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ARTIFICIAL NEURAL NETWORK BASED ULTRASONIC SENSOR SYSTEM FOR DETECTION OF ADULTERATION IN EDIBLE OIL

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Abstract

This paper presents the design, development and experimental validation of an ultrasonic sensor system for the detection of adulteration in edible oil. Variation of ultrasonic wave propagation characteristics like attenuation coefficient, reflection coefficient and velocity of propagation in pure and adulterated oil were used for developing the algorithm to detect the adulteration. Measurement cell was designed for operating ultrasonic transducer at 1 MHz using COMSOL 4.4. Artificial Neural Network (ANN) based algorithm was also developed for improving the efficiency of the sensor system. It is found that this system can detect adulteration with an accuracy of 99.53% for sunflower oil added in pure coconut oil, whereas 98.82% for palm oil added in pure coconut oil.

Keywords: Adulteration detection, Ultrasound, Artificial neural network, Non-destructive testing, sensor.

1. Introduction

Adulteration in food products means the addition of prohibited substance either partly or wholly for the state of financial gain or lack of hygienic conditions of processing and storing which leads to the consumer being cheated. Ignorance of this fact is not fair since this may endanger consumer health. For most of the vegetable oil, adulteration detection method is based on conventional chemical tests. Measurement of difference in fatty acid composition and triacylglycerol (TAG) have been utilized for adulteration detection in olive oil [1]. In some cases, the cheap oils used for adulteration have similar composition of TAG and hence the chemical tests may prove unreliable.

Nuclear magneto resonance (NMR) techniques are also being used to detect adulteration in oil, based on the quantitative and qualitative chemical information

Nomenclatures

A_{in}	Incident wave amplitude (Volt)
a_i	Time domain of reflected signal from i^{th} interface
a_T	Time domain of transmitted ultrasonic signal from transducer
A_{re}	Reflected wave amplitude (Volt)
A_x	Initial amplitude of the wave (Volt)
Ay	Deplete amplitude (Volt)
$A_i(f)$	FFT maximum magnitude of a_i at single frequency f
$A_T(f)$	FFT maximum magnitude of a_T at single frequency f
c	Velocity (m/s)
E	Elasticity (N/m^2)
f	Frequency (Hz)
k	Adiabatic compressibility
L	Distance travelled (m)
L_1	Thickness of buffer rode (m)
L_2	The distance between buffer rod and steel (m)
R_{12}	Reflection coefficient at buffer rod - sample interface
R_{23}	Reflection coefficient at sample - steel interface
t	Time (s)
T_{12}	Transmission coefficient from buffer rod to sample
T_{21}	Transmission coefficient from sample to acrylic
z	Acoustic impedance for a wave in a medium (Pa s/m^3)
z_1	Acoustic impedances of acrylic (Pa s/m^3)
z_2	Acoustic impedance of sample (Pa s/m^3)

Greek Symbols

α	Attenuation coefficient (dB/m)
α_1	Attenuation coefficient of buffer rod (dB/m)
α_2	Attenuation coefficient of sample (dB/m)
ρ	Density (kg/m^3)

Abbreviations

ANN	Artificial Neural Networks
DSO	Digital Storage Oscilloscope
FEM	Finite Element Method
FFT	Fast Fourier Transform
HDL	High-Density Lipoprotein
LDL	Low-Density Lipoprotein
MCT	Medium Chain Triglycerides
MCFA	Medium Chain Fatty Acids
MLP	Multi Layers Perceptron
MSE	Mean Squared Error
NMR	Nuclear Magneto Resonance
PMMA	Poly Methyl Methacrylate
TAG	Triacylglycerol
VCO	Virgin Coconut Oil

gathered from the resonance data. This is an expensive method [1]. The adulteration in edible oil can also be detected by other methods like density, viscosity [2], refraction measurements [3], fluorescence spectroscopy [4], chromatography/ mass spectrometry [5] and differential scanning calorimeter [6]. He et al. [7] developed a system for adulteration in oils using image texture analysis technology. Many years ago Clements et al. [8-10] and Valantina [11] realised the potential of ultrasound for characterization of vegetable oils and reported the ultrasonic analysis of edible fats and oils. Cataldo et al. [12] used microwave reflectometry for the classification and identification of adulteration in oils. Oliveros et al. [13] studied the potential of electronic nose based metal oxide semiconductor sensor for the detection of adulteration in olive oils. Moreover, Jin et al. [14] applied machine learning approaches to reveal the constituents and their comparative ratio in the oil adulteration. Ultrasound technique with neural network for milk adulteration detection is proposed by Nazário et al. [15].

Coconut oil is abundant in the southern parts of India and so is extensively used for edible purposes. Coconut oil is rich in Medium Chain Triglycerides (MCT) and Medium Chain Fatty Acids (MCFA) that are burnt immediately to produce energy and are not converted as triglycerides thereby accounting for increasing high-density lipoprotein (HDL) and lowering low-density lipoprotein (LDL). Coconut can be extracted through ‘dry process’ or ‘wet process’. The Virgin Coconut Oil (VCO) is extracted through wet processing. It involves no chemical treatment or heat treatment. The in vitro study by Nevin and Rajamohan [16] showed that VCO was capable of reducing low density lipoproteins oxidation. In view of its nutritional values and demand, coconut oil is expensive and high possibility of adulterating with less expensive oils. Therefore, we have used VCO for this study to develop a cost effective, reliable method to detect adulteration, which can be extended for other edible oils with some modifications.

When VCO is adulterated, its physical properties such as density, viscosity changes and has direct impact on ultrasonic velocity, reflection coefficient and attenuation when a wave propagate through it. Having this as the base, this paper proposes to develop handheld direct ultrasonic detection system which utilises the attenuation coefficient, reflection coefficient and velocity of propagation of ultrasound in the oil medium incorporating ANN based algorithm to reduce the percentage of error in the prediction.

2. Theoretical Background

Ultrasound velocity is very sensitive to intermolecular interactions and molecular organisation, which make ultrasound velocity measurements suitable for determining the physical state, structure, composition and various molecular processes. Attenuation coefficient and acoustic impedance are other parameters that relates with properties of materials. Attenuation is affected by compressibility, viscosity, scattering and absorption effects. Attenuation coefficient α is defined by [17]:

$$A_y = A_x e^{-\alpha L} \quad (1)$$

When an ultrasound beam comes in contact with an interface, it is partly transmitted and partly reflected. Acoustic impedance z for a wave in a less absorbing medium is the product of density and velocity of sound in that medium.

$$z = \rho c \tag{2}$$

Ultrasonic velocity in a medium can also be determined using Newton–Laplace equation,

$$c = \sqrt{\frac{E}{\rho}} \tag{3}$$

The woods equation shows the link between velocity of sound and density of solution:

$$c = \frac{1}{\sqrt{k\rho}} \tag{4}$$

The acoustic impedance mismatch between the boundaries results in reflections from the boundary between two materials.
The reflection coefficient *R* is defined as:

$$R = \frac{A_{re}}{A_{in}} = \frac{z_1 - z_2}{z_1 + z_2} \tag{5}$$

Mixing of adulterants in VCO causes changes its physical properties such as density, viscosity and homogeneity and have direct impact on the velocity and attenuation and reflection coefficient *R* of ultrasonic waves passing through these media. A sensor system can be developed using above mentioned parameters for the detection of adulteration.

3. Materials and Methods

3.1. Sample preparation

Virgin Coconut Oil (VCO) adulterated with cheap oil (easily miscible with VCO-varying from 5% to 100%) is used for this study. We have used palm oil and sunflower oil as adulterant in this study and performed the experiment by maintaining constant room temperature 30° C.

3.2. Experimental set up

As mentioned in Section 2, it is necessary to measure the ultrasonic wave parameters in the medium to develop the sensor system. Block diagram of the experimental setup for measuring the ultrasonic parameters is shown in Fig. 1. Ultrasonic transducer (1 MHz, Olympus V303) is used to generate 1 MHz pulse signal. Pulser/receiver (Olympus 5077PR) provides high voltage pulse required by ultrasonic transducer as well as amplification and filtration before the analogue signal passed to data acquisition device (Agilent 6012A). To measure the sample temperature a thermocouple is connected to a data acquisition system ((NI cDAQ-9172 with NI 9211). Real time data is acquired in the computer using LabVIEW 2013 and the velocity is calculated with respect to temperature.

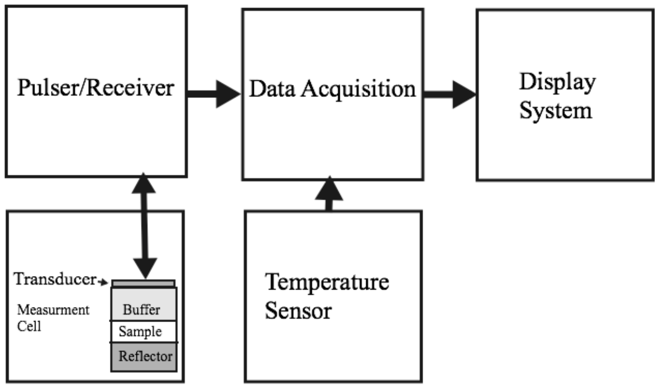


Fig. 1. Block diagram of experimental setup.

3.3. Measurement cell

Schematic of measurement cell is shown in Fig. 2, which consists of a buffer rod (PMMA), a chamber to keep the test samples, and steel reflector. Possible multiple reflections inside the cell when a ultrasonic pulse is transmitted through buffer is shown in Fig. 2. The proposed method will be using the amplitude of a_1, a_2 and a_3. Where a_1, a_2 and a_3 are the returned pulses from interface i1, interface i2 and interface i3.

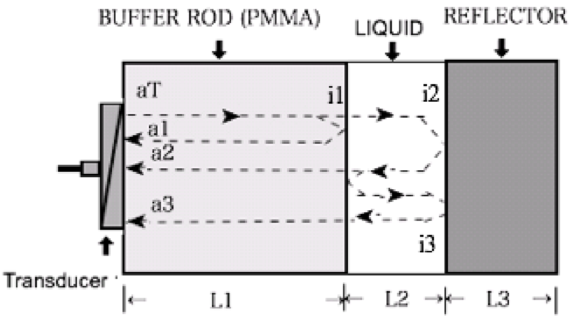
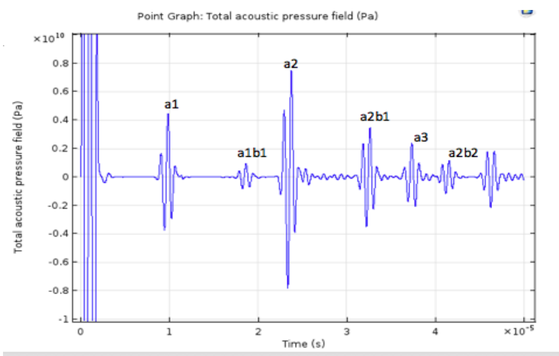
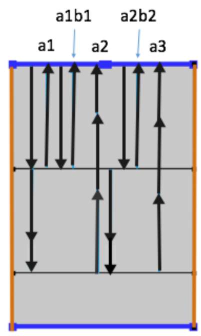


Fig. 2. Schematic of Measurement cell and multiple reflections inside.

Acoustic Module of COMSOL 4.4 is used for the design of measurement cell by studying the wave propagation through buffer, sample and reflector. Figure 3(a) shows the simulation of multiple reflections from measurement cell using the Acoustic Module of COMSOL 4.4. Figure 3(b) shows the multiple reflection path of ultrasonic signal. Flow point source is used to simulate the ultrasonic wave with sinusoidal burst at 1 MHz and two cycles. The transmitted ultrasonic wave a_T which propagates through the cell, when it reaches at the interface of oil and buffer, a portion of a_T is reflected and recorded as a_1 and remaining is transmitted through the oil which is again reflected back at the interface of oil and reflector. A portion of this reaches the transducer as a_2 signal and other portion is reflected at buffer and oil interface to reflector and return back to the transducer as a_3 signal.



(a) Simulation result in time domain.



(b) Multiple reflection path.

Fig. 3. Multiple reflections from measurement cell.

Secondary reflections of a_1 and a_2 are a_1b_1, a_2b_1 are due to the buffer rod - transducer interface and oil – buffer rod interface. These secondary signals may overlap with the signals a_2 and a_3. Therefore, it is essential to adjust the dimension of the cell to avoid these overlaps and a provision to clean the sample holder easily. In the simulation buffer rod length L_1 is kept at a constant value of 11.5mm and performed the simulation by varying L_2 value till we could avoid the overlapping of signals. Using this simulation study, we have found out the optimised values for L_1, L_2 and L_3. Figure 4 shows the fabricated the measurement cell.

Fig. 4. Transducer probe with reflector and buffer rod.

4. Results and Analysis

The attenuation coefficient α_2 , reflection coefficient R_{12} and velocity of propagation of ultrasound are calculated from a_1, a_2 and a_3 signals. The peak of these signal is obtained from their Fourier transform $A_1(f)$, $A_2(f)$ and $A_3(f)$, respectively

These signals are related by the following expressions:

$$A_1(f) = A_T(f)\, R_{12} e^{-2\alpha_1 L_1} \tag{6}$$

$$A_2(f) = A_T(f)\, T_{12} R_{23} T_{21} e^{-2\alpha_1 L_1} e^{-2\alpha_2 L2} \quad (7)$$

$$A_3(f) = A_T\,(f)\, T_{12} R_{23}^2 R_{12} T_{21} e^{-2\alpha_1 L_1} e^{-4\alpha_2 L2} \quad (8)$$

Reflection coefficient can be derived from above expressions as [18,19]

$$R_{12} = \sqrt{\frac{1}{1-x}} \quad (9)$$

where,

$$x = -\frac{|A_2(f)|}{|A_1(f)||A_3(f)|}$$

α_2 sample attenuation coefficient is defined as:

$$\alpha_2 = \frac{1}{2L_2} log_{10}\left(\frac{A_{1(f)}}{A_{2(f)}}\right) \frac{(1-R_{12}^2)}{R_{12}} R_{23} \quad (10)$$

where R_{23} is the reflection coefficient of the sample/reflector interface which is a considered as a constant because reflector impedance is known and does not vary considerably. The propagation velocity of the ultrasonic wave passing through the oil is calculated by $c = \frac{2L_2}{\Delta t}$, where Δt is the time difference between a_1 and a_2 to reach the transducer.

The wave form obtained from DSO is shown in Fig. 5. LabVIEW is used for the real time calculation of velocity, attenuation coefficient and reflection coefficient. LabVIEW front panel diagram of data acquisition system is shown in Fig. 6.

Figures 7 to 9 show the effect of adulteration on velocity, attenuation and reflection coefficient. It is found that the adulteration of sunflower oil and pam oil in VCO can be predicted using these values. We have found out empirical relations to predict the adulteration using these results. It is observed that the average error % for the prediction of adulteration using velocity variations is 13.1% for sunflower oil and 6.7% for palm oil. Similarly, error % using attenuation is 2.9 % for sunflower oil, 23.6% for palm oil and using reflection coefficient 5.5% for sunflower oil and 14.6 % for palm oil.

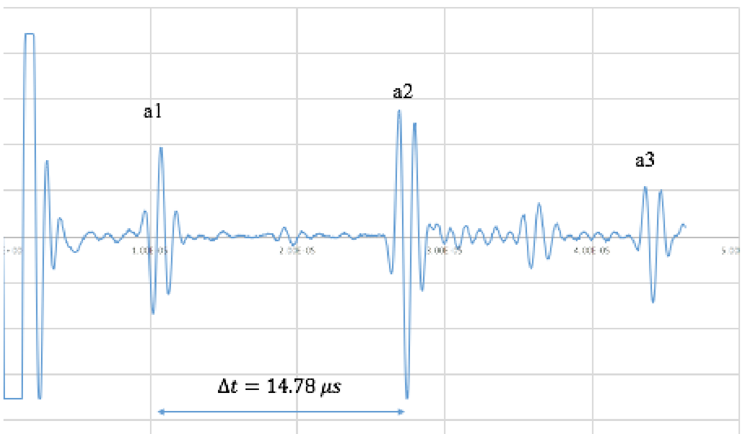


Fig. 5. Multiple reflections from measurement cell with VCO using DSO.

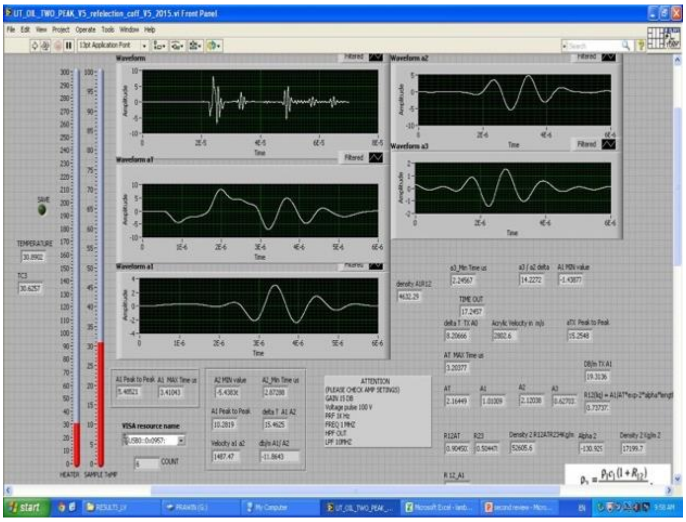


Fig. 6. LabVIEW front panel diagram of data acquisition system.

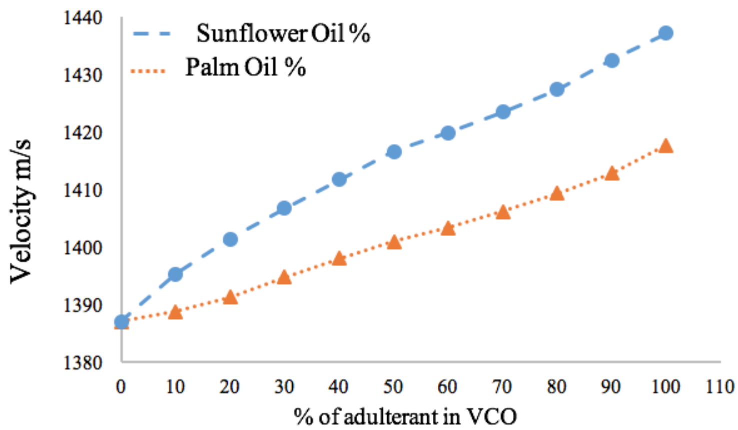


Fig. 7. Effect of adulteration on the ultrasonic velocity of VCO.

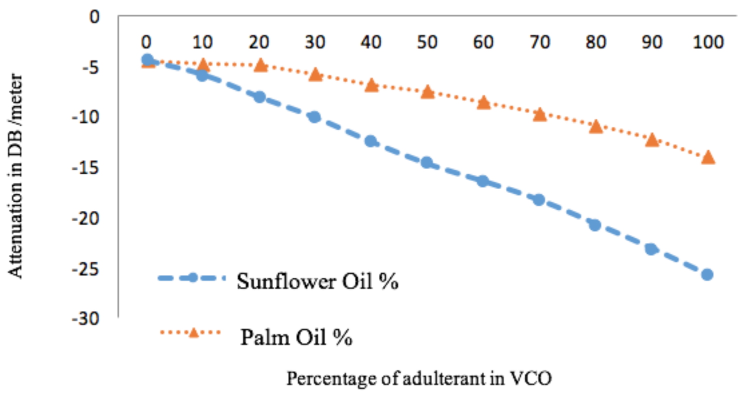


Fig. 8. Effect of adulteration on the attenuation in DB/mm of VCO.

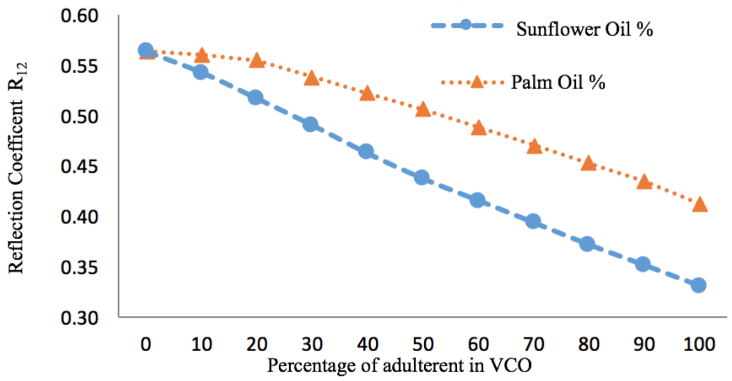


Fig. 9. Effect of adulteration on the reflection coefficient of VCO.

5. Neural Network

To improve the accuracy, we developed ANN based algorithm also. ANN is a model free estimator and learning highly non-linear input-output relationship through a process called learning [20, 21]. Back propagation neural network is used to detect the percentage of adulteration in VCO.

Table 1. ANN model 1 and ANN model 2 MSE obtained for varying the number of nodes hidden nodes.

ANN model 1		**ANN model 2**	
No. of hidden neurons	MSE Training data	**No. of hidden Neurons**	MSE Training data
48	0.14129	**30**	2.03544
47	0.184862	**27**	0.88256
24	0.294392	**24**	2.35414
10	0.06307	**22**	0.30996
7	0.045009	**21**	0.63555

Table 2. ANN model 1 and ANN model 2 prediction using test data set.

	% of Adulterant	**ANN model 1 % of Sunflower Oil in VCO**		**ANN model 2 % Palm Oil in VCO**	
Sample No.	x_i	Prediction y_i %	% Error	Prediction y_i %	% Error
1	5	4.9698	0.6040	5.2548	5.0960
2	15	14.9127	0.5820	14.7109	1.9273
3	25	24.7149	1.1404	24.8389	0.6444
4	35	35.0957	0.2734	35.4908	1.4023
5	45	45.3021	0.6713	44.9353	0.1438
6	55	55.0529	0.0962	54.2084	1.4393
7	65	64.7525	0.3808	65.4334	0.6668
8	75	74.8521	0.1972	75.2195	0.2927
9	85	85.3207	0.3773	84.1933	0.9491
10	95	95.3742	0.3939	93.6758	1.3939

The data set used in this study to train and test the ANN models have been the measured velocity, attenuation coefficient and reflection coefficient. Two models of ANN were designed one for the detection of % palm oil mixed in VCO and another for detection of % sunflower oil mixed in VCO. The three inputs to ANN are velocity, reflection coefficient and attenuation coefficient at 1 MHz and the output node represent the % of adulteration ranging between 0 to 1. The input data set randomly divided into three groups for training, validation and testing. The best network was obtained with a learning rate of $1x10^{-8}$ and 1000 epochs. Stopping criteria were with minimum MSE of 1×10^{-5} and minimum delta MSE of $1x10^{-8}$. ANN model 1 with 7 hidden neurons and ANN model 2 with 22 hidden neurons were found to give the least MSE values of 0.045009 and 0.30996, respectively (Table 1). Percentage of adulteration predicted by ANN model 1 and ANN model 2 is given in Table 2. Both trained neural networks have been proven to predict the adulteration of VCO, which is in good correlation with measurement and is given in the Table 2. Statistical analysis on the percentage of adulteration predicted using the test data set, correlation coefficients obtained for ANN model 1 and ANN model 2 are 0.999976 and 0.999851, respectively. Percentage of error in the prediction of adulteration is given in Table 2. Average adulterant prediction percentage error of 0.47% and 1.18% is achieved for ANN model 1 and ANN model 2 respectively.

6. Conclusions

The ANN based ultrasonic techniques to detect adulteration in coconut oil was investigated. The changes in physical properties are linked to changes in ultrasonic parameters. The data sets were used to design, validate and test an artificial neural networks, which allowed the detection of the adulteration in VCO. It is found that this system can detect adulteration with an accuracy of 99.53% for sunflower oil added in pure coconut oil, whereas 98.82% for palm oil added in pure coconut oil This method can be used for the development of handheld sensor system for monitoring the adulteration in edible oil.

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