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(Article begins on next page)

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CNN-Based Hotspot Detection in Small-Scale Composting from Multistatic Microwave Time-Domain Responses

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***Abstract*—Small-scale composting scenarios are highly sensitive to localized temperature peaks, known as hotspots, which can disrupt the overall composting process and degrade its quality. To address such issues, this study presents a deep-learning method to detect such hotspots using multi-static time-domain scattering responses. A large dataset is generated with an in-house full-wave Finite-Difference Time-Domain (FDTD) electromagnetic solver. The dielectric properties of compost and hotspot regions are modeled based on existing literature, and synthetic White Gaussian noise is added to recorded time-domain responses to mimic more realistic measurement conditions. The framework includes a physics-informed feature-extraction stage that encodes the time-domain signal signatures into feature vectors. These vectors are then processed by a compact 2-Dimensional Convolutional Neural Network (2D-CNN) to classify scattered signals in three categories: no hotspot, one hotspot, or two hotspots. The results indicate that the framework achieves over 95% accuracy at signal-to-noise ratio (SNR) levels similar to those found in practical microwave sensing systems.**

I. Introduction

Composting is a technical, controlled biological process that transforms organic materials into a stable, nutrient-rich, humus-like substance, the compost [1], [2]. The production of high-quality compost requires a carefully controlled process, as it is naturally fragile and can be easily corrupted by improper temperature, moisture imbalance, or insufficient aeration [1], [3]. An uncontrolled composting process can make the final product physiologically toxic to plants; therefore, the different composting phases must be regularly monitored and, when necessary, managed to ensure the proper conditions. These phases, in general, include decomposition and maturation. In the first phase, the microbial activity is high, and microorganisms break down degradable organic matter, generating heat and creating thermophilic conditions in the compost. In the second phase, microbial activity slows, temperature decreases, and complex organic compounds stabilize. The temperature is an important parameter in the whole process. Very high temperatures are usually undesirable because even thermophilic bacteria can be destroyed in such conditions.

The composting process is usually self-regulated; however, hotspots can occur when there is inadequate aeration or excessive microbial heat production [2], [4]. In industrial-scale composting, the massive compost mass enables mostly thermally self-regulated microbial activity [5]. In contrast, in small-volume domestic ones, the reduced compost volume cannot sustain a stable and self-regulated microbial activity, making it more sensitive to irregular hotspots and prematurely interrupting the process. Thus, timely and non-invasive detection of hotspots becomes important for the process. Nevertheless, the identification task is not trivial. Current solutions use temperature sensors and thermal cameras; however, they have intrinsic limitations. The former only provides punctual thermal information; as a result, if the spatial sampling is too sparse, some hotspots may remain undetected. Conversely, thermal cameras can cover a larger area, but have limited penetration depth. To overcome some of these challenges, microwave-based systems have recently been proposed to monitor the temperature of small-scale compost exploiting the dielectric contrast generated by such temperature changes, as validated in [6]. When microwaves propagate through compost, they can collect information about its dielectric distribution, which is nonlinearly encoded in the scattered field and, if accurately measured, can be used to identify thermal anomalies. Based on this principle, recent research in the microwave imaging field [6] has demonstrated its feasibility for compost monitoring. Moreover, supervised classification models, e.g. Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), have been used in many microwave-based systems [7], including also compost sensing applications

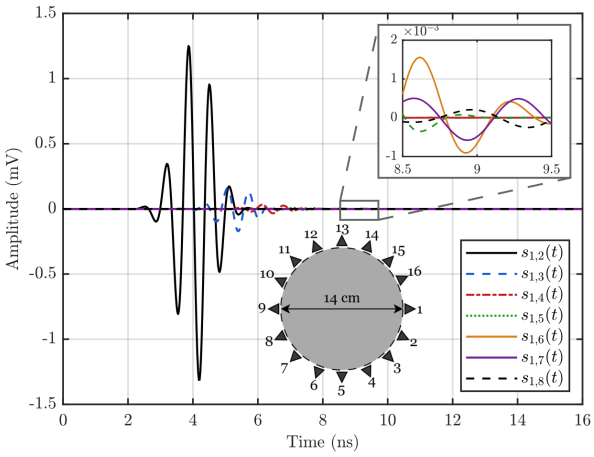


Fig. 1. Time-domain multi-static scattered signals of the simulated scenario, homogeneous dielectric permittivity of the background medium (compost).

[8], [9]. In particular, Deep Learning (DL), including CNNs have been extensively explored for general detection and classification tasks, inverse scattering problems, target detection in radar systems, microwave imaging, among others applications [10], [11]. In this study, we present a CNN-based deep learning approach to detect hotspots in compost. Specifically, the method leverages unique features encoded in time-domain scattered signals to classify the compost into three conditions: absence of hotspots, presence of one hotspot, and presence of two hotspots. The classification depends on a pre-trained two-dimensional convolutional neural network (2D-CNN). This network is trained on a subset of a time-domain scattering signal dataset generated from various compost conditions with different hotspot sizes and positions, different Signal-to-Noise (SNR) levels, and changes in the dielectric properties of both the compost and hotspot regions compared to values reported in recent literature.

II. Data generation

Synthetic data from an in-house two-dimensional finite-difference time-domain (FDTD) electromagnetic solver (EM) is generated to construct the dataset used for the training, testing, and validation. The computational model assumes a circular cross-section of compost mass with the dielectric properties reported in [6]. The background compost is modeled at approximately $22.9\,^{\circ}\mathrm{C}$, and the hotspot region at around $26.3\,^{\circ}\mathrm{C}$. The corresponding relative permittivity and conductivity for each region are randomly varied within $\pm 7\%$. The simulation domain is shown in Fig. 1, it is a circle of radius $14\,\mathrm{cm}$, surrounded by 16 uniformly spaced probes that continuously monitor the scattered field for a time window of 16 ns. The resulting dataset is composed of 2000 independent simulations, and three scenarios (classes) are considered: "no hotspot", "one hotspot", and "two hotspots", which indicate the absence of a hotspot, the presence of one hotspot, and the presence of two hotspots in the compost mass, respectively. The classes are randomly chosen to run the simulations in the FDTD EM solver. In the "two hotspots" class, any overlap between the hotspot regions is avoided. Each hotspot radius is randomly set between $1\,\mathrm{cm}$ and $3.5\,\mathrm{cm}$. This configuration generates a large dataset that covers a wide range of realistic conditions for small-scale composting. Each simulation generates a tensor $S^{(i)} \in \mathbb{R}^{16\times16\times700}$, where each entry (t_x, r_x, t_n) corresponds to a sample collected by the probe r_x of the scattered field at time t_n when the probe t_x generates the incident field. Fig. 1 shows the received signals $s_{t_x,r_x}(t)$ by the r_x probe when the probe t_x is transmitting.The dataset is randomly split into training, validation, and test sets in a 70%, 15%, 15% ratio of the full dataset.

III. Feature extraction

The proposed feature-extraction framework consists of a data-driven analysis of scattered signals in the time domain. The selected features are listed in Table I. They are chosen based on the electromagnetic wave propagation theory in a lossy and dispersive medium, where the signals can experience attenuation, dispersion, and multiple scattering effects that introduce changes in their amplitude, propagation velocity, energy distribution, and temporal shape. Therefore, the selected features are chosen to capture these signal features, and each tensor $S^{(i)}$ is reduced to a compact representation for a subsequent classification stage, i.e., each element $s_{t_x,r_x}(t)$ is mapped to an eight-dimensional vector. These features are computed from the envelope $e(t)$ of each $s(t)$. The resulting feature vectors are then concatenated to form a tensor $\mathcal{S} \in \mathbb{R}^{16\times16\times8}$. This tensor is the input to the Deep Learning (DL) model for both classification and validation stages.

TABLE I
Extracted features from the time-domain scattered signals.

Feature	Expression
Peak amplitude	$A_{\max} = \max_t e(t)$
Peak delay	$t_{peak} = \arg\max_t e(t)$
FWHM	$\Delta t_{\mathrm{FWHM}} = t_2 - t_1, \quad e(t_{1,2}) = A_{\max}/2$
Rise time	$t_r = t_{0.9A_{\max}} - t_{0.1A_{\max}}$
Envelope mean	$\mu_e = \frac{1}{T}\sum_{t=1}^{T} e(t)$
Envelope variance	$\sigma_e^2 = \frac{1}{T}\sum_{t=1}^{T}(e(t)-\mu_e)^2$
RMS amplitude	$\mathrm{RMS} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e(t)^2}$
Entropy	$H_{\mathrm{norm}} = -\frac{1}{\log T}\sum_{t=1}^{T} p_t \log p_t,$ $p_t = \frac{e(t)^2}{\sum_{n=1}^{T} e(n)^2}$

IV. Numerical Results and Analysis

To discriminate the presence of hotspots within the compost mass, the extracted features in the tensor $\mathcal{S}$ are processed by a compact 2D-CNN. The network architecture is shown in Fig. 2. It is composed of 2D convolution and pooling layers to capture local patterns and cross-feature relationships. A global average pooling layer then reduces the feature maps to a single vector, which is passed to a fully connected layer with a softmax activation function to assign probabilities for three classes: "no hotspot", "one hotspot", or "two hotspots".

In practical microwave systems, scattered signals often get affected by interference, e.g., electromagnetic and thermal noise from both the equipment and the surrounding environment. To simulate these conditions, additive white Gaussian noise is added to the raw data $S^{(i)}$. The noise level is adjusted to reach typical signal-to-noise ratio (SNR) values of commercial equipment such as VNAs, software-defined radios (SDRs), and transceivers, which has SNR values from about 10 dB to over 70 dB [12], [13]. Accordingly, SNR levels of 10 dB, 30 dB, 50 dB, and 70 dB are used to assess the performance of the CNN-based classifier in noisy conditions.

As illustrated in Fig. 3, the confusion matrices show that at high SNR values, 70, 50, and 30 dB, the model has excellent discrimination between three classes. At a lower

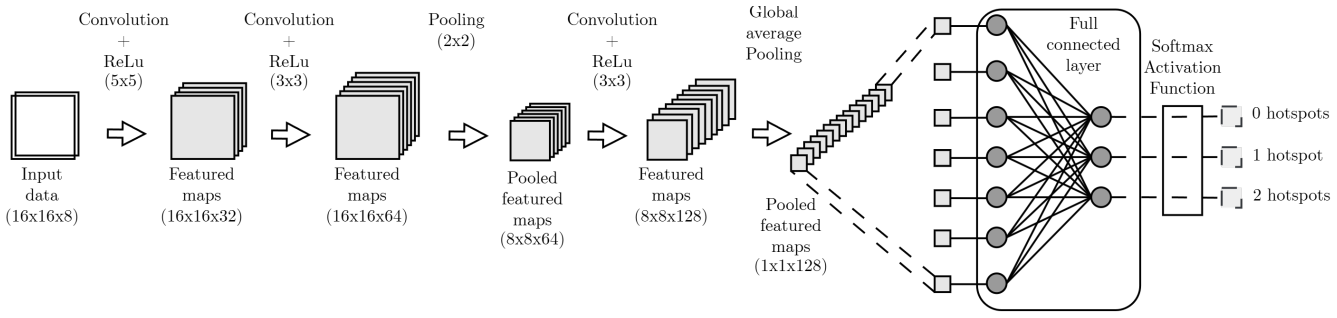


Fig. 2. Proposed 2D-CNN architecture for three-class hotspot classification

SNR, e.g., 10 dB, its performance degrades, and the classification becomes unreliable, with low accuracy. It is worth noticing that if the "one hotspot" and "two hotspot" classes are merged (dashed lines in Fig. 3) into a single "hotspot present" class that indicates that more than one hotspot is present in the comoost, the model maintains high accuracy, with only a maximum confusion of 1.9% for the 70, 50, and 30 dB SNR cases. The main confusion percentage occurs between the classes "one hotspot" and "two hotspots", which suggests that the model learns distinct but related features. In particular, the multiple scattering interactions between two closely spaced hotpots can produce similar signatures that are confounded with the response of a single hotspot. This behavior is consistent with the inverse scattering theory, where the scattered fields responses are highly non-linear dependent [14]. Additionally, the global performance metrics are reported in Fig. 3. At higher SNR values, 70, 50, and 30 dB, the accuracy, precision, recall, and F1-scores are above 95%, which is particularly significant, because these SNR values correspond to typical radio frequency (RF) measurements.

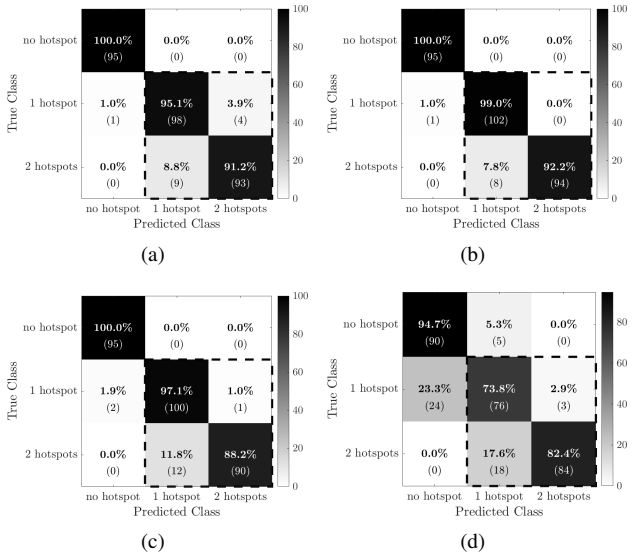


Fig. 3. Confusion matrices on tested data for different SNR values: (a) 70 dB, (b) 50 dB, (c) 30 dB, (d) 10 dB.

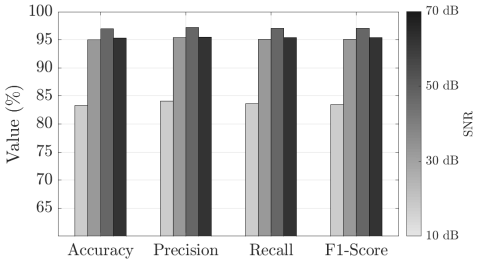


Fig. 4. Comparison of classification performance on tested data for different SNR values: 10dB, 30dB, 50dB and 70dB.

V. Conclusions and Future Work

This study introduces a deep-learning approach for hotspot detection in small-scale composting by classifying the multistatic time-domain microwave scattering signatures. A large multistatic EM dataset was created to test the framework, with controlled noise added into the recorded data. Moreover, a physics-based feature extraction approach was proposed to capture the temporal and dispersion characteristics of the scattered signals, and a compact 2D-CNN was trained to classify the compost state into three conditions. This approach achieves over 95% accuracy at various SNR levels, similar to those of a real-case scenario. This shows the high sensitivity of time-domain scattering signals to local thermal variations in compost that, if properly measured, can be used to monitor focalized localized high-temperature zones in small-scale composting setups. Future work will extend these results to cases with multiple hotspots and confirm them experimentally.

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