Wireless Power Transfer Sensing Approach for Milk Adulteration Detection Using Supervised Learning

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***Abstract*—With the increasing demand for wireless sensors due to the growing Internet of Things (IoT) industry, it becomes desirable to use existing technologies to realize new sensing functions. As wireless power transfer (WPT) becomes a standard feature in smartphones, this paper studies the non-invasive classification of liquid solutions with different concentrations, based on the WPT technology already deployed in mobile devices. Average accuracies of up to 97.6% were achieved utilizing supervised machine learning for the classification of milk adulterated with different water volumes. For these experiments, milk concentrations of 100%, 80%, 60%, and 40% were used for classification. Additionally, singular value decomposition and boxplot analysis were used to reduce the radio frequency bandwidth needed for classification to 9.45 MHz, leading to a drastic reduction in hardware complexity and computational cost.**

***Keywords*—sensor, singular value decomposition, supervised machine learning, wireless power transfer.**

I. Introduction

Wireless power transfer (WPT) is enhancing the development of wireless sensing technologies due to its capability of sensing changes in the electrical properties of objects that approach the WPT coils [1]. As WPT grows more common in smart devices (e.g., smartphones, laptops, cars, and smart house appliances), it becomes cost-effective to use the WPT coils already embedded in smartphones for sensing applications [2]. For instance, a WPT coil was used for human-machine interaction, detecting human hand gestures with high sensitivity and fast response [1]. Moreover, healthcare applications have also been reported. In [3], human cardiorespiratory activity was successfully monitored using tiny probing pads and coils.

Recently, radio frequency sensing of food quality and safety has caught the attention of the research community and food industry, since the electrical properties of food and beverage change along with the chemical reactions that occur when they get spoiled. Recent studies have proposed an immersible split-ring resonator to determine the concentration of water in commercially available adulterated alcoholic beverages [4]. Moreover, Radio Frequency Identification (RFID) stickers attached inside the food containers have been proposed for food quality and safety sensing [5]. Nevertheless, these sensors require direct contact with the food, which is not ideal for massive deployment, due to the increased cost and electronic waste. Additionally, it is undesirable from a sanitary point of view. To overcome this issue, a non-invasive method for milk freshness detection using a WPT coil was proposed in [2]. However, the feasibility of using a WPT coil for non-invasive liquid concentration characterization has not been explored yet. When an object approaches a WPT coil, a change in the coil impedance is induced, since inductive and capacitive links are formed between the object and the coil [1], [2]. The strength of these links and the changes in the coil's impedance are highly dependent on the object's electrical properties. Therefore, by measuring the induced changes in the coil's impedance, objects with different electrical properties can be classified. In this paper, a WPT technology for non-invasive milk adulteration detection compatible with smartphones is proposed. Furthermore, using singular value decomposition (SVD) and box plot analysis, the bandwidth (BW) needed for classification was reduced to 9.45 MHz, which results in a more appealing technology for mobile applications due to a lower hardware complexity and computational cost.

II. Milk Adulterant Dectection Theory

An electromagnetic field is established around a coil when a variable voltage/current is applied to it. Therefore, if a conductive material approaches the coil, an induced eddy current and electromotive force will be formed inside the object, leading to a change in the coil impedance [1]. These changes are due to the different electrical properties of the object and the air. Then, if a change in the concentration of a certain liquid disturbs the electrical properties of a liquid solution, it is possible to perform non-invasive liquid solution characterization by measuring the impedance changes induced to the coil.

In the coil and liquid solution interaction, both inductive and capacitive links are coexisting and consequently affecting the coil's impedance. The inductive link can be modeled as a mutual inductance coupling. If the disturbing object has a low resistivity, a large eddy current is induced, which leads to a strong inductive link. On the other hand, the capacitive link is related to the intrinsic capacitance present on every coil [2]. When an object perturbs the electric fields established among the turns of the coil, a change in the coil's intrinsic capacitance is observed, since the object dielectric constant is different from the air. A coil with a large number of turns (e.g., strong electric fields) will show a strong capacitive coupling. In [1], a circuit model including both, inductive and capacitive couplings was proposed, this model will be adopted in this paper. The coil's combined circuit model that includes both inductive and capacitive couplings is shown in Fig. 1, where L_o and C_o

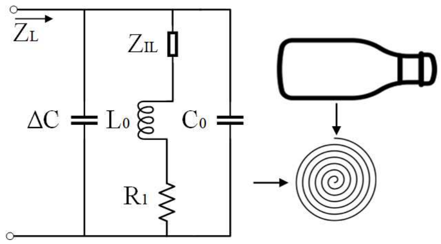

Fig. 1. Inductive and capacitive coupling for WPT-based milk adulteration detection.

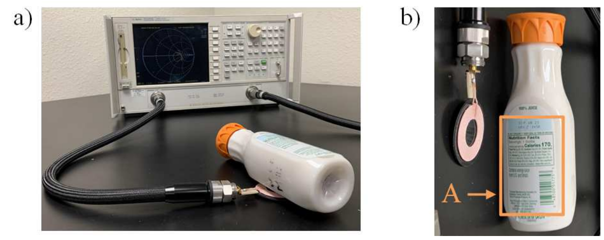

Fig. 2. a) VNA experiment setup, and b) the area where a reliable measurement can be performed is marked in box A.

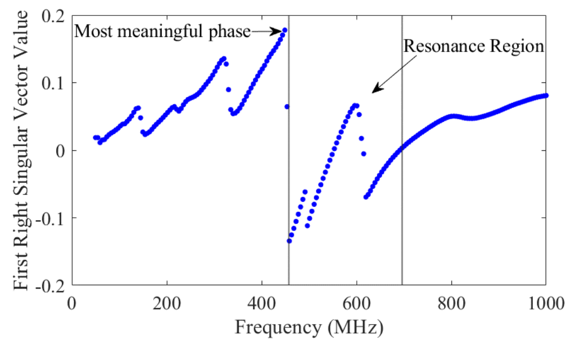

Fig. 3. First right singular vector values.

correspond to the intrinsic inductance and parasitic capacitance of the coil, Z_{IL} is the reflected impedance due to inductive link, ΔC is the coil's intrinsic capacitance variation due to coil-object interaction, and R_1 is the coil's parasitic resistance. The changes in Z_{IL} and ΔC consequently produce a change in coil impedance as

$$Z_{IL} = \frac{(R_1 + j\omega L_0 + Z_{IL}) \cdot \frac{1}{j\omega(C_0 + \Delta C)}}{(R_1 + j\omega L_0 + Z_{IL}) + \frac{1}{j\omega(C_0 + \Delta C)}} \quad (1)$$

As shown in (1), when a liquid solution approaches the WPT coil, the total coil's impedance is determined by the liquid's solution electric properties. By measuring the coil's impedance variations, liquid solutions with different electrical properties can be potentially classified. When milk is adulterated with water, it not only reduces the nutritional values but also reduces the quality of the milk [6] [7]. As shown in [6], the water alters the electrical properties of the milk (i.e., dielectric constant and loss factor). For instance, milk concentration of 70% has a dielectric constant of 76.4 and a dielectric loss of 233.8 while raw milk (i.e., 100% concentration) has 75.8 and 282.1 respectively, at a frequency of 27 MHz. Thus, diluted milk, at different percentage levels, contains different electrical properties that can be used to classify its adulteration status.

III. Data Collection and Analysis

A. Data Collection

The experimental setup is depicted in Fig. 2(a), an Agilent 8722ES vector network analyzer (VNA) was used to measure the reflection coefficient of the WPT coil (TKD-WT505090). To perform the measurements, a bottle filled with the desired liquid solution was placed on the WPT coil, as depicted in Fig. 2(a). Additionally, box A in Fig. 2(b) indicates the area where the coil can be placed without significant variation in the measurement results. A surface-mounted SMA connector was used to interface the VNA with the coil terminals. The measurement BW was set from 50 MHz to 1000 MHz, since the WPT operating frequency is in the MHz range. A total of 201 evenly spaced frequency points were measured along with the selected BW, for both, magnitude and phase. Therefore, a total of 402 features were recorded in each measurement.

For the experiments, different concentrations of milk/water solutions were used. Ten empty plastic bottles were filled with whole milk up to a certain percentage of their maximum volume (355 ml). Then, the remaining volume was filled up with water, so each bottle reached its maximum capacity. Milk concentrations of 100%, 80%, 60%, and 40% were used for the experiments. For instance, to achieve a milk concentration of 80%, the bottle was filled using 284 mL of whole milk and 71 mL of water. For each category, 2 bottles were used, and 10 measurements were taken per bottle. During the measurement process, the sensor was placed at different locations along with the bottle. Additionally, 20 measurements were taken when nothing, but the air was in front of the coil. Therefore, a dataset composed of 100 observations, 5 classes, and 402 features was obtained.

B. Analysis

The recorded data were analyzed applying SVD and boxplot analysis. Singular value decomposition (SVD) is a matrix decomposition of the form $M = U\Sigma V^*$, where U is an $m \times m$ matrix, Σ is a $m \times n$ diagonal matrix, and V is an $n \times n$ matrix. V and U return the left- and right-hand singular vectors of M, and Σ returns the singular values of M.

To narrow down the data's most meaningful components, SVD was applied to the recorded data. Then, the first right-hand singular vector values were used to find the most meaningful frequencies (MMFs) present on the measured BW (e.g., the higher the value, the more important the frequency component). As in [2], the superior performance of phase-detection was evidenced. Therefore, the data analysis was performed using only the recorded phase features. Fig. 3 shows the phase MMFs were found around 449 MHz, outside the resonance region.

Boxplot analysis was performed to further analyze the quality as a feature of the first eight phase-determined MMFs. Fig. 4(a)-(b) depict the box plot analysis of the 1st and 6th phase-determined MMFs. The central mark of each box represents the median, the top and bottom edges indicate the 70th and 25th percentiles, and the whiskers extend to the most extreme data points not considered outliers. To have a strong feature, it is desirable for each class to have a different statistical distribution

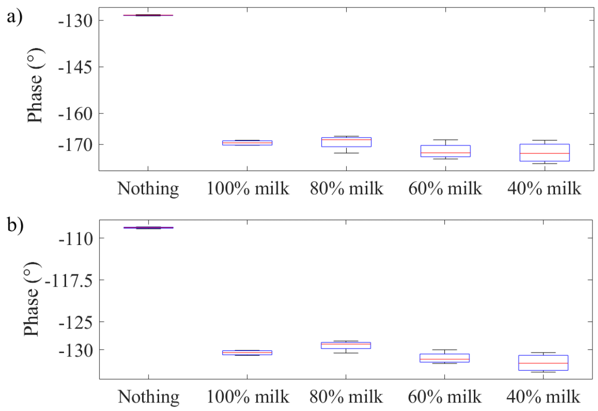

Fig. 4. Boxplot analysis, a) 1st MMF b) 6th MMF.

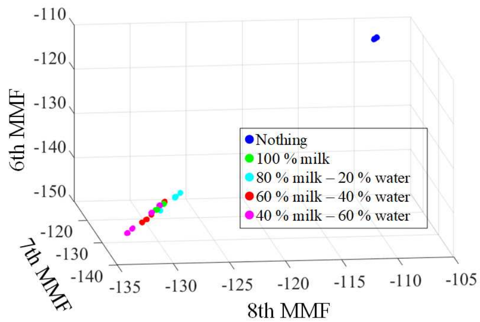

Fig. 5. Scatter plot of the three MMFs.

(e.g., the boxes do not overlap). By comparing Fig. 4(a)-(b), it can be observed that the 6th phase-determined MMF has a more desirable statistical distribution compared with 1st phase-determined MMF. In other words, the boxes corresponding to the 1st phase-determined MMF are more overlapped than the ones corresponding to the 6th phase-determined MMF. After applying this analysis to all the selected features, the 6th, 7th, and 8th phase-determined MMFs were selected to perform the classification.

The data were plotted using the selected features as depicted in Fig. 5. As can be seen, a single class can be represented by different clusters located at different intervals. This effect is because the sensor was placed at a different location along the bottle, which changes the measurement boundary conditions. However, this presents a more challenging classification scenario and adds robustness to the proposed system.

IV. Classification Results

The selected features (i.e., 6th, 7th, and 8th phase-determined MMFs) were used to train 24 machine learning classifiers that were available in the R2020b MATLAB Classification Learner application tool. Using this data set and a 25% holdout validation, an average accuracy of 97.6% was obtained with a standard deviation of 3.67 for the best 10 classifiers as shown in Table I. Fig. 6 shows two confusion matrices of these 10 classifiers to account for the best and worse classifier result. These confusion matrices show the number of false negatives, false positives, true negatives, and true positives of the Linear Discriminant model shown in Fig. 6(a) as well as the Fine Tree model shown in Fig. 6(b). As seen by the Fine Tree

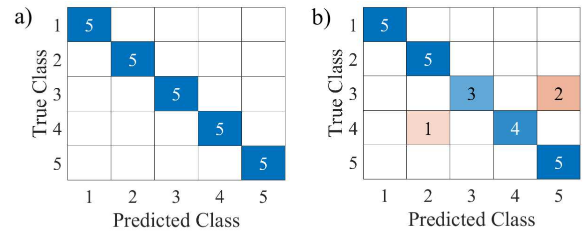

Fig. 6. a) Linear Discriminant confusion matrix, and b) Fine Tree confusion matrix.

Table I. Accuracy results for the 10 best classifiers.

	Reflection Coefficient	
	Model Type	***Accuracy***
Analysis	Linear Discriminant	100 %
	SVM: Fine Gaussian SVM	100 %
	KNN: Fine KNN	100 %
	KNN: Weighted KNN	100 %
	Ensemble: Bagged Trees	100 %
	Ensemble: Subspace KNN	100 %
	Quadratic Discriminant	96 %
	KNN: Cosine KNN	96 %
	Ensemble: Subspace Discriminant	96 %
	Tree: Fine Tree	88 %
Average		97.6 %
Standard deviation		3.67

model, 2 of the 80% milk – 20% water was mistakenly classified as 40% milk – 60% water, and 1 of the 60% milk – 40% water was mistakenly classified as 100% milk. These classification results are dependent on the 25% random holdout validation.

V. Conclusion

The WPT coil sensor is a promising technology in the food quality and safety area because its wireless interaction facilitates detection of adulteration in food without invading the container's food. Thus, the functionality of using a WPT coil to classify adulterated milk has been experimentally proven in this paper. Reduction of the BW to obtain the MMFs was acquired by using SVD and boxplot analysis to the phase changes. Models were effectively trained using supervised learning, and an accuracy of 97.6% in the classification was achieved. This technology opens new possibilities for WPT coil-based smartphone applications to detect variation in the electrical characteristics of samples.

Acknowledgments

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