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Machine Learning-Based Microwave Techniques for Dielectric Material Classification

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Abstract — This paper presents two innovative Microwave Non-Destructive Testing and Evaluation (MNDE) techniques designed specifically for characterizing planar dielectric materials, regardless of their thickness. These techniques involve measuring the reflection coefficient parameters S_{11} of the materials using two separate microwave characterization instruments: a monostatic free-space radar and an open-ended rectangular waveguide (OERW). Our objective is to develop a compact, low-power, fast instrument for classifying and evaluating the materials sensed by microwaves across a frequency range varying from 3.95 to 5.85 GHz. These approaches coupled with machine learning (ML) models, are employed and validated within two distinct environmental settings: controlled laboratory conditions and more challenging real-world noisy conditions. Furthermore, a comparative performance analysis is conducted between the two proposed techniques.

Keywords — radar, open ended rectangular waveguide, VNA, machine learning, material characterization

I. INTRODUCTION

Microwave nondestructive testing and evaluation field (MNDE) is a set of methods that enable the characterization and evaluation of material conditions within the microwave frequency range, without causing damage, whether during production, usage, or maintenance [1]. Advantages such as low-power, low cost and non-ionizing electromagnetic radiation have attracted the research community to contribute to the dissemination of MNDE techniques in various field [2 - 4]. By employing these techniques, electromagnetic waves penetrate dielectric materials and interact with their surface and internal structure. This interaction provides valuable information about the material under test (MUT), including its type, geometry, and the presence of surface or subsurface defects.

MNDE techniques for material characterization can be categorized into resonant and non-resonant methods. In resonant methods, a sample of the MUT is inserted at a predefined position, and the measurements focus on changes in the resonance frequency and quality factor (Q) [5]. The second category comprises non-resonant techniques. These methods use instead the scattering parameters as the primary parameter for extracting the dielectric properties of the MUT. The methods that fall under this category include waveguide open-ended probe, and free-space [6] methods. The dielectric properties of the MUT are then extracted from the measured S_{11} using appropriate conversion methods. This latter is

mandatory to identify the types of materials. Recently, ML algorithms have been emerged with microwave techniques as a powerful approach for material characterization. This combination enables accurate and rapid material characterization, even in complex scenarios. Moreover, it reduces the dependency on complex conversion methods and provides an automated process.

In this study, we proposed two new methodologies combining MNDE techniques and ML models to characterize dielectric materials regardless their thicknesses. We definitively target to classify the materials into four types: Air, glass, Plexiglas and wood. These methodologies offer advantages when analytical modeling is not feasible, and (ML) algorithms have a crucial role to play in addressing these challenges [7 - 8].

The remaining sections of the paper are structured as follows. Section II introduces the proposed methodology. Section III including the experimental procedures and details of the data collection setup. In Section IV, we present the results obtained from the experiments and discuss their performance. Finally, Section V concludes the paper and outlines future work.

II. METHODOLOGY

This section provides an overview of the proposed methodologies (figure 1) for classifying three well-known dielectric materials: wood, glass, and Plexiglas. Both methodologies follow identical steps.

Initially, the systems measure the broadband complex reflection coefficient S_{11} , capturing variations in magnitude and phase-shift across a frequency range varying from 3.95 to 5.85 GHz with a step of 2.2MHz. The recorded data is influenced by the type of MUT. The measurements were performed in two distinct environments. The first group of data was recorded under laboratory conditions, while the second group was obtained in noisy environments to simulate realistic conditions.

Then, parameters selection step is conducted. The purpose of exploring different training features is to identify the optimal features, achieving a balance between the number of features and the performance of the ML algorithm.

Following this, the dataset is divided into training and validation sets to train the ML algorithms. The output of these algorithms categorizes materials into one of the following classes: wood, glass, Plexiglas, or air.

To evaluate and compare the performance of different scenarios, a variety of evaluation metrics are used. These metrics provide valuable insights into the effectiveness of the proposed methodologies.

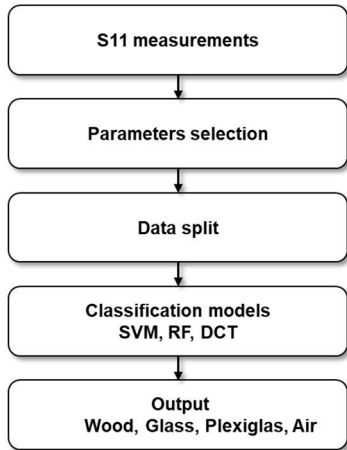


Fig. 1. Block diagram of the for material classification methodologies.

III. EXPERIMENTAL SETUP

In this section, the measurement system of each technique is introduced.

The first technique based on free space characterization is built up with a compact one-port VNA [Anritsu® MS46121B – figure 2(a)] connected to a horn antenna [ATM® P/N 187- 251-6 – figure 2 (b)]. The antenna is connected directly to the VNA. No coaxial cable is considered to reduce random errors commonly found and attributed to cable movement during measurement operation.

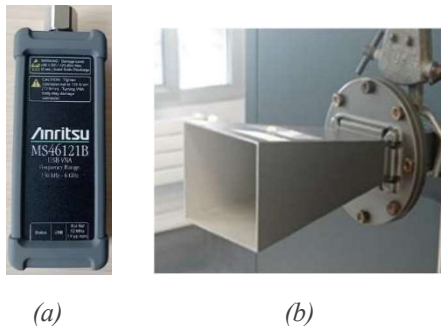


Fig. 2(a) Compact 1-port vector network analyzer Anritsu® MS46121B (150 kHz – 6GHz). (b) Horn antenna [ATM® P/N 187-251-6].

The second microwave system used in this work is built up with an OERW [ATM® P/N 187-251-6] presented in the figure 2 with the same VNA [Anritsu® MS46121B]. The waveguide has a cross section of 50 mm by 25 mm and it is connected to the input port of the VNA using N-to- SMA coaxial transition and SMA-to-waveguide transition. The measurement operates within the frequency covered by the waveguide between 3.95 and 5.85 GHz with a step of 2.2MHz.

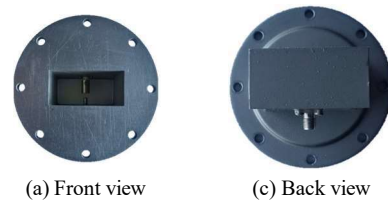


Fig. 1. Waveguide [ATM® P/N 187-251-6].

The Intermediate frequency bandwidth – IFBW is set to 100 (Hz) in both configurations. Before starting the measurement, the VNA is calibrated using the calibration-kit: OSLN50A-8 from Anritsu®).

Before initiating the measurements campaign, a repeatability study is considered to quantify the overall measurement uncertainty and to ensure the reproducibility of measurements including mechanical positioning of the MUT. To that end, in the free space configuration, the MUT consists of wood in planar structure was positioned at a stand-off distance set to 5 cm from the antenna. S_{11} is measured 10 consecutive times. The maximum standard deviation between all measurements are computed at each frequency. Maximum standard deviations of 0.0018 and 3deg, for the linear magnitude and phase-shift of S_{11} respectively, are obtained.

Same study is repeated for the contact configuration, the MUT consists of wood was positioned in contact with the OERW. The maximum standard deviation between all measurements are 0.0028 and 0.75 degree, for the linear magnitude and phase-shift of S_{11} respectively, are obtained.

IV. MATERIALS PREPARATION AND DATA ACQUISITION

A. Materials preparation

Samples with known material properties, such as, wood, glass and Plexiglas are used. Figure 1 shows photos of some samples, while table 1 presents the thicknesses of the samples.



Fig. 2. Some of the material samples considered for materials classification.

Material	Thickness (cm)
Wood	{ 0.6 ; 0.9 ; 1; 1.6; 1.8 }
Glass	{0.2; 0.4; 0.5 }
Plexiglas	{0.25; 0.4 }

Table 1. Thicknesses of the experimental samples.

B. Datasets

For the initial technique relying on free space characterization, the measurement process consists of two steps. Initially, S_{11} is measured without the presence of the MUT. Subsequently, S_{11} measurements are conducted for all samples with a stand-off distance of 5 cm between the antenna and the MUT (figure 3 (a)). The antenna is fixed for all experiments and only the MUT is moved using a mechanical displacement mechanism with 500 μ m displacement resolution.

In the second technique, which is based on contact characterization, the measurement campaign also follows the same two-step procedure. However, in this configuration, the MUT is in contact with the OERW (figure 3 (b)).

These steps are repeated under the two conditions: controlled laboratory and more challenging realistic conditions.

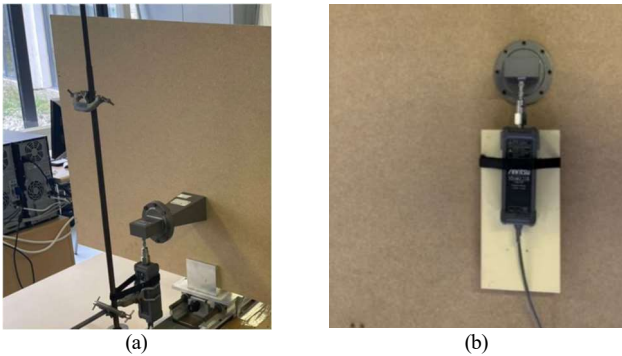


Fig. 3. Experimental set-up for microwave sensing: (a) using the antenna, (b) using the OERW.

Two novel and unique datasets have been generated: one employing the first technique, which relies on free space characterization with the antenna, and the other using the OERW in contact characterization. The data obtained under controlled laboratory conditions are categorized as Group I, while the data collected under more realistic conditions are classified as Group II. These datasets are detailed in Table 2.

Measurement system	Group I	Group II
Antenna	161	49
OERW	617	270

Table 2. Dataset of recorded measurements using the antenna and the OERW.

Figures 4 and 5 illustrate the S_{11} of different materials characterized by closely similar thicknesses, obtained through the antenna and the OERW based systems, respectively. Each material presents distinct S_{11} signatures, but even for identical materials, these signatures change as thickness varies, as demonstrated by previous results. Thus, it is challenging to characterize these materials with analytical models. This highlights the importance of using ML models to classify and characterize these materials, regardless their thicknesses; due

to the robust capabilities of ML models in handling complex and evolving patterns in the data.

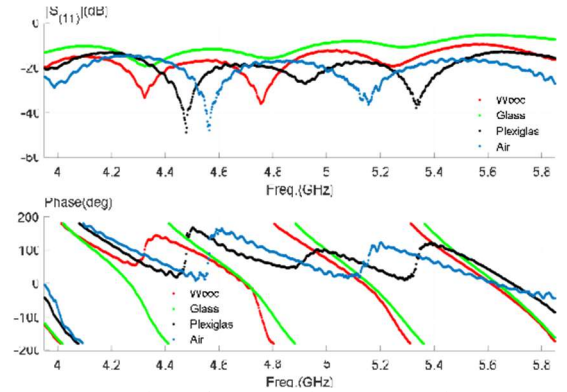


Fig. 4. Measured S_{11} of some samples types using the antenna.

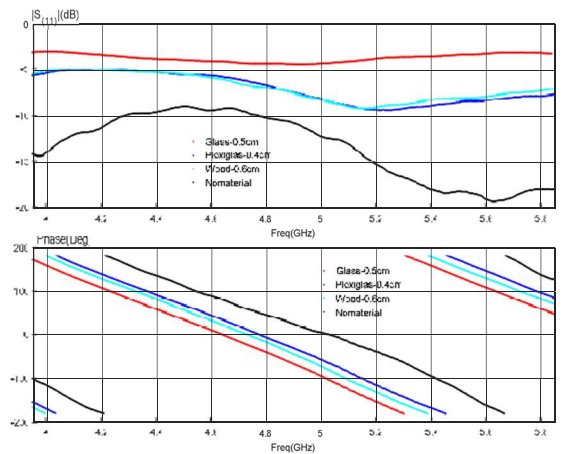


Fig. 5. Measured S_{11} of some samples types using the OERW.

V. DATA PROCESSING AND SUPERVISED CLASSIFICATION

Following the collection of datasets, a parameter selection step is conducted. In this step, two feature scenarios are proposed. Initially, the magnitude and phase-shift of the measured S_{11} , encompassing all parameters across all frequencies, are directly employed. Then to extract the most informative features and reduce dimensionality, principal component analysis (PCA) is applied to select the most representative features. It is the most popular dimensionality reduction technique widely used in various fields of data analysis and ML. In this study, specifically, we retain PCA components that contribute to more than 90% of the total variance in the magnitude and phase-shift data.

We then proceed with data splitting step. The dataset consists of two groups. Group I, referred to as the "non-testing subset," consists of the data recorded under controlled laboratory conditions, is divided into training and validation subsets using a 5-fold cross validation (CV) approach. One fold for validating and the remaining fold for training. Group II referred to as the "testing subset," consists of the data recorded under realistic conditions, is used for testing after the standardization and PCA projection. The testing subset, allows for an evaluation of the performance of the proposed classifiers on new unseen data

This division serves the purpose of training and validating the well-known supervised ML algorithms: random forest (RF) [10], and support vector machine (SVM) [9] with a three kernel functions: linear, polynomial (POL.) and radial basis (RBF). These algorithms are commonly used in the literature and they can provide excellent performance for classification.

The effectiveness of these models is computed using various performance metrics: Accuracy, and F1 score.

VI. RESULTS

Python was employed in this work for the purpose of data analysis.

Table 3 illustrates the classification performance outcomes of the dataset captured using the initial technique based on the antenna. The stand-off distance is fixed at 5 cm.

Table 4 illustrates the classification performance outcomes of the dataset captured using the second technique based on the OERW.

Two subsets are used: the CV subset (non-testing subset) and the unseen subset (Group II recorded under noisy conditions). Two separate feature representations are examined: the magnitude and phase-shift of S_{11} , and the PCA applied to the magnitude and phase-shift data.

Data Subset	Magnitude & Phase-shift		PCA (Magnitude & Phase-shift)	
	CV subset	Unseen subset	CV subset	Unseen subset
Accuracy (%)	99 ±0.3	95	99 ±0.5	91
F1_score (%)	98	95	98	90
Best Classifiers	SVM RBF		SVM POL SVM RBF	

Table 3. Performance evaluation of best ML classifiers trained with antenna-measured Dataset. Stand-off distance is set to 5 cm.

Data Subset	Magnitude & Phase-shift		PCA (Magnitude & Phase-shift)	
	CV subset	Unseen subset	CV subset	Unseen subset
Accuracy (%)	100	99.6	100	97.77
F1_score (%)	100	99.6	100	98.6
Best Classifiers	RF		RF	

Table 4. Performance evaluation of best ML classifiers trained with OERW-measured Dataset.

As shown, SVM gives the best performance on dataset recorded using the antenna. RF gives the highest performance when using the data recorded using the OERW;

Similar performance is demonstrated within the CV subset. However, an improvement in classifier performance is

observed when both magnitude and phase-shift features under unseen subset were used.

It is worth noting that the introduction of PCA led to a slight decrease in performance. Nevertheless, the use of PCA contributes to a reduction in computational complexity.

VII. CONCLUSION

This study proposed two MNDT&E microwave techniques for non-destructive dielectric material characterization regardless their thicknesses based on: free space characterization using a horn antenna and contact characterization using an open-ended rectangular waveguide. Both techniques are effective for material characterization. Each method will depend on the specific requirements of the application. For example, if high spatial resolution is required then an open-ended rectangular waveguide may be the best option. Otherwise, if the material to be characterized is at a distance, then free space radar may be the best option.

In a future work, the aim is to integrate the microwave instrumentations into an automated system designed to regulate and adapt the distance. This automation allows to take the benefits of integrating the two techniques.

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