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Xinyi LI

Chao FENG

Nana DING

Ju WANG

Jie XIONG
Singapore Management University, jxiong@smu.edu.sg

See next page for additional authors

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Author

Xinyi LI, Chao FENG, Nana DING, Ju WANG, Jie XIONG, Yuhui REN, Xiaojiang CHEN, and Dingyi FANG

Target Material Identification with Commodity RFID Devices*

Xinyi Li†, Chao Feng†, Nana Ding†, Ju Wang†,
Jie Xiong♯, Yuhui Ren†, Xiaojiang Chen†, Dingyi Fang†

†Northwest University, ♯Singapore Management University,
†{xinyili,chaofeng,nanading}@stumail.nwu.edu.cn, †{wangju,yhren,xjchen,dyf}@nwu.edu.cn, ♯jxiong@smu.edu.sg

ABSTRACT

Target material identification plays an important role in many real-life applications. This paper introduces a system that can identify the material type with cheap commercial off-the-shelf (COTS) RFID devices. The key intuition is that different materials cause different amounts of phase and RSS (Received Signal Strength) changes when radio frequency (RF) signal penetrates through the target. However, without knowing either material type, trying to obtain the information is challenging. We propose a method to address this challenge and evaluate the method's performance in real-world environment. The results show that we achieve higher than 94% material identification accuracies for 10 liquids and differentiate even very similar objects such as Coke and Pepsi.

CCS CONCEPTS

• **Computer systems organization → Sensors and actuators**;

1 INTRODUCTION

Device-free passive sensing, where no device is attached to the target, has recently received considerable attentions, such as human motion tracking [1, 9], gesture and activity recognition [7], and even localizing a person behind a wall [2]. Though a success in localization and gesture recognition, a missing research component of existing device-free sensing technology is using cheap commodity RF devices, such as RFID, to perform target material identification. Many applications would benefit from knowing the material of a target. For example, a robot can automatically adjust its grip strength if it knows the object is an egg instead of a stone by using material identification. It will be possible to differentiate Pepsi from Coke without labels or a taste test.

This paper introduces a system that can identify the material type of a target with cheap COTS RFID devices. Unlike existing systems which employ dedicated hardware or special-purpose large bandwidth signals to extract the reflectivity and permeability parameters for material identification [8], this paper exploits the phase and RSS changes when the signal penetrates inside a target for material identification. The phase and RSS measurements are widely available on commodity devices and our system works well with a small 4 MHz bandwidth. The material identification is based on the an observation that different materials and target sizes will cause different amounts of phase and RSS changes when the RF signal penetrates through a target. However, without knowing either material type, trying to obtain the information is challenging. We propose a method to address this challenge and evaluate the method's performance in real-world environment. The results show that we achieve higher than 94% material identification accuracies for 10 liquids and differentiate even very similar objects such as Coke and Pepsi.

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2 SYSTEM DESIGN

2.1 Preliminary Studies

To illustrate Our system's basic idea for material identification, Fig. 1shows an example where a directional antenna of an RFID reader is placed on the ground in an open space to minimize the amount of multipath. A plastic measuring cup with a height of 28.5 cm and a diameter of 19.7 cm is placed on top of the antenna. We place an RFID tag on top of the cup and pour the same amount (8 cm of height) of purified water, vinegar, skimmed milk, whole milk, Coke and Pepsi into the cup. We measure the phase and RSS readings before and after each liquid is poured into the cup, and then calculate the changes shown in Fig. 2.

We observe that the phase changes for water, vinegar, skimmed milk and whole milk are quite different. For Coke and Pepsi, the result is surprising since there is still around 0.2 radians phase change difference,[1] which is clear enough for us to differentiate them. The RSS changes for Coke and Pepsi are very similar but are quite different from other liquids. The observation implies that it is possible to employ the phase and RSS changes for material identification. Note that the commodity RFID reader eliminates the directly reflected signal from a target and only keeps the signal from the tag [6].

[1]Impinj R420 reader [6] has an analog to digital converter of 12-bit which achieves a phase resolution of 0.0015 radians.

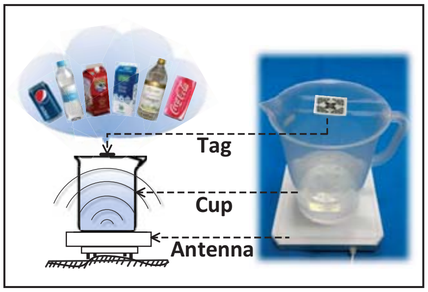

Figure 1: Experimental setup.

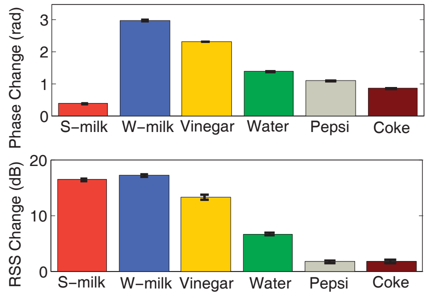

Figure 2: Phase/RSS changes in different materials.

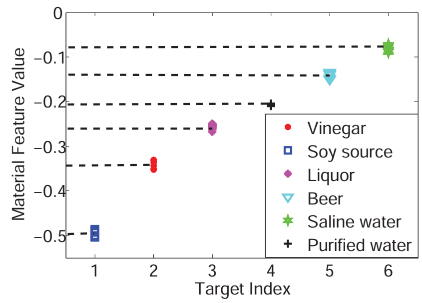

Figure 3: Differentiating materials with feature Ω.

2.2 Target Material Identification

We first introduce the phase and RSS changes caused by a target and then describe our material identification method.

Phase changes after a target shows up. The wavelength of RF signal changes when the signal travels from one material into another while the frequency does not change [3]. As a result, the phase changes are different when the RF signal travels inside different materials, even if the propagation distances are the same. Considering the direct path between the reader and tag, where the RF signal penetrates through a target. Let L and L' denote the distances along the direct path from the reader to tag and to target, respectively. D is the propagation distance inside the target. Let ϕ^{air} and ϕ^{tar} be the measured signal phase before and after the target blocks the direct path. The phase change $\Delta\phi = \phi^{tar} - \phi^{air}$ after the target shows up is given by:

$$\begin{aligned}\Delta\phi &= [2(L-D)\frac{2\pi}{\lambda_{air}} + 2D\frac{2\pi}{\lambda_{tar}} - 2L\frac{2\pi}{\lambda_{air}}] \mod 2\pi \\ &= [2D(\frac{2\pi}{\lambda_{tar}} - \frac{2\pi}{\lambda_{air}})] \mod 2\pi \\ &= [2D(\beta_{tar} - \beta_{air})] \mod 2\pi, \qquad (1)\end{aligned}$$

where λ_{air} and λ_{tar} are signal wavelengths in the air and in the target. The $\beta_{air} = \frac{2\pi}{\lambda_{air}}$ and $\beta_{tar} = \frac{2\pi}{\lambda_{tar}}$ are defined as the signal's *phase constant*[3] in the air and in the target.

RSS changes. The RSS measurement also changes when the RF signal travels through different target materials. Specifically, the amplitude has an $e^{-\alpha}$ attenuation over a unit prorogation distance, where α is the attenuation constant which only depends on the target material [3]. Let R^{air} and R^{tar} be the RSS measurements before and after the target blocks the direct path. Then, the RSS change $\Delta R = R^{tar} - R^{air}$ is given as:

$$\begin{aligned}\Delta R &= 20\log(\frac{A_{tar}}{A_{air}}) \\ &= 20\log\frac{A_S \cdot e^{-\alpha_{air}2L'}e^{-\alpha_{tar}2D}e^{-\alpha_{air}2(L-L'-D)}}{A_S \cdot e^{-\alpha_{air}2(L'+D+L-L'-D)}} \\ &= 20\log[e^{-2D(\alpha_{tar}-\alpha_{air})}], \qquad (2)\end{aligned}$$

where A^{air} and A^{tar} are the measured signal amplitudes before and after the target blocks the direct path, A_S is the amplitude of the transmitted signal, α_{air} and α_{tar} are the signal's *attenuation constants* in the air and in the target. In the experiments, the empty container (i.e., cup) is included when we carry out the baseline measurements. Thus, the effect caused by the container is totally removed, i.e., the material and the thickness of the container will not affect the identifcation of the internal material. Note that Eq. (1) and Eq. (2) also show that the distance L between tag and reader does not affect Our system's performance, since it is cancelled out when calculating the phase change and RSS change measurements.

Material feature extraction. To identify the material type, we need to extract features that are uniquely related to the material. The phase and RSS changes can not be used directly, since they are also related to the target size, i.e., the propagation distance D. Compared with the phase and RSS changes, the phase constant β and attenuation constant α are more promising candidates to serve as features for material identification. Different materials have different β and α values [3]. However, it is a challenge to estimate the values of β and α at the same time since there are three unknown parameters including the propagation distance D in the two equations Eq. (1) and Eq. (2). We address this problem with a novel method. Instead of seeking the absolute values of phase constant β and attenuation constant α, we prove that the relative relationship of β and α calculated by the RSS change and phase change is a parameter independent of target size, and also is unique for each material. Specifically, based on Eq. (1) and Eq. (2), we have:

$$2D = \frac{\Delta\phi + 2\zeta\pi}{\beta_{tar} - \beta_{air}} = \frac{\ln 10^{\Delta R/20}}{\alpha_{air} - \alpha_{tar}}, \qquad (3)$$

where, ζ is an integer.[2] Based on Eq. (3), we define a feature, i.e., RP-rate Ω, which is related to the ratio of RSS change and phase change as:

$$\Omega = \frac{\ln 10^{\Delta R/20}}{\Delta\phi + 2\zeta\pi} = \frac{\alpha_{air} - \alpha_{tar}}{\beta_{tar} - \beta_{air}}. \qquad (4)$$

Note that (i) β_{air} and α_{air} are constants, since they are the phase constant and attenuation constant in the air; (ii) the values of β_{tar} and α_{tar} are also fixed for a given material. Thus, the right side of Eq. (4) is a constant and Ω is unique for a particular material. To this end, we successfully avoid solving β_{tar} and α_{tar} but employ Ω estimated by Eq. (4) for material identification. The feature Ω is independent of the signal propagation distance inside a target which enables material identification without a need of knowing the target size. We show through benchmark experiments that Ω is a fine-grained feature sensitive enough to identify different target materials. We test 6 liquid materials, i.e., "Vinegar", "Soy source",

[2] ζ=0 for relatively small objects. The propagation distance inside the water needs to be more than 84.25 cm to cause a phase change of more than 2π.

Table 1: Test liquids for material identification.

Liquids	Vinegar	Soy Source	Coke	Liquor	Beer
Compositions	Acetate 50%; Carbohydrate 4.9 g/100 ml.	Amino acids 0.4 g/100 ml; Carbohydrate 6.7 g/100 ml.	Carbohydrate 3.5 g/100 ml.	Ethyl alcohol 50% vol.	Ethyl alcohol 3.1% vol.
Liquids	Purified Water	Saline Water	Sweet Water	Whole Milk	Skimmed Milk
Compositions	——	Salt 10.9 g/100 ml.	Sugar 25.3 g/100 ml.	Fat 4.0 g/100 ml.	Fat 0 g/100 ml.

"Liquor", "Beer", "Saline water" and "Purified water". We conduct experiments in the lab-office environment based on the deployment shown in Fig. 1. We run the experiments 40 times and calculate the values of Ω based on Eq. (4). The results in Fig. 3 show that the Ω values of 6 liquids are clearly different from each other.

Material identification. There are two steps for material identification. First, we build a feature database which maps the materials to feature (Ω) values. Specifically, for each material, we collect the phase and RSS change measurements in an open space, and then calculate its feature value according to Eq. (4). Note that this process happens only once. Second, based on the phase and RSS change measurements of a test material, We calculate the new feature value and employs the KNN classifier [4] to identify the material type with the database.

3 PERFORMANCE EVALUATION

Implement. The system setup is shown in Fig. 1. An Impinj Speedway R420 reader [6] is employed in our experiments without any hardware or firmware modification. The R420 reader operates in frequency range of 920.625 − 924.375 MHz. The default antenna used by R420 reader is a directional antenna with a 9 dBi gain and 70° elevation and azimuth beam widths. The cheap (i.e., 5 cents per tag) Alien tag [5] is used in our experiments. We conduct experiments in a 3.2 m × 3.2 m open area of a lab-office environment. To evaluate the material identification performance, we use 10 different liquids as test targets. The liquids are listed in Table 1.

Identification accuracy. For each identification, we repeat the experiments 30 times by using 10 different liquids with the same material but different capacities, i.e., we pour liquid into the cup with random capacity among 50 to 150 ml. For each target, we collect 100 samples and set the number of "Nearest Neighbors" as 12 in the KNN classifier based on our empirical knowledge. Fig. 4 shows the identification accuracy is more than 94% for 10 liquid materials. We run additional experiments to identify the same type of liquids with slightly different concentrations, e.g., sweet water with sugar concentration 8.3 g/100ml, 16.7 g/100ml and 25.3 g/100ml. Fig. 5 (up) shows that we still achieve a high accuracy of at least 96%. Finally, we attempt to differentiate between "Coke", "Pepsi", "Whole milk" and "Skimmed milk". Fig. 5 (below) shows that we achieve 100% accuracies in differentiating the two types of milk since their phase difference is big as shown in Fig. 2. The difference between "Coke" and "Pepsi" is relatively small but we still achieve a higher than 90% accuracy.

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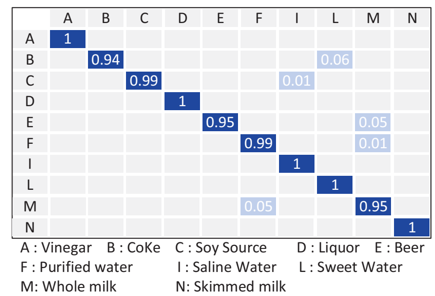

Figure 4: Confusion matrix: material identification results for the 10 liquids.

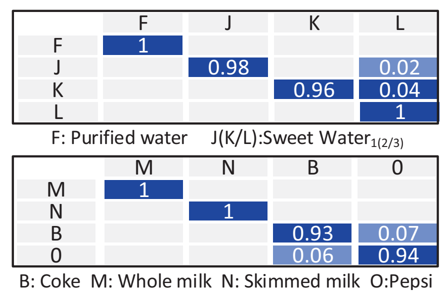

Figure 5: Confusion matrix: material identification results for the similar liquid materials.

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