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A Method for Defect Detection of Objects Using Acoustical Signal Processing

R.M.P.M.D. Rathnayake, W.D.S.S. Bandara and S.N. Gunasekara

Abstract: Objects which are made of glass, porcelain, steal, plastic, ceramic, etc. play a vital role in industry and in households. These objects can be damaged during the production, store-in, and delivery. It is very important to deliver damage-free or non-defective objects and even the expired food or beverage packages can be considered as defective items. Therefore, in this research, a method is proposed to overcome costly systems available in industry for detection of defective objects through frequency spectrum analysis. An algorithm is developed to extract features to make the comparison between defective and non-defective items. The frequency spectrum is obtained using the Fast Fourier Transform (FFT) and the features are extracted using Cross-Correlation and Mel Frequency Cepstrum Coefficients (MFCC) to identify a defective item from a good one. The comparison process involves the use of the Euclidean distance which measures the percentage of dissimilar bits out of the number of comparisons made. The proof of the results of this investigation is given by testing samples of glass container. Therefore, this methodology can be applied for inspecting any kind of defective item as mentioned above

Keywords: Cross-Correlation, FAR, Feature Extraction, FFT, FRR, MATLAB, MFCC

1. Introduction

Glass is super cooled liquid that can create marvellous objects. Silica is the main raw material, which is taken from sand filtered to eliminate $CaCO_3$, $MgCO_3$, and Na_2CO_3. To form different kinds of glass containers, raw materials are melted and passed through various metallic moulds to obtain different glass-container designs. The following diagram in Figure 1 shows the basic idea of the manufacturing process of glass containers.

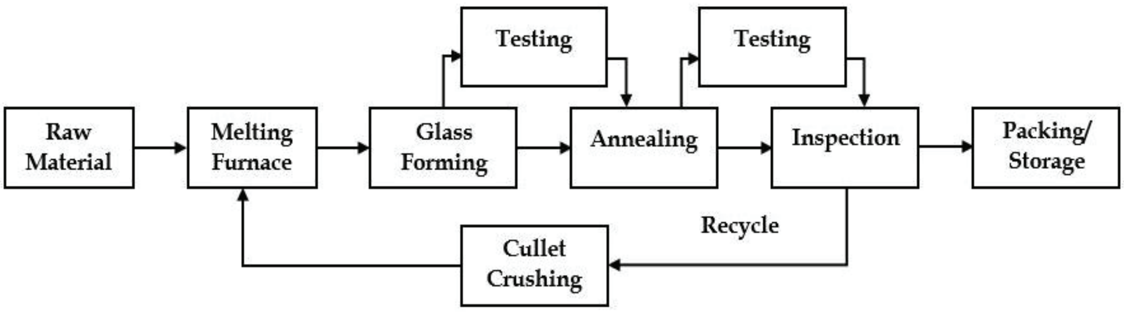

Figure 1 - Glass Container Manufacturing Process

Most of the food, beverage, and medicine packages are made of glass. Since glass is fragile, these packages can be easily damaged during the store-in, and delivery. Not only that, there are many defects that can develop in a container during the manufacturing process, such as cracks, air bubbles, freaks etc. (Anon, 1967). Hence, it is essential to detect defective containers to deliver a quality product N that will go through the customer's filling line without causing any difficulty. The various types of defects that can be present in the glass container during the manufacturing process and those defects are named under parts of a container as shown in Figure 2 and Table 1 summarizes some of the defects.

Eng. R.M.P.M.D. Rathanayake, AMIE(SL), BTech(Eng)OUSL, MIT-Reading(UCSC), Lecturer (Probationary), Department of Mechanical Engineering, The Open University of Sri Lanka, Nawala, Nugegoda.
Email:pmdrathnayake@gmail.com
https://orcid.org/0000-0002-0953-272X
Eng. W.D.S.S. Bandara, AMIE(SL), BSc (Eng) Peradeniya, MEng(AIT), Senior Lecturer, Department of Electrical and Computer Engineering, The Open University of Sri Lanka, Nawala, Nugegoda.
Email:wdssbandara@gmail.com
https://orcid.org/0000-0003-2250-6945
Dr. S.N. Gunasekara, BSc Eng (Peradeniya), M.Sc (Peradeniya), PhD (Peradeniya), Senior Lecturer, Department of Mechanical Engineering, The Open University of Sri Lanka, Nawala, Nugegoda
Email:sngun@ou.ac.lk
https://orcid.org/0000-0001-8460-8758

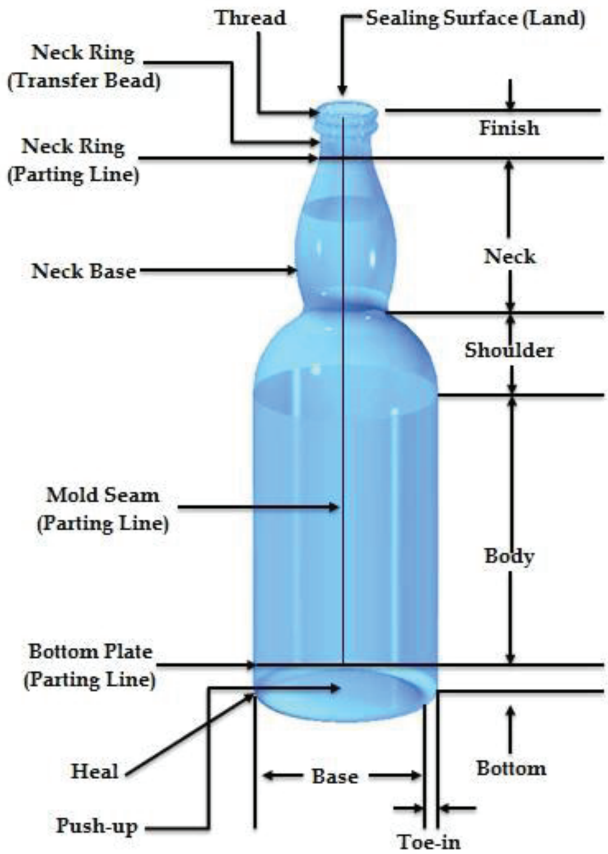

Figure 2 – Parts of Glass Container

Table 1 – Types of Defects Contain in a Glass Containers

Critical Defects	Body Defects	Finish Defects	Neck Defects	Bottom Defects	Shoulder Defects
Freaks	Stringy Glass	Offset	Seam on Neck	Flanged Bottom	Shoulder Check
Spikes	Bulged Sides	Off Gauge	Dirty Neck	Wedge Bottom	Sunken Shoulder
Checked and Split Finish	Hot or Panel Check	Bulged and Chipped	Bent Neck	Heavy Rocker	Thin Shoulder
Crizzeled Finish	Pressure and Letter Checks	Over Pressed	Ling Neck	Baffle Marks	
Checks under Finish	Blow Mold Seam	Corkage Check	Hollow Neck	Swung Baffle	
Unfilled Finish	Bird Cage	Neck Ring Seam	Pinched Neck	Wedge Bottom	
Chocked Neck or Bore	Cold Molds	Bent or Crooked	Danny Neck	Thin Bottom	
Bottom Check Thin Ware	Wash Modes	Tear Under Finish			
Stuck Glass Particles	Sunken Sides	Dirty or Rough			

This work is mainly focused on the inspection and testing stages of the manufacturing process of glass containers. In the glass containers that contain perishable food or beverages, the presence of air can cause bacterial spoilage and other health concerns. In medical stream, non-defective glass containers are essential because any leakage will cause health issues to the patients. Therefore, glass container is a critical item to prove the results of this investigation.

Manual inspection process which is used so far is slow, time consuming and prone to human error. However, the evolution of machine-vision technology has been implemented in some developed factories to facilitate the inspection process. In certain years, image analysis technique has been increasingly used in industries for surface inspection, whereas one must detect small defects that appear as local anomalies in material surfaces [12]. But these systems are very expensive to establish. Hence, it is better to develop an automated and cost-effective detection method to facilitate the work of operators or sales to introduce a quality product.

2. Existing Defect Detection Methods

Most of the time the defect detection is done by humans, which is slow and affects the accuracy of measurements. But some developed factories use image processing technique for inspection process. Acoustic based detection methods are used for some defect inspection such as filling characteristics and coating check as well.

2.1 Machine Vision Based Defect Detection

Image processing is the latest technique which is used for defect detection today where an image of an object is scanned and compared with existing image templates in a database and then find defective object and reject them [11, 12].

The processing difficulty of the crack detection completely depends on the size of the image. Recent digital cameras have the image resolution beyond 10 megapixels. This increase in resolution enables the acquisition of detailed images of concrete surfaces. By using trendy commercial cameras, a wide range of concrete surfaces can be acquired in a single shot. For inexpensive applications, a wide range of images can be used for practical crack detection [10, 11]. However, some defects are inspected through manual examination, which cannot be detected by image processing.

2.2 Photo-Electric Crack Detector for Glass Bottles

This system introduces apparatus for photo-electrically detecting cracks or flaws in the bottoms, necks, or lips of glass bottles while being rotated and traversed in a single line through a test path, storing the effect of a signal resulting from the presence of such a defect, and utilizing said stored effect to cause ejection of defective bottles after they pass beyond the test area [13].

2.3 Plastic Coated Bottle Testing

This system tests plastic coat of the bottle by its sound characteristics and rejects the defective bottles. Bottle is struck by an impact mechanism.

The sound of impact is detected, and the sound decay characteristics are utilized to determine whether the bottle is solid and acceptable or whether it is cracked or broken and thereby rejected [8]. This system has been developed to check only coated bottles but can be used to detect empty glass containers.

2.4 Method and Apparatus for Analysing the Fill Characteristics of a Packaging Container

This system is about filling characteristics defects. It introduces a method for analysing the internal pressure of a closed container and includes inducing vibration on a surface of the container, detecting sound resulting from the vibration, deriving information representing the detecting sound, and predetermining whether this information corresponds to a predetermined spectral frequency condition and a predetermined spectral amplitude condition [15]. This idea can be used to detect defects which are developed during the manufacturing of glass containers.

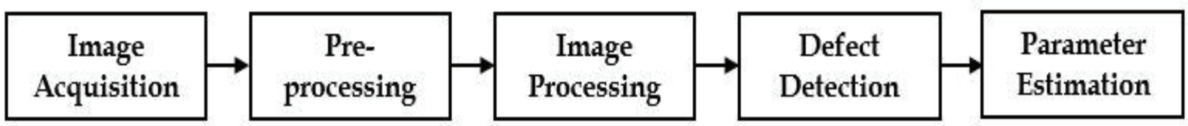

Figure 3 – The Architecture of Image Processing Based Defect Detection

2.5 Acoustic Based Systems

There are many systems implemented all over the world based on acoustic characteristics such as acoustic accident detection system, car accident detection and notification, engine fault diagnosis using acoustic signals, leak detection in gas pipelines by acoustics and detection of diesel engine injector faults, etc. [2]. This work is developed to detect faulty objects.

3. Methodology

In this work, a methodology is proposed to detect defective objects based on their acoustic behaviour. After taking audio (sound) signals of objects, signal processing and analysis techniques are applied to isolate the differences in frequency responses of non-defective and defective objects.

Therefore, a database is developed by including about 25 samples of recorded soundtracks of non-defective glass containers. Figure 4 shows signals of two non-defective sound samples and Figure 5 shows a signal of a defective sound sample.

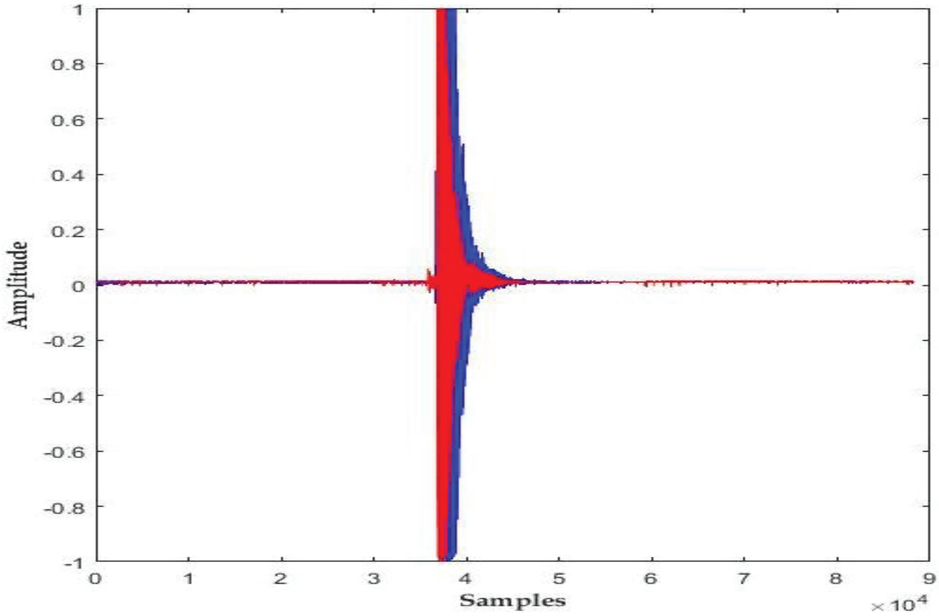

Figure 4 - Sound Samples of two Non-Defective Glass Containers

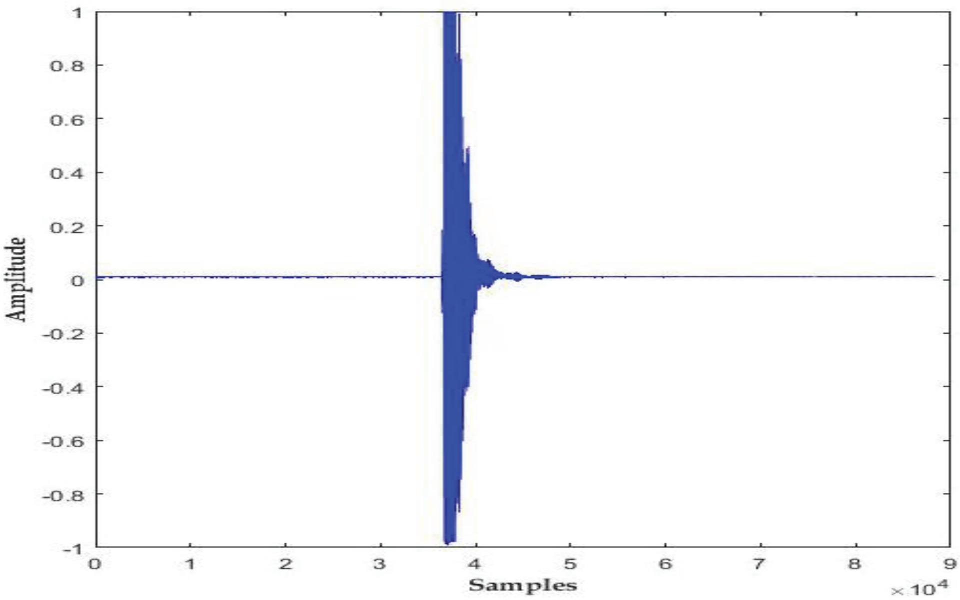

Figure 5 - Sound Sample of a Defective Glass Container

It is approached through the frequency spectrum analysis over non-defective items and defective items. Since we used same type of glass containers for testing, acoustic features are extracted from the samples of recorded soundtracks and compared them with the soundtrack templates of non-defective containers available in the database.

The frequency spectrum is obtained by using the Fast Fourier Transformation (FFT) technique. Spectrums of each signal must be analysed to identify differences of sound signals of glass containers. Therefore, decision making unit involves two feature extraction methods which are used in signal processing. The two methods are Mel Frequency Cepstrum Coefficients (MFCC) and Cross-Correlation which are implemented in MATLAB environment.

While inspection, the spectrums obtained for all non-defective sound samples in the database and for presence of a glass container at that particular time features are extracted. Extracted features are matched using a mathematical function called Euclidian Distance to allow making the final decision whether a presented glass container is defective or not.

The implementation of the system includes a striking device which is used to excite vibration on the glass container and the sound signal is detected by a microphone sensor and amplified. The amplified signal is then passed through a band-pass filter to obtain a narrow signal envelope as it facilitates the process of comparison of defective signals with non-defective signals. Then the defective container is rejected through the signal processing. The block diagram of the system is given in Figure 6. This methodology can be used for any kind of object such as steal packages, ceromic, plastic or other glass objects, porcelain items, etc., as it is developed based on the acoustical behavior of objects.

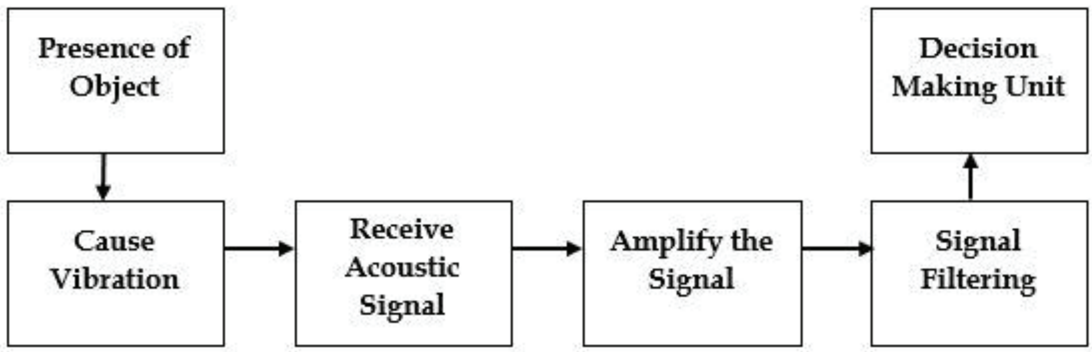

Figure 6 - Block Diagram for the Proposed System

4. Theoretical Analysis

The proposed method is developed by analysing sound wave outcome of objects. The sound is a type of energy made by vibration when a particular object vibrates, causing movement of the air particles or molecules which bump into other air particles close to them make further vibration and bumping into more air particles. This movement of air particles is called a sound wave. Considering a glass bottle, the sound of this instrument is created when energy is applied to the glass and the physical properties of the glass start to resonate.

4.1 Audio Signal Processing

Audio signal processing is an engineering field that focuses on the computational methods for intentionally altering auditory signals or sounds, in order to achieve a particular goal. In real-life signal processing, all signals have finite length, hence time domain truncation always occurs.

Once recorded in the time amplitude domain, the signal must be processed in order to recover its frequency information. To decompose a complex signal into simpler parts to facilitate analysis, differential and difference equations and convolution operations in the time domain become algebraic operations in the frequency domain. Therefore, a fast algorithm is introduced to analyse audio signals [2].

4.1.1 Fast Fourier Transformation (FFT)

Frequency spectrum of sound signals is obtained by applying the mathematical process of Fast Fourier Transformation which converts the amplitude data into frequency data. For any given time-window of a sound recording, FFT calculates the frequency components of the signal and their relative amplitudes produce a frequency spectrum [5].

Discrete Fourier Transform (DFT) is given by,

$$x(n) = \Sigma\, x(nT_s)e^{-j2\pi fnT_s} \quad \dots (1)$$

where, T_s is the sampling interval.

FFT signal spectrum is given by:

$$X(k) = \Sigma\, x(n)e^{-j2\pi(kn/N)} \quad \dots (2)$$

where, N is number of samples.

4.2 Algorithm for Feature Extraction

In the algorithm which is developed in this work involves audio feature extraction. Feature extraction is the computation of a sequence of feature vectors which provides a compact representation of the given audio signal. It is usually performed in three main stages [6].

i.) The acoustic front end which performs spectra-temporal analysis of the audio signal and generates raw features describing the power spectrum for short audio intervals.

ii.) Compiles an extended feature vector composed of static and dynamic features.

iii) Transforms these extended feature vectors into more compact and robust vectors that are then supplied to the recognizer.

According to the direction of this work, to analyse and identify differences between objects, an algorithm is developed to obtain the spectrums of each signal and applied two audio feature extraction methods called Cross-correlation and Mel Frequency Cepstrum Coefficients (MFCC) [6].

In feature extraction, each audio signal segment is divided into a relevant small number of parameters or features which describe each segment in such a characteristic way that other similar segments can be grouped together by comparing their features.

4.2.1 Cross-Correlation

Correlation function gives similarity study between signals [2]. The cross-correlation function is given by;

$$r_{xy}(n) = \sum_{k=0}^{2(N-1)} x(k).\, y(n-k) \quad \dots (3)$$

where, N is number of samples.

4.2.2 Mel-Frequency Cepstrum Coefficients (MFCC)

MFCC are coefficients that represent audio. They are derived from a type of cepstral representation of the audio clip (a "spectrum-of-a-spectrum"). The difference between the cepstrum and the Mel-frequency cepstrum (MFC) is that, in the MFC, the frequency bands are positioned logarithmically (on the Mel scale) which approximates the human auditory system's response more closely than the linearly spaced frequency bands obtained directly from FFT or DCT (Discrete Cosine Transform). This can allow for better data processing [3, 6]. Figure 7 explains the process of MFCC test.

(1) Pre-emphasis
Pre-emphasis filter is used to balance the frequency spectrum by amplifying high frequencies [3]. The pre-emphasis filter can be applied to a signal x(t) using the first order filter in the following equation.

$$y(t) = x(t) - \alpha x(t-1) \quad \dots (4)$$

where, typical values for the filter coefficient (α) is 0.95 or 0.97.

(2) Framing
It is difficult to do Fourier transformation across the signal because frequencies in a signal change over time. To avoid this, frequencies in a signal are kept stationary over a very short period which is called “frame” and do Fourier transform over this frame [3].

(3) Hamming Windowing
Then, each frame is multiplied with a hamming window. A Hamming window has the following form:

$$w[n] = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right) \quad \dots (5)$$

where, $0 \le n \le N-1$ and N is the window length.

(4) Fast Fourier Transform
Fast Fourier Transform (FFT) is applied to each frame which transforms signal to frequency domain. Thus, the spectrum for each frame is obtained. It still contains lot of information not required for feature matching stage. The feature matching algorithm cannot discern the

difference between two closely spaced frequencies [9].

(5) MEL Filter banks
Clumps of spectral bins are taken and sum up to get an idea of how much energy exists in various frequency regions. This can be performed by multiplying each frame with Triangular MEL Filter banks [9]. The Mel-scale aims to mimic the non-linear human ear perception of sound, by being more discriminative at lower frequencies and less discriminative at higher frequencies. We can convert between Hertz (f) and Mel (m) using the following equations.

$$m = 2595\log_{10}(1 + \frac{f}{700}) \quad \ldots (6)$$

$$f = 700(10^{\frac{m}{2595}} - 1) \quad \ldots (7)$$

(6) Discrete Cosine Transform (DCT
The log Mel scale spectrum is converted to time domain using Discrete Cosine Transform (DCT). DCT is defined by the following:

$$X_k = \alpha \sum_{i=0}^{N-1} \cos\left\{\frac{(2i+k)\pi k}{2N}\right\} \quad \ldots (8)$$

where, N is number of samples.
The result of the conversion is called Mel Frequency Cepstrum Coefficient. The set of coefficients is called acoustic vectors. Therefore, each input utterance is transformed into a sequence of acoustic vectors.

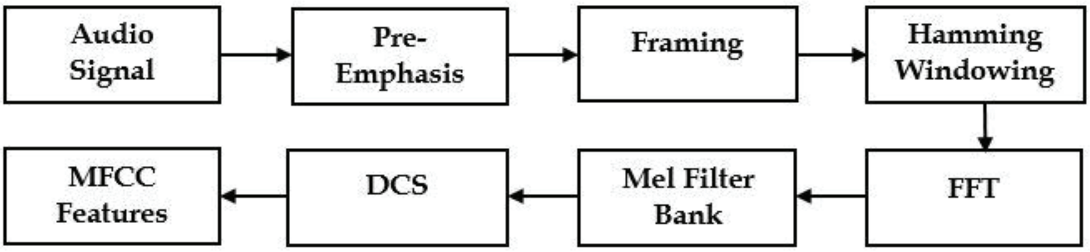

Figure 7 - Flow Diagram of MFCC Process

4.3 Algorithm for Feature Matching
The feature matching process in the algorithm involves Euclidean distance function and for making the final decision involves the false acceptance and false rejection rates.

4.3.1 Euclidean Distance
The comparison process involves the use of a Euclidean distance to evaluate the results of MFCC tests. The Euclidean distance measures the percentage of dissimilar bits out of the number of comparisons made [4]. Ideally, when a sound wave of a non- defective glass container is input, nearly its entire features match and when a sound wave of a defective-glass container is input, which does not fully match, then the system will reject the defective container.

4.3.2 False Acceptance Rate (FAR) and False Rejection Rate(FRR)
The final matching decision is taken based on matching score and acceptance rates. The performance of the system is evaluated using two parameters called False Acceptance Rate (FAR) and False Reject Rate (FRR) [9].

FAR is calculated as [FP/ (TN + FP)] * 100 %
FRR is calculated as [FN/ (TP + FN)] * 100 %
where,
FP is the False Positive i.e. incorrectly identified.
TP is the True Positive i.e. correctly identified.
TN is the True Negative i.e. correctly rejected.
FN is the False Negative i.e. incorrectly rejected.

5. Results

For different types of bottles, the range of frequency outcome changes according to the characteristics of the bottle type such as size, volume, colour, weight, etc. The evaluation of this work is done using a 125 ml Alpha (A) bottle which is shown in Figure 8.

Figure 8 – 125 ml Alpha (A) Bottle

Therefore, the obtained frequency spectrums of sound signal of containers lie between 5.5 kHz and 7.5 kHz.

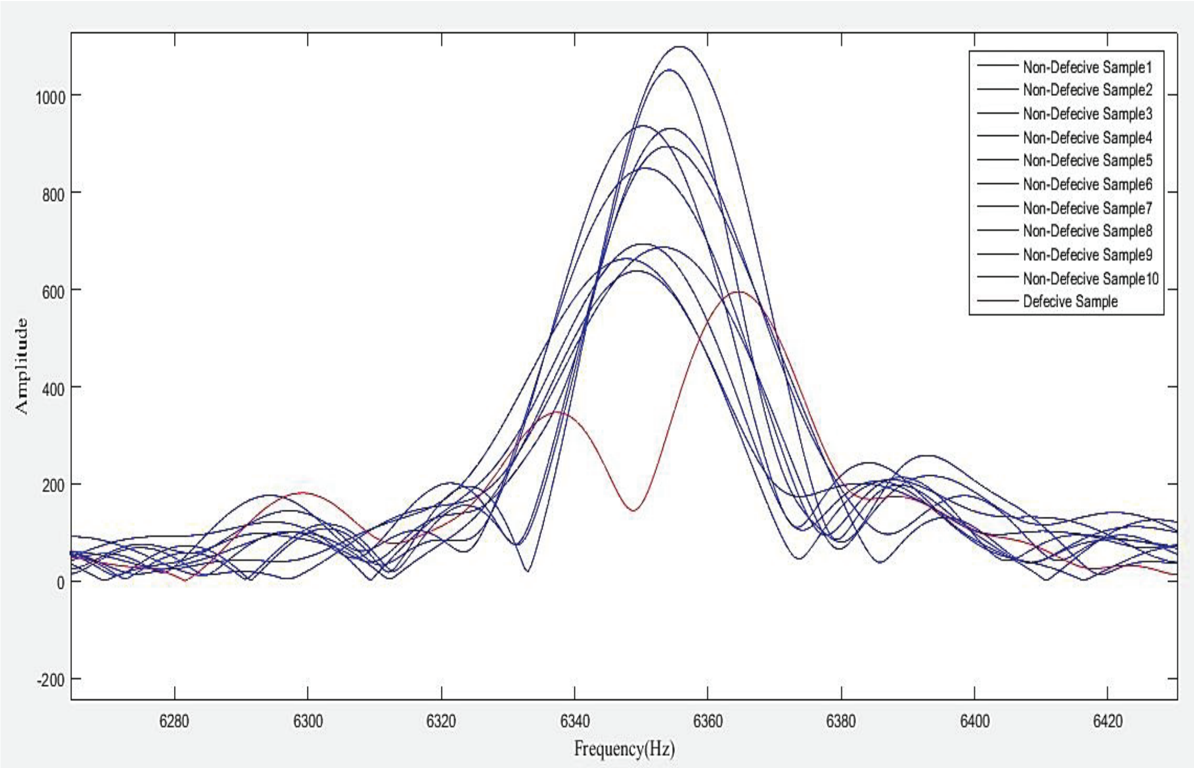

Figure 9 - Comparison of Frequency Spectrums of Non-Defective Glass Containers verses Defective Glass Container

According to the observations, spectrums of non-defective containers are quite similar while defective containers give slightly different spectrums as shown in Figure 9.

Since the database consists of 25 sound samples of non-defective containers, only 10 spectrums of them are taken to give a clear view which is represented in blue colour. In addition, the spectrum represented in red colour is one of the defective container sound samples.

Each test used for feature extraction and matching gives a vector table. The database is created including 25 audio samples of non-defective glass containers which were recorded for 2 seconds. For the real-time testing, audio signal recording time for a given glass container is stationary for 2 seconds as well.

According to the presence of a container which is going to detect its condition through the testing process, test sound file of that container which is recorded is overlapped with the sound files in the database and their features are extracted using the Cross-Correlation and MFCC methods. For each test, vector tables are generated and these vector tables are used to evaluate the final decision. Therefore, several tests are done to identify threshold levels for both methods used to direct the comparison process. According to the results for both methods, if the test container is detected as good, final prediction concludes the container is accepted, otherwise it is rejected.

The effect of background noises in the manufacturing plant can be reduced using filters or else can apply this process in a sound proofed section that can be attached to the manufacturing process.

5.1 Cross-Correlation Test

According to the evaluation of the vector tables received for cross-correlation test, the maximum correlated value of each test is considered to identify a threshold level for the prediction of the container. It is identified that maximum correlated values received for non-defective containers laid above 600 and values received for defective containers laid below that level. The correlated values obtained after applying the Cross-Correlation test, similar type defects contain in containers are received with slight differences and for different types of defects will be generated correlated values with high differences. But, in both cases, values are laid below the level 600 as shown in Figure 10. Therefore, that value is taken as the threshold level for comparison of containers. Therefore, in the design, it checks whether the maximum values obtained in the vector tables during the cross-correlation test exceed the threshold value. If a processed audio wave for a given glass container exceeds the threshold value, then it gives the result that the container is not defective. If that value lies below the threshold value, the container is identified as a defective one. According to the use of cross-correlation method, Table 2 shows the results for three tests which are compared with 10 sound samples in the database.

The Figure 10 shows a clear idea of Table 2. Green line in Figure 8 represents the threshold level which is concluded for the prediction of container status. The result of a test which is laid below the threshold value (i.e. 600) is identified as a defective container.

Table 2 - Results for Cross-correlation Test

Database	Defective Container 1	Defective Container 2	Non-Defective Container
Sample 01	447.120	367.913	1147.097
Sample 02	434.258	366.530	1030.859
Sample 03	535.043	351.768	511.014
Sample 04	357.698	321.715	712.359
Sample 05	511.716	376.805	1142.853
Sample 06	375.490	342.189	767.511
Sample 07	434.338	372.178	1016.184
Sample 08	442.189	340.933	891.427
Sample 09	490.659	399.687	969.486
Sample 10	458.603	372.689	1016.389

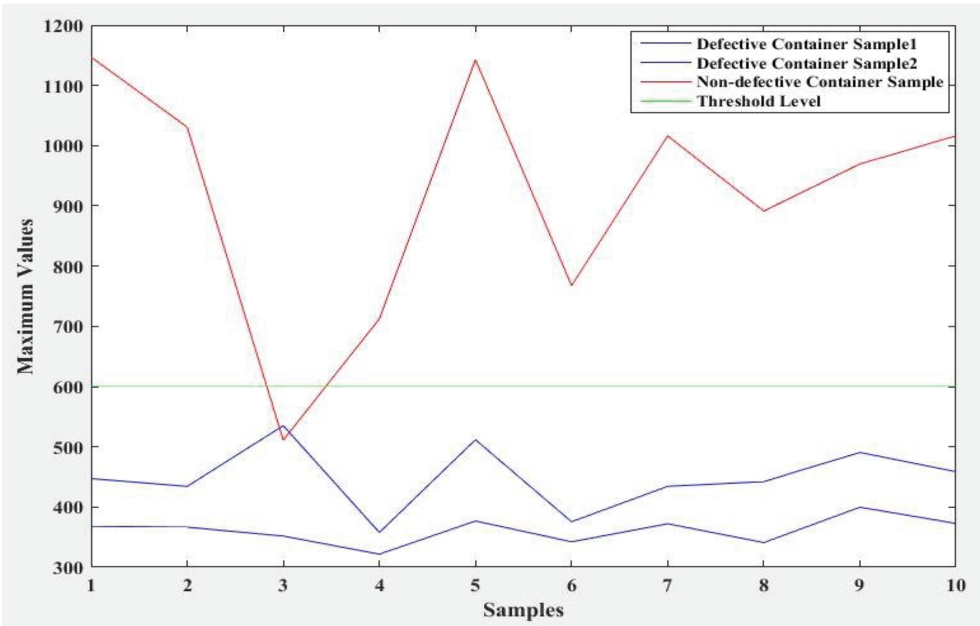

Figure 10 - Cross-Correlation Results of Three Tests

5.2 MFCC Test

As cepstral features are computed by taking the Fourier transform of the warped logarithmic spectrum, they contain information about the rate changes in the different spectrum bands. Cepstral features are favorable due to their ability to separate the impact of source and filter in an audible signal. Higher order coefficients represent increasing levels of spectral details, depending on the sampling rate and estimation method; 12 to 20 cepstral coefficients are typically optimal for audible signal analysis. Selecting a large number of cepstral coefficients results in more complexity in the models [9].

Since the signal outcome of containers lay in an audible range, 13 cepstral coefficients are used for this analysis. In the MFCC test, it calculates 13 MFCC coefficients of each audio sample. To apply MFCC method, following parameters should be defined according to the type of the container.

Table 3 – Parameter Values for MFCC Test

Parameter	Value
Analysis Frame Duration	25 ms
Analysis Frame Shift	10 ms
Pre-emphasis Coefficient	0.97
Centre Frequency of Lowest Mel-filter	5000 Hz
Centre Frequency of Highest Mel-filter	7000 Hz
Number of Mel bands	40
Sampling Frequency	44100 Hz
Number of Cepestral Coefficients	13

Euclidean distances between the test audio sample and audio samples in a database are calculated to direct the comparison process. It gives distance vectors of 13x13 matrices for each comparison. The 13th column of each distance vector gives the variation for distances. Therefore, each 13th column of each vector table is evaluated to obtain a threshold level for direct comparison process. According to the evaluation of vector tables, a threshold level is identified as 860. This is the maximum possible distance value for a non-defective container can acquire. Table 4 and Figure 11 show the test results of three tests with same glass containers used for cross correlation test given above.

Figure 11 shows a clear view of the above table. Therefore, threshold level which is identified through the tests done for MFCC test is represented by the green line (i.e. 860). If the maximum value of a distance vector exceeds the threshold level, the test sample is identified

as a defective container. As we can see in the table, values received for defective containers have slightly different variations. According to the type of the defect, these values can be much different but not exceeding the threshold level, which is predicted for the comparison process.

5.3 FAR and FRR

The final prediction is done by comparing both test results and the obtained FAR is around 10%, and FRR is around 18%. The FAR and FRR test results of 60 tests are given in Table 5.

Table 5 - Test Results of FAR and FRR

Test	FAR %	FRR %
1 - 10	9	16
11 - 20	7	18
21 - 30	10	16
31 - 40	6	15
41 - 50	11	11
51 - 60	8	18

Table 4 - Results for MFCC Test

Database	Defective Container 1	Defective Container 2	Non-Defective Container
Sample 01	829.202	822.740	909.947
Sample 02	838.892	831.818	918.037
Sample 03	815.817	810.244	889.153
Sample 04	835.219	828.556	912.36
Sample 05	848.772	842.516	926.526
Sample 06	815.817	810.244	889.153
Sample 07	846.629	840.0711	925.312
Sample 08	829.137	822.744	904.835
Sample 09	832.081	825.059	913.496
Sample 10	842.095	835.531	922.505

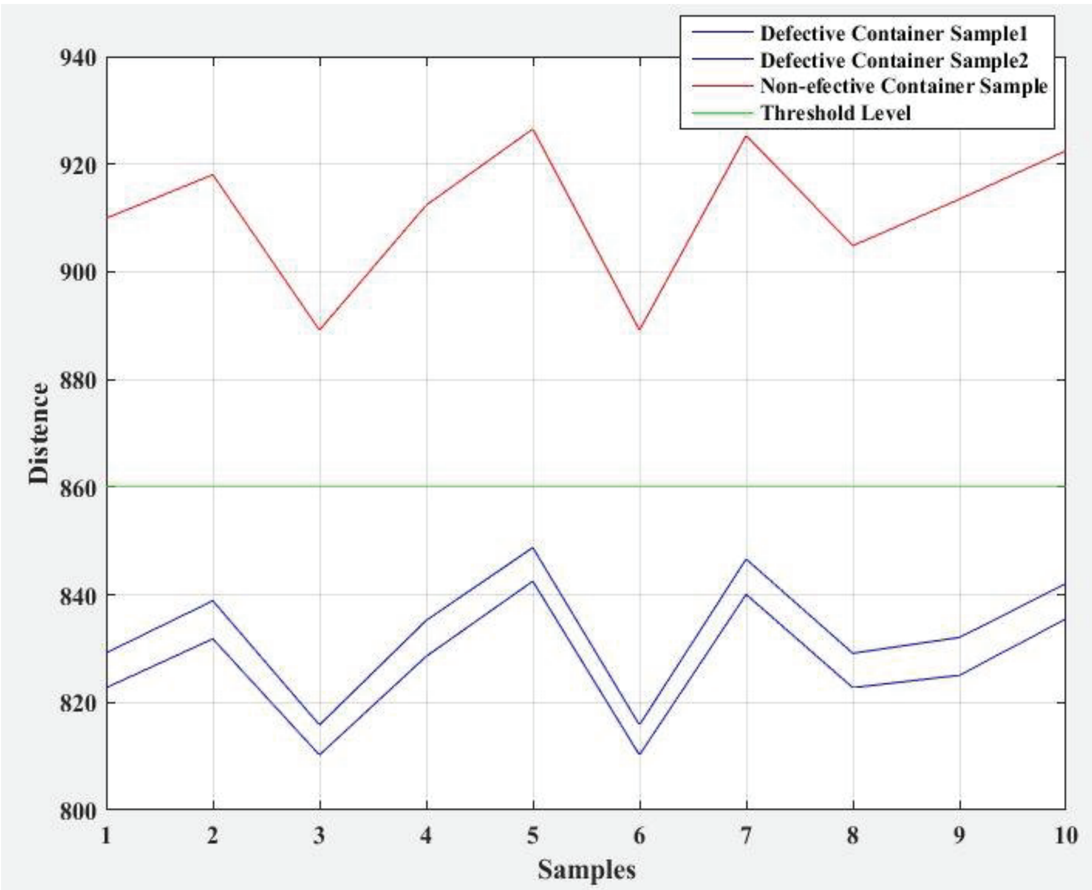

Figure 11- MFCC Result for three Tests

6. Conclusion

This investigation approached through frequency spectrum analysis of objects. The test results are taken by using non-defective and defective glass container samples. By vibrating a glass container its sound outcome is recorded to extract acoustic features which are then compared with non-defective sound templates available in the database. Therefore, frequency spectrum is obtained by using Fast Fourier Transform (FFT) technique and features are extracted using Cross-Correlation and Mel Frequency Cepstrum Coefficient (MFCC) methods to isolate the defective containers from non-defective containers. The comparison process involves the use of a Euclidean distance which measures the percentage of dissimilar bits out of the number of comparisons made. The final prediction is done by comparing both test results, and the obtained FAR is around 10% and FRR is around 18%.

This methodology can be further developed for defect detection of all kind of objects that are made of various materials such as plastic, porcelain, steal, etc. where an inspection process is needed. Only the vibration mechanism should be changed according to the material of an object that can receive a better outcome of acoustic signals, which facilitates the analysis process.

Not only for defect detection, this method can also be applied for quality measurement of objects. Because, unlike surface inspection that uses image processing for defect detection, analysis of frequency spectrum can be used to measure the compound of an object whether it is containing the right amount of compound. Therefore, this will be another advantage because it can identify both the defects and compound measurement of objects at the same time.

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