهای d2 و d3 بیشتر از آسیب سطح 1 بود (P < 0.01) ولی بین سطوح آسیب 1، 2 و 3 اختلاف معنی‌دار نبود. در این حوزه مقدار کورتوسیس سیب‌های آسیب دیده سطح 1، در دیتلز d4، 86% بیشتر از سیب‌های سالم بود و در اپروکسیمیت a4 اختلاف بین مقدار کورتوسیس سطوح آسیب 1، 2 و 3 معنی دار بود (P < 0.01). بنابراین ترانسدیوسر های پیزو الکتریک با استفاده از ویژگی کورتوسیس قادر به تشخیص غیر مخرب سطوح لهیدگی سیب می باشند.

INTRODUCTION

The apple fruit (*Malus domestica brokh*) is rich in vitamin C and pectin. It has high calorie content *(Nunes, 2008)*. Iran has the eighth ranking between the apple producers of the world in 2015 with the production of 1.7 million tons (FAO, 2015). The fruit quality can be determined by external (i.e. weight and colour) and internal (i.e. firmness, sugar content and acidity) characteristics *(Rostampour et al., 2013)*. The apple quality contains different factors such as external features, texture, acidity, and soluble solid contents (SSC). There are different methods for measuring these criterions including destructive and non-destructive techniques. It can be said that non-destructive methods have no invasive effect on thermal, chemical, mechanical, photo physical, and photo chemical properties of agricultural products. The principle of using sound properties of materials (acoustic method) is one of the non-destructive evaluations *(Arana et al., 2004)*.

In recent decades, various non-destructive methods are presented to evaluate bruises in fruits. Most of these methods are sensitive to the physical characteristics of the fruit. These characteristics are mechanical (force-deformation curve, sound and impact responses, and ultrasonic methods), optical (visible and NIR spectroscopy), electromagnetic (nuclear magnetic resonance), and chemical (the olfactory machine) **(***ElMasry et al., 2009)*. The non-destructive methods are providing higher velocities in quality measurements. The bruises are one of the external damages of fruits that occur during harvest and post-harvest operations. The bruises are the second important factor of quality after flourished in apple *(Stajnko et al., 2004)*. It happens due to applying a mechanical force to the texture of fruits. Bruise detection in "Red Delicious" apples by using image analysis and similar techniques has a low accuracy *(Kleynen et al, 2005)*. Bennedsen et al. *(2005)* used digital imaging technique for bruise detection in apples. The results showed that it was able to distinguish bruised fruits from intact ones with the accuracy of 85%. The sound and vibration response method is one of the non-destructive methods to evaluate the textural quality of agricultural products.

The amount of bruises depends on elastic parameters of the environment called Young's modulus E(Pa) or shear stress modulus G(Pa) *(García et al., 2005)*. Vibrational sensors, used for identifying and measuring the propagated signals by fruits, are classified into contact and non-contact sensors. The contact sensors (usually piezoelectric device or accelerometer) are connected directly to the surface of fruit, but non-contact sensors (usually microphone) do not have any contact with the samples.

According to the high importance of quality control in post-harvest period and separation of damaged textures in fruits, the objective of the current study is checking out the ability of piezoelectric transducer as a non-destructive method aimed at detecting bruised textures. Herein, two piezoelectric transducers have been used to detect the bruises in "Red Delicious" apples. The performance of the developed system is evaluated in bruise detection at three levels. The signals are processed in time and time-frequency domain by wavelet transformation. Then, two features, RMS and Kurtosis, are extracted from signals.

MATERIALS AND METHODS

SAMPLE PREPARATION

"Red Delicious" apples have been harvested from a garden in West-Azerbaijan province of Iran in 2017. Then, samples were washed and allowed to dry under the free flow of air. The samples were transferred to post-harvest laboratory in the Biosystems department of Urmia University in order to perform the related tests. Different levels of bruises have been shown in table 1.

Table1

Different levels of bruises

Level3	Level2	Level1	Bruises levels
0.6	0.40	0.30	Depth (cm)
3.4	2.22	1.58	Diameter (cm)

PIEZOELECTRIC SET-UP

The experimental set-up based on sonic vibration response was designed and made. Piezoelectric transducers contain two PZT layers with the thickness of 0.19mm. In this system, a linear voltage amplifier (Model EPA-104) has been used. The non-destructive device has been shown in Fig1.

Fig.1- Non-destructive set-up to evaluate bruises

This set-up contains a soft bed with two piezoelectric transducers: one for sample excitation and another as a sensor. The vibration passes the fruit and is received by the receiver sensor. For this reason, the received signal goes into a microprocessor. Then, noise and disturbing vibrations were removed by low-pass filters. Finally, filtered signal appears in voltage through the amplifier. The received signal has been sent to a PC by USB port with a 1000 Hz sampling speed. It is notable that the receiver sensor was on bruise areas during the experiments.

SIGNAL PROCESSING

The vibrational signals were processed in time and time-frequency domains by wavelet transformation. In this study, two features, Root Mean Square (RMS) and Kurtosis, were used to compare the output signals from fruits.

ROOT MEAN SQUARE (RMS)

Root Mean Square (RMS) is one of the popular quantities in vibration science. RMS is calculated from Equation (1) for digital and random signals *(Mohammad et al, 2013)*:

$$a_{RMS} = \left[\sum_{k=1}^{N} a^2(t_k) \right]^{\frac{1}{2}} \tag{1}$$

Where a is the amplitude at the moment of t_k and N is the number of samples.

KURTOSIS

Kurtosis expresses the magnitude and sharpness of signal extreme. Kurtosis (K) is calculated from Equation (2) for digital and random signals (x (t)) with N samples *(Hong & Dhupia, 2014)*:

$$k = \frac{\frac{1}{N} \sum_{i=1}^{N} x(i)^4}{\frac{1}{N} \sum_{i=1}^{N} x(i)^2 j^2} \tag{2}$$

WAVELET TRANSFORMATION

In Wavelet transformation, the signal is passed through a series of upstream and downstream filters. Signal is divided in two parts; the section, which passes from a high-pass filter, contains high frequency data i.e. noise. It is called details. The second section, which passes from a low-pass filter, contains low frequency data and identity features of signals. In general, if x(t) is the main signal and is decomposed into x levels, the first signal can be achieved from the sum of approximation signal at the last level and detail functions at different levels (Equation (3)) *(Zanardelli et al., 2005; Soman et al., 2010)*:

$$x(t) = a_n(t) + \sum_{j=1}^{n} d_j(t) \tag{3}$$

Decomposition operations can be continued until there is no significant data in approximations. So, the first signal can be rebuilt using details signals without losing any necessary data. Function type selection is different for various problems in wavelet transformation. The Daubechi function (DB) has been used in most of the studies. The efficiency of Daubechi function is acknowledged. Hence, the mentioned function is used in this research to decompose the signals. Herein, Daubechi function with four decomposition levels was selected after try and error. Therefore, the signal can be written as Equation (4), (d_1- d_4 are details and a_4 is approximation):

$$x[n] = a_4 + d_4 + d_3 + d_2 + d_1 \tag{4}$$

Where *x[n]* is the main signal and indexes are related to the decomposition level of signal.

STATISTICAL ANALYSIS

The received signals from intact and damaged apples were compared with each other. In total, there were 48 samples and data acquisition was repeated 12 times per treatment. MATLAB R 2014a software was used for signal processing. Duncan method compared the means with each other and SAS 9.1 software was used for statistical analysis.

RESULTS

SIGNAL PROCESSING IN TIME DOMAIN

Fig. 2 shows the received signals from intact and damaged apples at levels 1, 2, & 3 in time domain. As seen, the received signals were same for both intact and damaged samples. Consequently, there was no obvious difference between them. Therefore, RMS and kurtosis was extracted from the signal for an accurate processing.

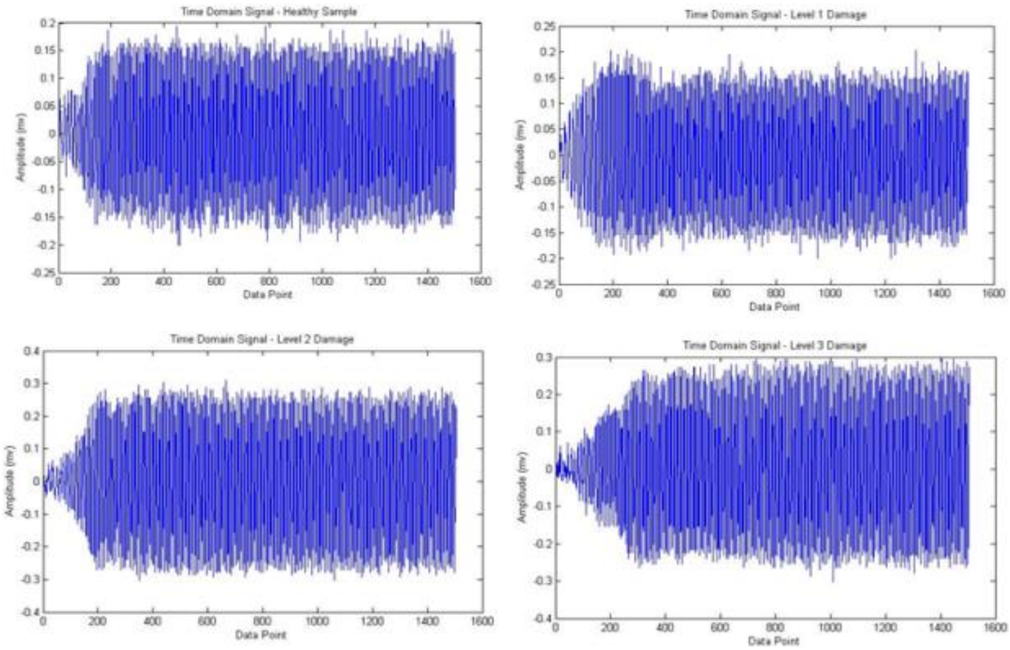

Fig. 2 - Time domain signals for intact and damaged samples at levels 1, 2, & 3

RMS and kurtosis amounts are shown in Fig. 3 for time domain signals of intact and damaged samples at levels 1, 2, & 3. The RMS amount for damaged apples of level 1 was 22% less than for intact ones ($p<0.5$). However, there is no significant variation in RMS amount according to the increase in the damage region from level 1 to level 2 and from level 2 to level 3. So, the RMS can detect presence or absence of injuries in apples at the confidence level of 95%, but it cannot be considered as a suitable criterion in detecting different levels of injuries.

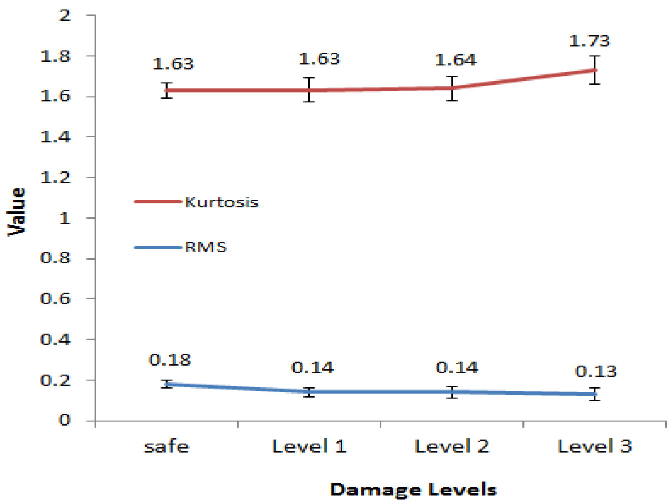

Fig. 3 - RMS and kurtosis amounts for intact and damaged samples at levels 1, 2& 3 in time domain

Additionally, the kurtosis amount was approximately same for intact and damaged samples in time domain signals and means differences were not statistically significant. Hence, kurtosis in time domain signals was not able to detect damages.

SIGNAL PROCESSING IN TIME-FREQUENCY DOMAIN

Due to accurate processing of signals, wavelet transformation was used. Lt transferred signals to time frequency domain and converted the main signal to some sub-signals. An example of a main signal and sub-signals is shown for intact and damaged samples at level 3 in Fig. 4 and Fig. 5 respectively.

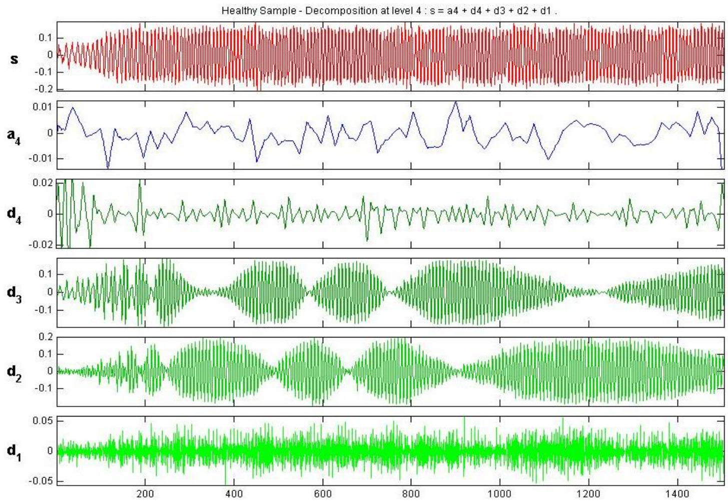

Fig. 4 - The main signal and sub-signals for an intact apple

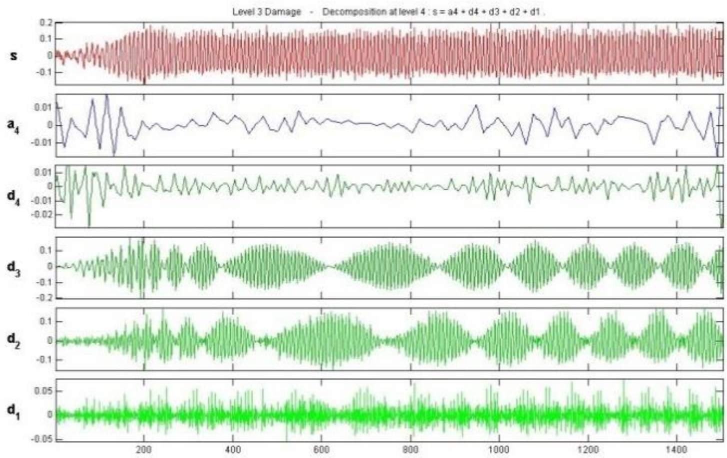

Fig. 5 - The main signal and sub-signals for a damaged apple at level 3

The main signals *(s)* in Fig. 4 and Fig. 5 do not show any difference among the studied treatments, but some differences can be seen with the naked eye after decomposing signals and studying sub-signals. For example, the amplitude of d_4 sub-signal for damaged samples of level 3 is less than that for intact ones at first moments of applying vibration. It can be also seen that d_2 and d_3 sub-signals in damaged apples of level 3 have more beating situation than intact ones. This difference can be related to the presence of weakness in system structure and consequently manipulate the output signal. However, there was no definite conclusion, and for better comparison, RMS and kurtosis values of decomposed signals were calculated.

In Fig. 6 the RMS values of sub-signals and in Fig.7 the kurtosis values of sub-signals, in two sections of approximates and details for healthy and damaged apples, in levels 1, 2 and 3 are shown. Given that the signals were decomposed in 4 levels, the results are presented in 4 levels of approximation (a_1 to a_4) and 4 levels of details (d_1 to d_4).

As seen in Fig. 6 RMS amount in damaged samples is less than that in intact ones according to all sub-signals of approximations ($a_1 – a_4$) and details ($d_1 – d_4$). Decreasing the RMS can be due to softening the texture of damaged fruits and attenuating the passing signal from fruit. RMS amounts of intact and damaged fruits were not significantly different at third and fourth approximations (a_3 & a_4) (Fig.6).

However, the RMS amounts of intact and damaged fruits were significantly different at first and second approximations (a_1 & a_2) ($p<0.01$). It shows that RMS amounts among damaged samples of levels 1, 2, & 3 are not statistically significant. Also, this amount is not significantly different in first and fourth details (d_1 & d_4), but it is statistically significant in second and third details (d_2 & d_3) at the confidence level of 1%.

It demonstrates that RMS is not significantly different among damaged samples of levels 1, 2, & 3. Consequently, RMS feature is not suitable for detecting damaged samples of levels 1, 2, & 3 from each other even using wavelet transformation and decomposing the main signal to sub-signals. Hence, the RMS can only detect intact apples from damaged samples of level 1 in some sub-signals.

In Fig.7, the comparison of kurtosis amounts between details sub-signals shows that kurtosis in damaged samples of level 3 is 221% more than that in damaged apples of level 2 in fourth approximation sub-signal (a_4). Additionally, this amount for damaged apples of level 2 is 325% more than that for damaged ones of level 1. As shown in Fig. 7, the kurtosis in damaged samples of level 1 is 86% more than that in intact ones according to the fourth details sub-signal (d_4). It can be concluded that the kurtosis in the fourth details sub-signal (d_4) is used for detecting damaged samples of level 1 from intact ones.

However, the kurtosis in fourth approximation sub-signal (a_4) can be used for separating different levels of injuries. The sensitivity of a4 and d4 toward the changes in fruit conditions can be due to the destruction of homogenous structure in intact apples and disorders in passing signals from the texture of damaged samples. These disorders in damaged samples of level 1 make little changes in general process of signal and can be only shown in the main sub-signal of details (d_4). However, the mess in the vibrational signal increases with the increase of injuries to levels 2 and 3. So, it influences the general structure of signal or fourth approximation (a_4).

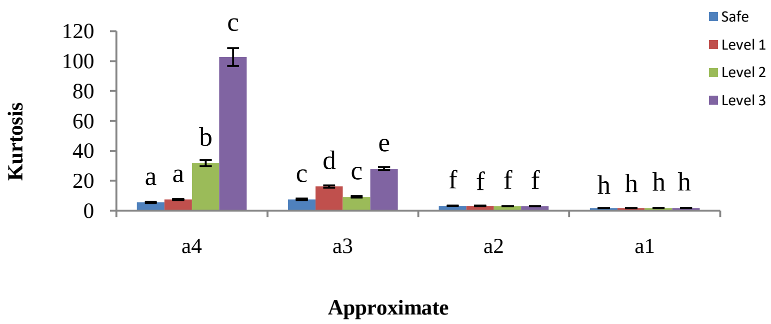

Fig. 6- The kurtosis of intact and damaged samples in approximations signals

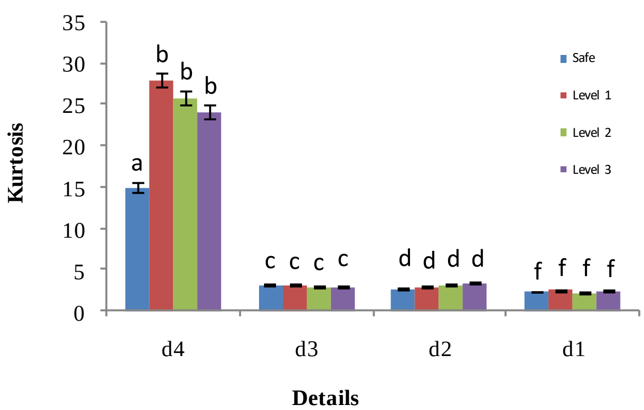

Fig. 7- The kurtosis of intact and damaged samples in details signals

CONCLUSIONS

In this article, two piezoelectric transducers were used to detect bruises in “Red Delicious “apples, non-destructively. In this technique, vibrational signals were passed through the texture of fruits. These signals were processed in time and time frequency (decomposition with wavelet transformation) domains. The results demonstrated that piezoelectric transducers could correctly detect the bruises in “Red Delicious” apples. The detection of different levels of damages was impossible in time domain, but it was possible by using wavelet transformation and sub-signals processing. Signal analysis in time domain showed that only RMS could distinguish intact apples from damaged ones, but it was not helpful in the detection of different levels of injuries using wavelet transformation in time-frequency domain and comparing the kurtosis of sub-signals could be useful in detection of intact samples from damaged apples and in separating the different levels of damages from each other.

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