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Neural Network and Microwave Sensing for Food Contamination Monitoring

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***Abstract*—In this paper, a technique covering the lacks in currently adopted food safety devices is presented, through a microwave-sensing prototype combined with a neural network. An antennas array, composed by 6 low-cost printed circuit boards, surrounds the product to analyze. Their positions and number have been chosen as a trade-off between an optimal coverage of the volume of interest and the physical constraints of an industrial device, i.e., the conveyor belt, moving at production speed. The signals are recorded and used to train a neural network, resulting in an overall 99.45% success rate in classification.**

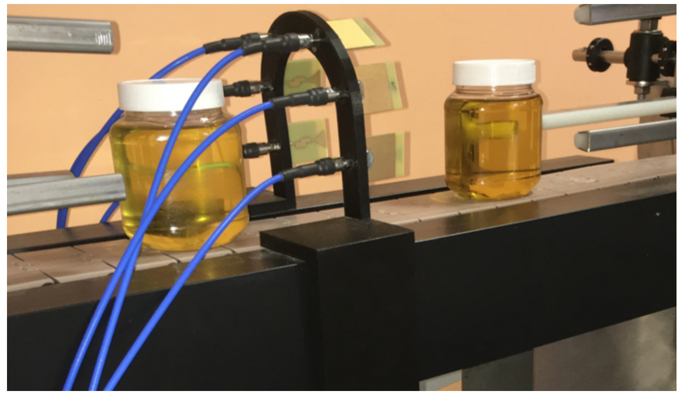

Fig. 1. An overview of the sensing system: two jars passing through the arch support holding the PCB antennas array.

I. Introduction

Nowadays, customers expect high quality standards from packaged food and drinks. Given the constant increase in mechanized processes in food production, the need of improving the quality of detection devices arises, and food industries must face this issue. Food contamination has always been and still is a major concern all over the world [1], [2]. Physical contaminants indeed, may result seriously harmful if ingested: foreign matters as glass fragments or plastic pieces can cause hazards for the digestive system; risks are even higher for seniors and children. Commonly employed inspection devices have still limitations: metal detectors (MD) can only identify conductive materials, while X-Ray imagers have a detection principle based on the matter density, resulting in missing low-density plastics, widely used in packaging; further, it exploits ionizing radiations, which are an additional issue to monitor, especially for operators working around such devices.

Electromagnetic (EM) sensing is showing promising performance in the last few years, exploiting information at different ranges of the spectrum: terahertz is one of the examples [3]. Its limitation lays in the scarce penetration depth, so resulting capable to detect superficial defects only. On the other hand, microwaves (MW) sensing allows to cross a product whose dimensions are up to centimeters. The alteration of the scattered waves, due to the potential presence of a contamination, can be recognized by a MW sensing system, making it suitable to detect also low-density materials, by even reconstructing an image of the target [4]. Nevertheless, food manufacturing companies are mainly interested in recognizing the presence of contamination of packaged products, no matter its position inside the product. That is why we explored the possiblity to monitor the products moving along a conveyor belt with a MW sensing system and a Machine-Learning (ML) approach to classify them as safe or contaminated. In [5], ML has been used to monitor food and agricultural products, but in a different frequency range and in a static environment.

In this paper, we show the first prototype of the MW sensing system and a ML classifier able to detect millimetric-sized contaminants in a food product (hazelnut-cocoa cream jars) on a conveyor belt moving at production speed. The motion adds significant difficulties, mainly due to time constraints and synchronization issues. The antennas array surrounding the object allows a complete view of the target. The scattered signals are recorded and used to train and test a neural network to validate this approach.

II. Microwave Sensing Architecture

The MW sensing system is shown in Fig. 1; an arch-shaped 3-D printed support is holding the antennas in a fixed position around the target. Their number and position have been evaluated considering the degrees of freedom theory [6]

Fig. 2. A picture of the contaminants used for testing, and a ruler as a dimensions reference.

TABLE I

CONFUSION MATRICES OF THE SELECTED MODELS CALCULATED ON THE VALIDATION, TEST AND OVERALL SETS.

Confusion Matrix Val Set	**Confusion Matrix Val Set Percentage**	**Confusion Matrix Test Set**	**Confusion Matrix Test Set Percentage**	**Confusion Matrix Overall**	**Confusion Matrix Overall Percentage**
$\begin{pmatrix} 153 & 3 \\ 1 & 143 \end{pmatrix}$	$\begin{pmatrix} 51.0\% & 1.0\% \\ 0.3\% & 47.7\% \end{pmatrix}$	$\begin{pmatrix} 144 & 3 \\ 0 & 153 \end{pmatrix}$	$\begin{pmatrix} 48.0\% & 1.0\% \\ 0.0\% & 51.0\% \end{pmatrix}$	$\begin{pmatrix} 996 & 7 \\ 4 & 993 \end{pmatrix}$	$\begin{pmatrix} 49.8\% & 0.4\% \\ 0.2\% & 49.6\% \end{pmatrix}$

combined with physical constraints mainly represented by the movement along the conveyor belt. The obtained number of antennas, adapted to the considered realistic scenario, is equal to 6.

The considered products are hazelnut-cocoa cream jars, here replaced it with safflower oil (as shown in Fig. 1), equivalent from a dielectric point of view, but much easier to handle and to be visually inspected for intrusions. The chosen system working frequency is 10 GHz, according to the designed number of antennas and allowing a sufficient penetration depth of around 4 cm (the jar diameter is 5.5 cm) in the oil medium within the jar (the measured oil relative permittivity is 2.86). A further constraint is the conveyor belt speed: to replicate the industrial environment, we set it up at 30 cm/s, comparable to the speed in industries. The 6-port PXI VNA [7] has been programmed accordingly, with a photocell triggering the start of the measurements. Thanks to the 6 available receivers in parallel, a full measurement, i.e. a full 6×6 scattering matrix with all the possible interactions among the antennas in the array, is completed in around 0.05 s, making it adequate with the relative jar motion.

The contaminants which have been tested in this assessment are shown in Fig. 2: splinters and samples whose minor dimension is millimetric-sized, of various materials, in particular: plastic, nylon, wood and glass. They were placed in random positions in the target volume. A thousand measurements were taken, including all contaminants, and an equivalent number with several different "clean" jars.

III. NEURAL NETWORK DESIGN AND PERFORMANCE

The neural network for pattern recognition is sketched in Fig. 3: the number of inputs corresponds to the full 6×6 scattering matrix, excluding the reflection terms, so globally 30 complex numbers; their real and imaginary parts were splitted, and that is the reason why the input in the figure exhibits a 60. This level is followed by 8 hidden layers, connected to the output layer, which provides a boolean response, i.e, the jar is contaminated or not. As common practice, the whole dataset is divided into training, validation and test set, respectively the 70%, 15% and 15% of the 2000 samples. Confusion matries, in which correct matches, true positive and true negative are displaced along the main diagonal, are shown in Table I. The results are extremely satisfying, making the prototype to successfully classify the target in 99.45% of cases, with a relatively simple network architecture. This allows the possibility to install the device at the end of a production line non-invasively, without impactful modifications needed.

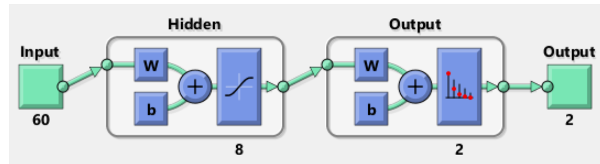

Fig. 3. Pattern Recognition Neural Network scheme.

Further, it would be viable to monitor the products real-time, such that the production processes can go on without interruptions or delays.

IV. CONCLUSIONS AND PERSPECTIVES

This paper demonstrates the feasibility of a combined microwave sensing and machine learning approach to complement the inspection devices along production lines, to increase the expected quality standards. Its functioning can be extended to other food categories, by tailoring the system with a proper architecture and adjusting the frequency to get a sufficient penetration depth in the considered medium.

ACKNOWLEDGEMENT

This work was supported by the Italian Ministry of University and Research under the PRIN project "BEST-Food, Broadband Electromagnetic Sensing Technologies for Food Quality and Security Assessment."

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