



EXPLORING ACOUSTIC RESONANCE AS A POSSIBLE METHOD OF MATERIAL IDENTIFICATION IN METALS

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ABSTRACT

Materials exhibit characteristic and unique vibrational responses when exposed to external excitation. Resonance based material characterization can use distinct resonant frequencies and the broader frequency spectrum to investigate the physical properties and characteristics of a material. This study investigates whether the entire shape of a resonance frequency graph can serve as a reproducible “signature” for metal identification, rather than relying solely on distinct peaks that alter slightly each trial.

An experimental setup was constructed using two speakers to excite metal coin samples across a frequency range of 7,000 - 22,000 Khz, while a piezoelectric sensor recorded each coin’s vibrational response and graphed it digitally. A Faraday cage was used to reduce electromagnetic interference from the surroundings. Frequency-response graphs were generated and compared between aluminum and zinc samples to evaluate the similarity of their overall profiles, including the lines shape and resonance peaks.

The preliminary results showed highly similar spectral profiles between tested samples within the same metal group. These findings suggest that the overall frequency graphs may contain reproducible information that could contribute to a more accessible way of metal identification. Further analysis is needed to quantify graph similarity and establish whether the profiles of metals across a wider range can be distinguished continuously. If evaluated and proven true, this approach could potentially contribute to existing nondestructive material identification methods by offering an accessible way to compare the vibrational signatures of metal samples.

INTRODUCTION

I. The Importance of Metal Identification Methods and Their Applications

Metal identification is an important part of manufacturing, quality control, construction and material inspection. Industrial producers must submit specifications for their material’s chemical composition and physical properties to ensure that they perform as intended and described. An example of this is a manufacturer confirming that two stocks of metal they ordered to create the same product are truly the same alloy. Confusing two metals or alloys can create quality control problems, especially when materials have different mechanical or chemical properties such as specific heat, melting point, durability, and elasticity. Standard 4.1 of American Society For Testing and Materials, a global 501(c)(3) dedicated to accurate material identification, describes

maintaining metal identity throughout the production, storage, receipt, and creation of a product as a key concern in materials management [1].

II. Limitations and Alternatives to Conventional Identification

Although established analytical methods such as PMI are useful, the equipment and services required present practical barriers that make them virtually impossible for the average consumer. Handheld XRF machines within PMI are specialized instruments that require additional investment in equipment, while outsourcing those same machines adds service charges, scheduling, and transportation of samples to the cost. Costs do vary according to the provider, quantity, testing requirements, and location, but the average price costs beyond the budget of any smaller scale project. For example, one industrial surveyor from the Texas Flange indicates how paying \$150 dollars per stock (stock used as the unit per part) is disproportionate to the \$200 dollars per material that may already be included within the budget of manufacturing [4].

Other methods can also be used to sort or characterize metals, including electrical conductivity measurements, eddy current testing, thermoelectric testing, and spark testing for special cases [2]. These techniques rely on different material properties and have different strengths and limitations. ASTM's guide on metal identification [2] describes several of these approaches, distinguishing techniques that directly measure elemental composition from methods that may solely infer material characteristics through physical responses. Therefore, completing several of these methods alongside a complementary non-destructive method, such as using resonance graphs in identification, could be useful in situations where a more accessible and rapid comparison is needed, giving a workaround to financial and technological limitations.

Reliable identification is also relevant to the verification of any supplied/used materials. Incorrect material grades or fraudulent certification documents have been seen in industrial supply chains [5], creating a market need for independent verification rather than relying on labels constructed in seller's paperwork. A low cost screening method would not automatically establish the chemical composition or authenticity of a material, but it would allow a buyer to compare one sample they know is real with a suspected fraudulent sample, and flag any difference from the expected result.

III. Resonance as A Possible Accessible Material Signature

Materials exhibit characteristic vibrational responses when exposed to external mechanical excitation. Resonance occurs when an object is excited at or near one of its natural frequencies, resulting in an increased vibrational response. The natural frequencies of an object are determined by its physical properties, including its stiffness, mass, and geometry (*Figure 1*). A simplified model for understanding this relationship is the mass-spring system, in which the natural frequency can be calculated using:

(f) = natural frequency (Hz)
(k) = effective stiffness (N/m)
(m) = effective mass (kg)

$$f = \frac{1}{2\pi} \sqrt{\frac{k}{m}}$$

Figure 1. Natural Frequency Formula In A Mass-Spring System

This relationship demonstrates that natural frequency increases with stiffness and decreases with mass, assuming the other variable remains constant. Although this equation represents a mass-spring system rather than the vibrational behavior of a metal disk, it illustrates how an object's physical properties influence its resonance. At this time there is no formula that can predict the qualities tested in this lab as it is regularly determined experimentally and varies with trial.

Different metals can exhibit different resonance frequencies because their material properties are not identical. Metals have different densities and elastic properties, which influence how they respond to excitation. One important property is density, which describes the mass per unit volume of a material, and due to the chemical composition of each element, even at an identical sample size coins composed of different metals would have different densities and therefore different resonance frequencies and resonance graphs.

Comparing the overall shapes of graphs can provide information that may not be captured by their individual data points alone. In the article *"Determining the Statistical Significance of the Difference Between Arbitrary Curves: A Spreadsheet Method."* Hristova and Wimley [6] describe a method for evaluating whether differences between two curves are statistically significant. Their approach provides a framework for examining differences across entire curves, as isolated values and ranges can differ from one trial to another. While isolated points like resonance peaks can help determine characteristics on the graph, their constant movement in each trial, even by a slight amount, can make them a non-constant way to determine if the comparison between one material and another unknown material is correct.

This concept is relevant to the present study because the goal is to determine whether the overall shape of a metal's frequency-response relationship graph can help distinguish it from other metals. Instead of comparing only the locations of individual resonance peaks, the complete graphs can be examined for similarities and differences. If repeated measurements of the same metals produce similar curves, while the measurements of different metals produce distinguishable different shaped curves, the overall graph may be useful for visually separating materials and analytically determining a percent relationship. This study investigates whether a similar approach to curve comparison can be applied to a metal frequency comparison.

IV. Analytical Methods Of Comparing Graphs

Visual comparisons of frequency response graphs can reveal similarities between samples, but they do not provide a numerical measurement of how closely two curves match. To evaluate the similarities between samples of the same metal and determine whether different metals can be distinguished, several statistical measurements can be applied to compare their frequency response data.

Pearson's Correlation Coefficient (r) (Figure 2) measures the strength and direction of the linear relationship between two sets of data. When comparing frequency response curves, a coefficient closer to +1 indicates that the curves follow a similar pattern.

$$r = \frac{(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}}$$

Figure 2. Pearsons Correlation Coefficient Equation

Root Mean Square Error (RMSE) (Figure 3) measures the average magnitude of the differences between corresponding data points on two curves. A lower RMSE corresponds to values that are closer together. Normalized Root Mean Square Error (NRMSE) adjusts this measurement relative to the range of the data, allowing the differences to be interpreted in relation to the scale of the frequency response measurements.

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(y_i - \hat{y}_i)^2}{n}}$$

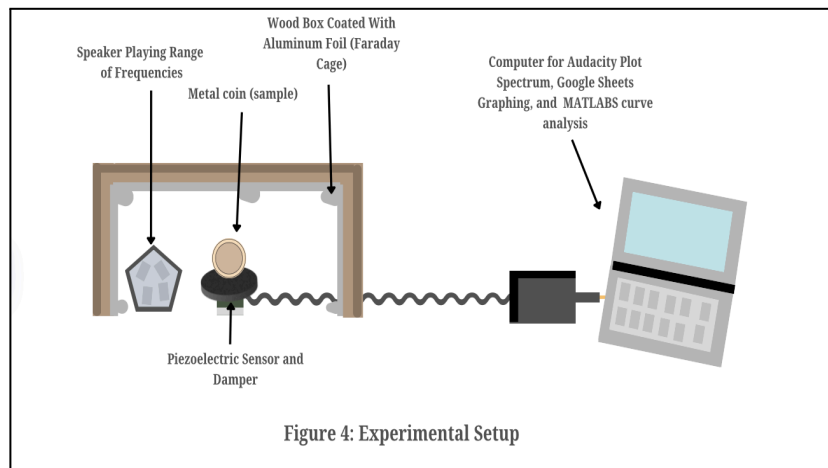
Figure 3. Root Mean Square Error Equation

Additionally, a calculation labeled “Similarity Percentage” in later tables was determined using the formula $\% = (100 * (1 - RMSE))$. This calculation provides a more accessible numerical representation of how closely two frequency response curves’ points match, with higher values indicating greater overlap of points.

METHODOLOGY

I. Materials

This experiment used metal samples with matching dimensions to reduce differences caused by resonance’s natural change to material dimension. This setup includes speakers to excite the samples, a piezoelectric sensor to detect any vibrations, a computer with audio (piezoelectric responses) recording on Audacity, a spectral analysis software, and a Faraday Cage (Figure 4).



Equipment Or Material	Function
Metal Samples (ESICO set of metal disks - Zinc, Aluminum, and Copper Used - 2 samples each)	Materials that were used to collect a resonance frequency spectra - both a “known” labeled sample and an “unknown” unlabeled sample.
Speakers	Provided external excitation across the tested frequency range of 7,000 - 22,000 KHZ
Piezoelectric Sensor	Detected mechanical vibrations and converted them into electrical signals
Audio Interface and Recording Software	Recorded the sensor output through a transducer, and made it compatible for Computer Based Spectral Recording
Faraday Cage	Reduced electromagnetic interference that could affect measurements.
Computer Based Spectral Recording (Audacity Spectral Record & Analysis)	Recorded the spectral graph of 13,000 data points per a trial.
Computer Based Spectral Analysis and Graphing (Google Sheets Data Organization and Graphing Function)	Organized the data into columns, creating comparable graphs.

Matlabs Curve Analysis	Used to find RMSE, NRMSE, Pearson Correlation Coefficient, and Similarity %.
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II. Prevention of Experimental Error

Several of the factors within this experiment during the initial trials affected the repeatability of measurements, and were ultimately able to be solved in order to achieve error reduction. These include variation in the position of the sample on the sensor, the contact point between the sensor and the sample, the intensity of excitation (the strength the speaker was set at), and background noise (including electromagnetic interference).

Using samples with similar dimensions helps reduce the influence that the geometry of the object has on the results of the experiment, removing it as a factor. This also allowed for the objects to be placed in the exact same position, half off the sensor facing the speakers and a half attached to the sensor. Keeping the sensor placement, speaker strength, sample geometry and placement constant allowed for differences in repeated measurements to be used as experimental results, rather than error.

The Faraday cage was included to reduce electromagnetic interference. Although, it does not eliminate all sources of error, but rather targets electromagnetic interference specifically. The cage should be understood as a measure of improving measurement conditions, but not a means of preventing all issues such as internal speaker resonance.

III. Experimental Procedure

The experiment was designed with the intention to measure the frequency responses of multiple metal samples in a controlled environment when interacting with frequencies from 7-22 kHz.

Step 1: Preparation of Metal Samples

Two samples of each metal type were selected for testing, consisting of a labeled sample and its corresponding unlabeled sample. The samples were standardized in size and thickness to minimize differences in resonance behavior caused by variations in geometry. Each sample was prepared for testing by positioning it on the piezoelectric sensor.

Step 2: Experimental Setup and Frequency Excitation

Each metal sample was placed inside a Faraday cage to reduce electromagnetic interference during recording. Using the speaker system, frequencies ranging from 7,000 Hz to 22,000 Hz were played to excite the metal sample and produce vibrations. The piezoelectric sensor detected these vibrations and converted them into electrical signals that could be recorded and analyzed.

Step 3: Recording Frequency Response Data

The output from the piezoelectric sensor was recorded using Audacity. The recorded signal was then analyzed using Audacity's Plot Spectrum feature, which generated a graph displaying amplitude in relation to frequency. The resulting frequency response data was exported for further analysis.

Step 4: Repeated Trials

Three trials were conducted for each metal sample to evaluate the consistency of the recorded frequency response. The same procedure was repeated for the corresponding unlabeled sample of each metal type. This provided multiple measurements for comparing samples of the same metal and evaluating the reproducibility of their frequency response profiles.

Step 5: Graphical Comparison

The exported frequency response data was organized into graphs to compare the samples visually. The graphs were examined for similarities in their overall shapes and resonance peaks between samples of the same metal type. Comparisons were also made between different metal types to identify differences in their frequency response profiles.

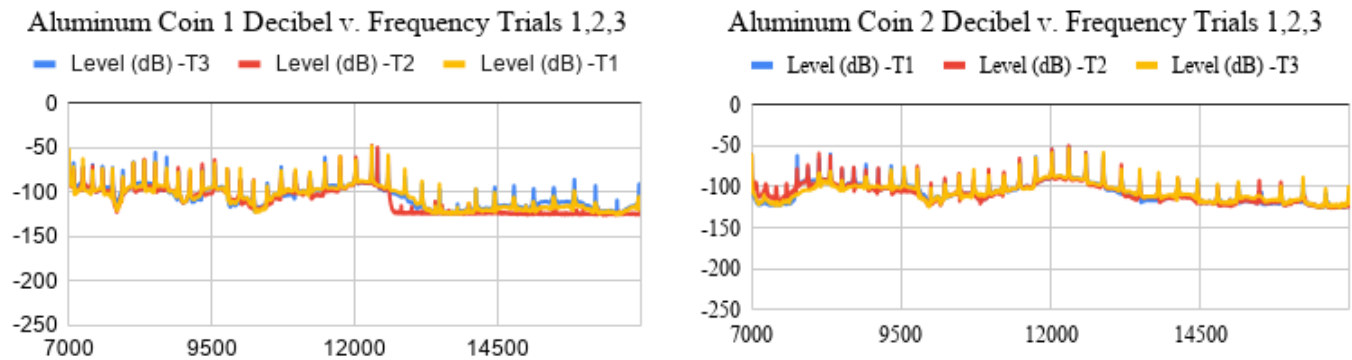
Step 6: Quantitative Analysis Using MATLAB

MATLAB was used to quantitatively compare the frequency response curves. Four measurements were calculated: Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Similarity Percentage, and Pearson's Correlation Coefficient. These measurements were used to evaluate the numerical differences and similarities between the frequency response curves of samples belonging to the same and different metal types.

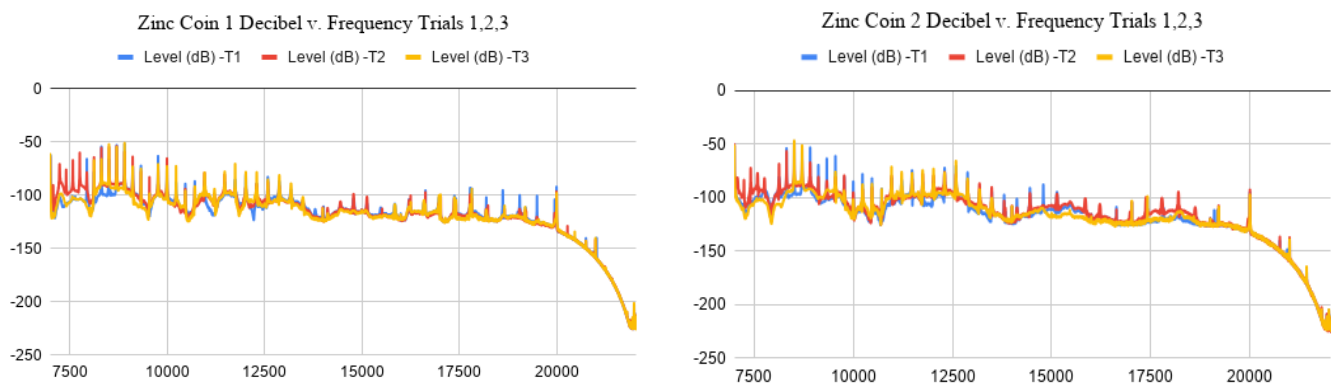
RESULTS

I. Comparison of Frequency Response Graphs Graphically

After the frequency response data was collected, the exported measurements were organized and graphed. The resulting graphs displayed the amplitude of each sample across the tested frequency range of 7,000–22,000 Hz. Upon visual examination, similarities were observed between samples of the same metal type. These similarities extended beyond the locations of individual resonance peaks and could also be seen in the overall shapes and patterns of the frequency response curves. This suggested that the entire frequency response profile, rather than only specific resonance frequencies, could contain distinguishing characteristics of each metal type. The graphs were also compared between different metal types to identify visual differences in their frequency response patterns.



(Figure 5 & 6) Aluminum Coin 1 and 2 Showing Visually Similar Resonance Graphs Across 3 Trials Each



(Figure 7 & 8) Zinc Coin 1 and 2 Showing Visually Similar Resonance Graphs Across 3 Trials Each

II. Analytical Similarities Between Coins of The Same Metal Types

To further evaluate the visual similarities between samples of the same metal type, the frequency response curves were quantitatively compared using MATLAB. RMSE, NRMSE, Similarity Percentage, and Pearson's Correlation Coefficient were calculated between repeated measurements and between the two corresponding samples of each metal. These measurements provided numerical comparisons of the curves, allowing the consistency of the frequency response profiles to be evaluated beyond visual observation. The resulting measurements for aluminum, nickel, and zinc are shown below (Figure 8):



Analytic Comparison of Aluminium Coin Samples' Resonance Data (7,000 - 22,000 Hz)

Sample Resonance Data	Compared Data Collection	RMSE	Normalized RMSE	Pearson Correlation Coefficient ($-1 < r < 1$)	Similarity % (100 (1-NRMSE))
Coin 1 Collection 1	Coin 1 Collection 2	9.193	0.052	0.916	0.948
Coin 1 Collection 1	Coin 1 Collection 3	5.892	0.033	0.964	0.967
Coin 1 Collection 1	Coin 2 Collection 1	8.574	0.048	0.922	0.952
Coin 1 Collection 1	Coin 2 Collection 2	8.472	0.047	0.924	0.953

Analytic Comparison of Zinc Coin Samples' Resonance Data (7,000 - 22,000 Hz)

Sample Resonance Data	Compared Data Collection	RMSE	Normalized RMSE	Pearson Correlation Coefficient ($-1 < r < 1$)	Similarity % (100 (1-NRMSE))
Coin 1 Collection 1	Coin 1 Collection 2	5.148	0.030	0.971	0.970
Coin 1 Collection 1	Coin 1 Collection 3	4.129	0.024	0.980	0.976
Coin 1 Collection 1	Coin 2 Collection 1	6.410	0.036	0.952	0.964
Coin 1 Collection 1	Coin 2 Collection 2	7.165	0.040	0.952	0.960
Coin 1 Collection 1	Coin 2 Collection 3	7.240	0.041	0.941	0.960

Analytic Comparison of Nickel Coin Samples' Resonance Data (7,000 - 22,000 Hz)

Sample Resonance Data	Compared Data Collection	RMSE	Normalized RMSE	Pearson Correlation Coefficient ($-1 < r < 1$)	Similarity % (100 (1-NRMSE))
Coin 1 Collection 1	Coin 1 Collection 2	10.904	0.062	0.852	0.938
Coin 1 Collection 1	Coin 1 Collection 3	5.665	0.032	0.852	0.968
Coin 1 Collection 1	Coin 2 Collection 1	10.042	0.056	0.876	0.944
Coin 1 Collection 1	Coin 2 Collection 2	12.382	0.069	0.808	0.931
Coin 1 Collection 1	Coin 2 Collection 3	10.806	0.060	0.853	0.940

Inter-Metal Comparison of Coin Samples' Resonance Data (7,000 - 22,000 Hz)

Sample Resonance Data	Compared Data Collection	RMSE	Normalized RMSE	Pearson Correlation Coefficient ($-1 < r < 1$)	Similarity % (100 (1-NRMSE))
Zinc Coin 1 Collection 1	Aluminum Coin 1 Collection 1	9.045	0.123	0.630	0.877
Zinc Coin 1 Collection 1	Nickel Coin 1 Collection 1	13.138	0.165	0.584	0.835
Aluminum Coin 1 Collection 1	Nickel Coin 1 Collection 1	15.588	0.196	0.488	0.804

Figure 8. RMSE, Normalized RMSE, Pearson's Correlation Coefficient & Similarity Percentages.

III. Distinguishing Between Metal Types

To determine whether the frequency response curves could distinguish between different metal types, the same statistical measurements were used to compare aluminum, nickel, and zinc samples against one another. Compared to the same-metal comparisons, RMSE and NRMSE values generally increased when different metal types were compared, indicating greater numerical differences between their frequency response curves. However, the resulting Similarity Percentages remained relatively high, ranging from 80.41% to 87.70%. This suggests that the Similarity Percentage alone may not reliably distinguish between different metals, as overlapping portions of the frequency response curves can result in relatively high similarity values even when the samples consist of different metals.

Pearson's Correlation Coefficient demonstrated a more noticeable separation between the same-metal and different-metal comparisons. While comparisons between samples of the same metal produced coefficients ranging from 0.8075 to 0.9797, comparisons between different metal types produced coefficients ranging from 0.4876 to 0.6296. This decrease indicates that the overall patterns of the frequency response curves were less closely related when different metals were compared. Among the four measurements, Pearson's Correlation Coefficient therefore provided the clearest distinction between the tested metal types. These results suggest that comparing the overall patterns of frequency response curves may be more effective for distinguishing metals than relying solely on the numerical differences between corresponding data points.

DISCUSSION

I. Interpretation of the Results

The initial similarity between the frequency-response graphs from samples within the same metal group suggested that analysis of the full spectrum may result in a meaningful statistic for metal identification. Instead of relying exclusively on an individual resonance peak, this approach considers the distribution of peak shapes across a wide range of input frequencies.

Using the entire graph could be useful if the relative arrangement of peaks and the broader pattern of graph shape remain consistent across multiple trials. In that case, the several similar characteristics could contribute to a sample's measured 'signature' based on the entire line, reducing dependence on a single resonance peak that may shift in between measurements.

The current observations do not establish that every metal has a unique frequency-response signature across its entire graph shape. In order to identify this as a natural pattern within similar metal samples, and establish that the factor which changes the pattern is metal type, more tests across a wider range of metals in similar geometries would be needed. Further testing would

successfully evaluate if this method can be used as a metal classification feature, and if it would create an accessible criteria of comparison between samples.

II. Potential Applications and Relationships to Existing Methods

The current established PMI techniques identify metals by analyzing their elemental composition. XRF and OES (previously discussed in 1.1) are two commonly used approaches with varying capabilities.

The proposed resonance based approach investigates a different type of information based on the measured response of a sample to external excitation. If further research showcases that this response can be measured consistently and be distinguished across metal types, it could be used as a preliminary screening method.

For example, a resonance based system might compare an unknown sample against an index of previously measured resonance spectra graphs for different metals. If the unknown graph closely matches one group and differs from all other groups, the system could suggest a possible match that can justify further investigation using more expensive methods such as PMI.

This current application, though, is primarily hypothetical. This current study does not entirely demonstrate that resonance analysis can determine a complete material composition in the same way more advanced methods do, but rather it investigates a comparatively simple measurement that could be used when comparing samples initially. In order to establish this system, it should be used along existing peer-reviewed methods of identification, and should be evaluated for if it yields similar results.

In order for this to as well be established as a cost effective and more accessible method, cost would need to be analyzed comparatively to other methods for similar sized units. The current cost of this system including speakers, a piezoelectric sensor, and calibration (440 hz tuning stick) in this experiment is \$110 (excluding the computer cost), although the cost per trial does not increase, differing it from methods like PMI, where 3rd party retailers charge per unit.

III. Experimental Limitations

Several limitations affect the conclusions that can be drawn from the experimental portion of this study. Firstly, the number of tested samples is limited. The small sample size cannot be used to establish how consistently this method works across different production batches of the same metal or different manufacturers. Additional samples are needed to determine whether the observed similarities in the study generalize beyond the metals tested.

Secondly, the sample geometry can affect resonance behavior. Difference in thickness, diameter, and shape can change the measured spectrum even when two samples have the same chemical composition. A future system would need a way to account for these differences, with one solution being creating an index for common shapes of each metal produced.

Third, the experimental setup may introduce variations in the resonance graphs. Sensor placement, excitation intensity, background noise, and mechanical contact between the sample and its sensor can alter these measurements. These factors must be controlled and documented to determine whether the observed differences are associated with material properties or the process in which the measurements were taken.

Finally, the measured spectrum should not be associated exclusively with the composition of the metal. The results can reflect a combined variation caused by metal geometry, composition, experimental testing and noise. Therefore, any future proposed method must first make these variations controlled.

FURTHER EXPERIMENTATION

I. Testing a Wider Variety of Samples and Geometries

Future experiments should include a larger number of samples from each metal group. This would help in establishing the amount of variation that is expected within a group and make it possible to compare that variation with the differences between groups.

Samples with similar dimensions should be tested first to isolate material related differences. Later experiments could examine samples of different sizes and shapes, such as flat circular coins and larger cube or tube based subjects. These tests would help determine how strongly geometry affects the entire frequency response graph.

For example, a future experiment could test the frequency-response difference between 10 samples of copper and silver coins, determine the percentage of variation between coins of the sample group and coins of the second group. After this, the test could change the shape to be other common industry shapes such as cubes of the same metal types, making the sole difference between the tests the geometry of the subject.

II. Developing a Mathematical Classification Model

If additional experiments produce consistent differences between metal groups, the resulting data could be used to develop a mathematical model for comparing unknown samples using the data from a known resonance spectra.

The first step would be to conduct multiple experiments that alter one variable in geometry, while keeping the metal type and other dimensions (such as thickness of a coin) the same. An example of this could be recording sets of copper coins with the only difference in geometry being the length of the radius, and then creating a relationship between the resulting measurements knowing that radius alters, or doesn't alter, the given results.

This model could evaluate several features, including the positions of prominent peaks, the amplitude of those peaks, and the overall shape of the graph. Rather than relying on a single characteristic, this model could combine multiple features to determine which reference group most closely resembles the unknown sample.

III. Improving Reliability and Accessibility

Further work should investigate how to make the measurement process more consistent. This could include developing a fixed sample holder, standardizing the placement equipment, controlling the conditions and setting a standard for strength of excitation, and documenting the procedure in greater detail to make it more reproducible.

Variations caused by the surrounding environments should be measured rather than assumed to be negligible. Repeated trials under the same conditions would help create reproducibility, while changing one environmental condition in each trial could help determine the effect that condition has on the finalized measurements.

If these improvements lead to consistent frequency-response graphs and reliable classification of samples, this method could be used as a preliminary tool for comparing metal specimens. Its practical value would ultimately depend on how accurately and to what extent it can distinguish materials, how well it performs under varying conditions, and how its cost compares to existing methods such as PMI.

CONCLUSION

This study investigated whether the overall shape of measured frequency-response graphs can provide useful information for identifying metals. Initial comparison showed similarities between spectra from samples of the same metal type, suggesting that the measured response may contain repeatable features that can be used for preliminary material comparison in industry.

With testing showcasing that resonance frequencies differed when the only variable changed was metal type, the study concluded that it may be a worthwhile endeavor to investigate this hypothesis further and on a larger scale.

However, repeatability between the metal types is only one requirement to determine whether resonance is a successful method of identification. This method must also in the future demonstrate that different metal types across a larger range produce sufficiently distinct spectra and these differences remain consistent when different samples are tested in similar conditions.

Further experimentation should focus on increasing the numbers of samples, quantifying and identifying similarities and differences of metal types, and developing a model that can be used to help identify unknown specimens. Overall, full spectrum resonance analysis may have the potential to be an accessible, nondestructive method for preliminary metal screening. Currently, it should be considered an experimental approach, needing further validation by future experiments.

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