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CHARACTERIZING POLYMER O-RINGS NONDESTRUCTIVELY USING RESONANT ULTRASOUND SPECTROSCOPY

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ABSTRACT

Polymer O-rings are an essential part of many designs, including mission and safety critical systems. Currently, there are no accurate destructive tests for measuring the polymer properties of O-rings (e.g. durometer) let alone nondestructive methods. As such, it is difficult to identify substandard, nonconforming, or counterfeit O-rings. This work combines resonant ultrasound spectroscopy (RUS) with machine learning and predictive analytics to sort O-rings based on material and durometer (multinomial classification) and to accurately estimate the mass and durometer with an ultrasonic examination that takes less than 10 seconds. Results from a population including eight materials and six durometers are presented and discussed.

Keywords: Resonance, Resonant Ultrasound Spectroscopy, RUS, Polymer, Machine Learning

1. INTRODUCTION

Detecting substandard, nonconforming, improperly processed, or counterfeit parts become an increasingly important topic for private companies and government agencies alike. Polymer O-rings are essential to many mission and safety critical systems. Yet, there are little to no nondestructive evaluation methods available. A fast, accurate, and reliable NDE method for O-rings is needed to guarantee safety and mission success.

Currently, there are no accurate and reliable methods to measure the durometer of an O-ring or to nondestructively characterize its material [1, 2]. The standard durometer measurement method is a semi-destructive Shore hardness A test, which is not applicable to O-rings. The semi-destructive Shore micro-harness M test is not accurate or reliable due to the deformation of the O-ring during testing. Existing material characterization methods, like Fourier Transform Infrared Spectroscopy (FTIR), are destructive, slow, and labor-intensive.

An alternative approach to material characterization and durometer measurement in O-rings is needed. By characterizing the filtering effects of O-rings on a resonance spectrum, extracting signal features, and analyzing with machine learning, differences between O-rings can be distinguished.

This paper presents a novel nondestructive method for determining the material and durometer of polymer O-rings using RUS and a Random Forest machine learning algorithm. Using this approach, O-rings were accurately sorted by classification into eleven groups and their durometer was accurately estimated to within the standard tolerance.

2. MATERIALS AND METHODS

The materials used in this study can be grouped into eleven distinct classes (not including age and batch) combining eight polymer materials and six durometers. Table 1 provides a list of materials and durometers.

Since this study focused on detecting substandard, nonconforming improperly processed, or counterfeit parts the form factor of the O-rings was kept constant. O-ring material, durometer, age, and batch were allowed to vary. The term “nominal durometer” is used in this paper since the durometer of each O-ring has not been measured and cannot be accurately determined. Nominal durometers of each population were determined by the manufacturer by collecting Shore hardness A measurements from witness coupon(s) fabricated with each batch. A standard tolerance of ±5 is allowed when vendors report the durometer of their products [2]. Thus, a whole batch of O-rings may have durometers that are more than five points off from their declared durometer due to the standard tolerance and the differences between O-rings and coupons.

TABLE 1: LIST OF MATERIAL AND DUROMETER GROUPS.

Material Groups		Durometer Groups (±5)	
1	BunaN	1	65A
2	CRBunaN	2	70A
3	EPDM	3	75A
4	Florosilicone	4	80A
5	Polyurethane	5	90A
6	PTFE	6	98.5A
7	Silicone		
8	Viton		

A – Shore hardness A A – Shore hardness A

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Several environmental and operational factors affect the durometer of the individual O-rings. These include variations due to temperature fluctuations, degradation from fluid and chemical attack, as well as operational condition. These increase the uncertainty in the actual durometer of each O-ring. The measurements used in this study were collected at near constant temperature (±1°C).

2.1 Linear System Approach

Soft polymers are attenuative and viscoelastic in nature which presents difficulties for standard ultrasonic inspections and for resonance inspection in particular. Soft, rubber-like materials are difficult to drive to resonance and usually produce signals with very low amplitude, broad peaks that prevent a reliable, accurate resonance inspection. An alternative approach is needed to inspect polymer O-rings.

The RUS system used in this study could be characterized as a linear system since it followed the homogeneity, additivity, and shift invariance rules of linear systems. Thus, the ultrasonic linear system model popularized by Schmerr & Song [3] was applicable. The portion of the received signal due to the O-rings (and the variances therein) were determined by deconvolving the system transfer function out of the signal. The resultant signal was then the transfer function for each individual O-ring, which in this case was acting like a filter. The system transfer function was determined by replacing the O-ring with water.

2.2 Experimental Configuration

The experimental configuration for this study included two specially fabricated piezoelectric transducers, a combination function generator and spectrum analyzer (Vibrant Corp., Albuquerque, NM), and a 20dB attenuator (CATTEN-0100-BNC, Crystek Corp., Fort Myers, FL). A diagram of the configuration is given in Figure 1. The transducers (designed to act as resonating bodies) were fabricated out of brass and employed PZT crystals with center frequencies of ~125kHz. A stepped frequency sine wave within the range of 20-200kHz was used to excite resonances.

Full sweeps were collected for several parts and frequency windows of interest were identified. For each window, the raw signals were collected, the system transfer function deconvolved, and signal features extracted. For this work, the extracted signal features include max amplitude, skew, kurtosis, and spectral energy. These, along with other features, were fed into a machine learning algorithm.

2.1 Machine Learning

After collecting the spectra from the O-rings and extracting the signal features, a subset of the O-rings was fed into a machine learning algorithm along with classification information and properties. This subset is called the "training set" and changes based on the analysis. The algorithm identified which combination of features yielded the best sort or produced the best estimate of properties. This work utilized a Random Forest algorithm from Python's Scikit-learn library [4].

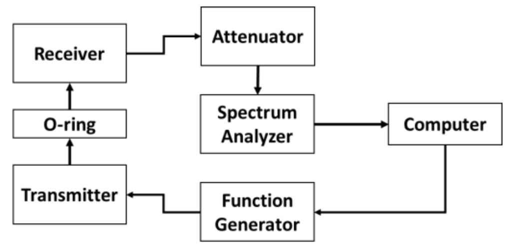

FIGURE 1: BLOCK DIAGRAM OF THE ULTRASONIC SYSTEM CONFIGURATION.

3. RESULTS AND DISCUSSION

Typical signals collected from the O-ring population are shown in Figure 2 for a single collection window. The colors represent different polymer materials. It is clear from this figure that significant behavioral differences exist between the different polymers in this window. Take Viton (blue) and BunaN (red) for example. These two exhibited significantly different amplitudes and shapes. Although some polymers may have exhibited similar behavior in any given window, that did not hold true for all windows.

A Random Forest model was trained to sort the O-rings based on material type and durometer. Combinations of eight material types and six durometers yielded eleven distinct classifications. The likelihood of randomly selecting the correct classification for each part was therefore ~9%. Table 2 presents the results of the multinomial classification. The Random Forest Model trained on resonance signal features was able to correctly

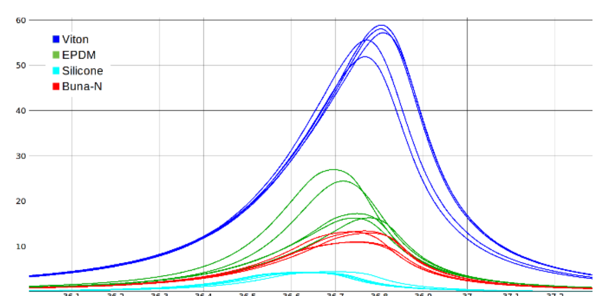

FIGURE 2: EXAMPLE OVERLAY OF A SMALL SECTION OF THE SPECTRA FOR O-RINGS. COLORS INDICATE MATERIAL TYPE.

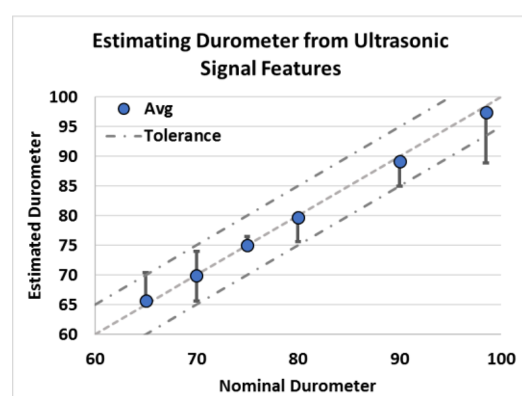

FIGURE 3: DUROMETER ESTIMATES FOR POPULATIONS OF O-RINGS USING ULTRASONIC SIGNAL FEATURES.

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TABLE 2: RESULTS OF O-RING MULTINOMIAL CLASSIFICATION SORTING USING A RANDOM FOREST ALGORITHM. THE HIGHLIGHTED CELLS INDICATED THE FRACTION OF PARTS CORRECTLY SORTED FOR EACH CLASSIFICATION.

		Sorted Classification											
		65A **BunaN**	70A **BunaN**	90A **BunaN**	70A **CRBunaN**	70A **EPDM**	80A **EPDM**	70A **Florosilicone**	70A **Polyurethane**	98.5A (55D) **PTFE**	70A **Silicone**	75A **Viton**	**#Samples per Actual Class**
Actual Classification	65A **BunaN**	**0.89**	0.09	0	0	0	0	0	0.02	0	0	0	**97**
	70A **BunaN**	0.02	**0.91**	0	0.01	0.05	0	0.01	0	0	0	0	**224**
	90A **BunaN**	0	0	**0.95**	0	0	0	0	0	0.05	0	0	**21**
	70A **CRBunaN**	0.10	0.06	0	**0.84**	0	0	0	0	0	0	0	**31**
	70A **EPDM**	0	0.11	0	0	**0.89**	0	0	0	0	0	0	**129**
	80A **EPDM**	0	0	0	0	0	**1.00**	0	0	0	0	0	**19**
	70A **Florosilicone**	0.03	0	0	0	0	0	**0.94**	0.03	0	0	0	**32**
	70A **Polyurethane**	0.19	0	0	0	0	0	0	**0.81**	0	0	0	**31**
	98.5A (55D) **PTFE**	0	0	0.06	0.03	0	0	0	0	**0.88**	0	0.03	**33**
	70A **Silicone**	0	0	0	0	0	0	0	0	0	**1.00**	0	**130**
	75A **Viton**	0	0	0	0	0	0	0	0	0.01	0	**0.99**	**143**
#Samples per Sorted Class		**101**	**229**	**22**	**29**	**125**	**20**	**32**	**28**	**31**	**130**	**143**	**890**

identify the material and durometer of 890 O-rings with and accuracy of ~93%, which is excellent for a preliminary examination. Silicone-70A and Polyurethane-70A were the best and worst performers respectively. Similar materials and similar durometers were the main source of confusion in sorting, which was expected given the uncertainty in the durometer of each individual O-ring.

Additional Random Forest Models were trained to estimate part mass and durometer. Part mass was measured and the durometer was taken to be the nominal durometer of the batch. The Random Forest then estimated both parameters for all 890 O-rings with an accuracy of ~±2g for the mass and ~±5 for the durometer (Figure 3). Recall that the uncertainty in the O-ring durometer from the manufacturer was ≥ ±5. These results are excellent for a preliminary examination of this method. It is likely that the results could be improved with more accurate measurements of O-ring durometer.

4. CONCLUSION

Polymer O-rings comprise an entire class of components (with the potential to be safety/mission critical) that is currently underserved by NDT&E. This paper demonstrates that resonance methods are sensitive to material differences for polymer O-rings. A preliminary study used RUS and machine learning to sort O-rings based on material and durometer into eleven distinct classifications with 93% accuracy using a test that took less than 10s per part. In addition to the multinomial sort, this work was able to correctly estimate both the mass (to within a few grams) and durometer (to within manufacturer tolerance) using a test that took less than 5s.

Given the standard method for determining durometer of O-rings, the results presented in this paper are limited in scope due to the uncertainty of the durometer. The scope of these results is also limited by holding O-ring sizes constant. Future work should focus on verification and validation of the relationship between resonance signal features and polymer material properties. Using Shore A coupons would greatly assist in that effort. Additional topics for future work include identifying the minimum training set required and detecting polymer degradation and age.

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