Microwave Sensing for Food Safety: a Neural Network Implementation

(Article begins on next page)

Microwave Sensing for Food Safety: a Neural Network Implementation

Marco Ricci
Department of Electronics and Telecommunication
Politecnico di Torino, Italy
marco.ricci@polito.it

Jorge Alberto Tobon Vasquez
Department of Electronics and Telecommunication
Politecnico di Torino, Italy
jorge.tobon@polito.it

Giovanna Turvani
Department of Electronics and Telecommunication
Politecnico di Torino, Italy
giovanna.turvani@polito.it

Ivan Sirena
Laser Spectroscopy Division (L-Pro) - FT System part of Antares Vision Group
Mestrino (PD), Italy
ivan.sirena@ftsystem.com

Mario Roberto Casu
Department of Electronics and Telecommunication
Politecnico di Torino, Italy
mario.casu@polito.it

Francesca Vipiana
Department of Electronics and Telecommunication
Politecnico di Torino, Italy
francesca.vipiana@polito.it

***Abstract*—Customers' attention in packaged food quality is arising in the last few years, as physical intrusions can still be found in commercialized products. Frightful newspapers articles attract consideration on this matter, and pose a serious health issue: accidental ingestion of foreign bodies can severely damage the digestive system, or even cause choking, with seniors and children being particularly exposed. Existing devices to monitor food products have lacks, missing certain classes of contaminant, low-density ones in particular, due to intrinsic limitations to their working principle, based on materials density in the case of x-rays inspection. Here, we propose a novel detection principle, based on microwave-sensing and exploiting the dielectric contrast between the potential intrusion and the surrounding matter. The realized microwave-sensing device is, then, combined with a machine-learning approach, with a classification mechanism capable in discerning clean from contaminated samples. The microwave-sensing device is applied to an industrial food production line, showing a remarkable precision in correctly detecting millimetric-sized intrusions made of plastic, glass or wood, which are the classes of materials unlikely to be located by existing inspection devices.**

***Index Terms*—microwave sensing, non-invasive diagnostic, pattern recognition neural network, food inspection, food safety**

I. Introduction

Physical contamination is still nowadays a major issue affecting food and beverage manufacturing industries. The potential risks are primarily related to health hazards: accidental ingestion of foreign bodies, indeed, may severely damage the digestive system or even cause choking, for children and seniors in particular. Moreover, this would affect a brand reputation, leading to a loss in customers loyalty, or even expensive legal consequences. The amount of customers complaints, increasing in the last few years [1], is an indicator of shortcomings in currently employed automated inspection systems. As a matter of fact, the most spread inspection devices in food industries are metal detectors (MD), which can detect conductive materials only, or x-rays systems, employing ionizing radiations to inspect the inside of products along a conveyor belt, and detecting potential contamination having different density with respect to the food content. The lack lays in the nature of materials widely employed for packaging, as plastics or glass, whose density is really low [2], [3]. Even with dual-beam x-ray technology, an improvement in the detecting capabilities of such devices, these classes of materials stay hardly detectable and may lead to contaminated products going to market. Further, the nature of these kind of radiations requires an intensive and long process to be accepted and certified in a strictly controlled industry, as food and beverage is.

The studies on microwave technology to complement quality monitoring is arising in the last few years [4], [5]. Our proposal consists in a microwave-based prototype, composed by an array of low-cost printed circuit boards antennas, which surround the products passing by a production line, and analyze real-time every item at the production process end [6], [7].

In this assessment and for the tested food sample, specifically jars of hazelnut-cocoa cream, the adopted central frequency is 10 GHz, which allows to sufficiently penetrate the product under test. The collected signals are scattered by six antennas positioned along the line in an arch-shaped architecture. They are then used to feed a machine learning classifier, as preliminary tested in [8]. In this work, we employ a neural pattern recognition classifier, trained to discern contaminated from clean samples, extending and assessing the detection principle in a relevant industrial environment. The microwave-based prototype was installed at the facilities of FT System, part of Antares Vision Group, leader in inspection, tracing and smart data technologies for the food and beverage packaging sector. The excellent classification results demonstrate the feasibility of such an approach, which can be considered as a viable mean to complement and strengthen product quality check along production lines.

II. Microwave Sensing System and Acquisition Strategy

The microwave-based prototype is sketched in Fig. 1: the antennas surround the jar to be inspected. They are held thanks to a 3-D printed support, ensuring the positioning which has been numerically assessed. Another constraint to consider is the need to check-over all the items to ensure

Fig. 1. Antennas array surrounding the item to inspect

Fig. 2. A chocolate cream jar running below the antennas array, protected by the shielding box

the highest degree of safety, but without interrupting or delaying the production process. Therefore, the acquisition of the 6×6 scattering matrix must be performed considering the production speed, which in the case of such products is approximately 30 m/min. A 6-port vector network analyzer [9] allows to accomplish this need. Its acquisition time for the whole matrix is in the order of 50 milliseconds. In that amount of time, the object moves of around 2.5 centimeters below the arch, staying visible by the antennas array. The measurement start is triggered by a photocell, detecting the passage of the jar and piloting the start of the signal transmission at the proper time frame. All the measurements were controlled by a script to handle the acquisition properly, waiting for the trigger and allowing the start of the acquisition at the right time.

Furthermore, in order to avoid any interference at those frequencies, as well as multiple reflections in such an environment, a shielding box has been added around the antennas as shown in Fig. 2. It consists of a metal box, protecting the acquired signals from outside noise, with a layer of absorbers placed on the inner surfaces, to avoid internal multiple reflections.

The proposed microwave sensing system has been installed in the FT System facilities, where a loop line is available for testing, allowing to perform a consistent number of measurements (in the order of few thousands) with limited effort.

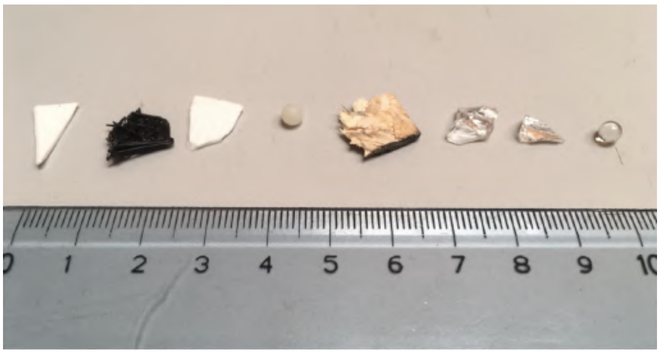

Fig. 3. Some of the tested millimetric-sized intrusions

Fig. 4. Initial placement of different types of intrusions inside the tested products

The acquisitions are then used to train the pattern recognition neural network and discern contaminated samples from clean ones. To simulate an actual production facility, the tested products flowing along the line have different relative inter-distance.

The foreign bodies have been displaced in different part of the food item volume, so to make the classifier robust and trained properly for generalization purposes. The tested contaminants are millimetric-sized samples, as glass, wood or plastic splinters, little pieces of jar cap, which can accidentally break during the production process, or even spherical samples commonly used to test the detection capabilities of new devices, whose materials are nylon, polytetrafluoroethylene (PFTE) or soda-lime glass (see Figs. 3 and 4). These are all kind of materials which are unlikely to be detected by the mentioned existing inspection devices. To avoid false positive and properly train the neural network, different samples of uncontaminated jars have been measured as well.

The resulting scattered data are organized in a 6×6

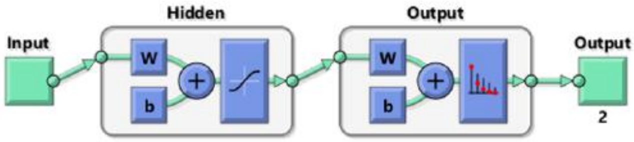

Fig. 5. Neural pattern recognition network architecture

complex scattering matrix. The reflection coefficients, i.e., the terms on the main diagonal, have been excluded, providing no useful information. So, the collected data result in a 30 elements array of complex numbers for each frequency. Precisely, 11 frequency points are acquired at each measurement, equally spaced between 9 GHz and 11 GHz, resulting in a total amount of 330 complex numbers. An equivalent number of measurements with different jars of uncontaminated products was performed as well, since it is also important to properly recognize clean products, the classification must work properly also in this sense. False negative would impact by causing unnecessary waste and a loss for production companies.

III. Neural Network Implementation and Experimental Results

The measured data are used to train a neural pattern recognition classifier, sketched in Fig. 5. It is composed of an input layer, then the first block of hidden layers, followed by an output block, which collects all the inputs to give a binary output (i.e., the product is contaminated or not).

The results are displayed in the so-called confusion matrices. One for each different set is computed, in particular: the training set includes samples used for learning, to fit the parameters of the classifier; the validation set is used to tune those parameters; the test set is held back from the training part, and includes samples used only to assess the performance of a fully-specified classifier [10]. Each confusion matrix shows on the main diagonal (the green squares) a successful classification for the two cases. The red boxes show the number of errors in classification. Both number and percentages are shown. The four light grey boxes depict the total amount of items classified for each single output class and target class respectively, with a green number showing the successful classification for that given class, and a red number for misclassified ones. Finally, the grey box on the bottom-right resumes the percentage of all the cases in each confusion matrix.

Figure 6 shows the obtained classification results for the case, where all the frequency points are used to train and test the neural network: an input composed by 330 complex numbers is employed in this case (6×6 scattering matrix elements, without the reflection coefficients, so a total amount of 30 values for each of the 11 frequencies). As it can be easily noticed, all the items are classified correctly, with a success rate of 100%.

Figure 7 shows the results with a similar approach (same input size and number of frequencies employed), but reducing the number of samples used in the training phase. Now the number of samples used to train, validate and test the network are equal to 30%, 35%, and 35% respectively,

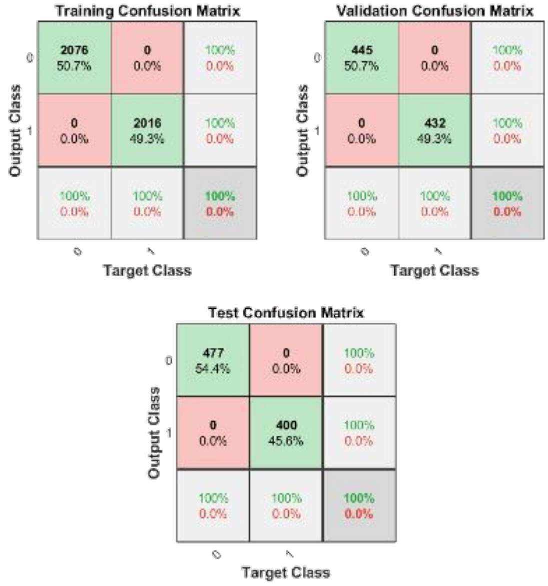

Fig. 6. Confusion matrices obtained by employing all acquired frequencies; the 70% of the total amount of measurements is used to train the neural network, the 15% to validate and a further 15% to test; architecture composed by 2 hidden layers.

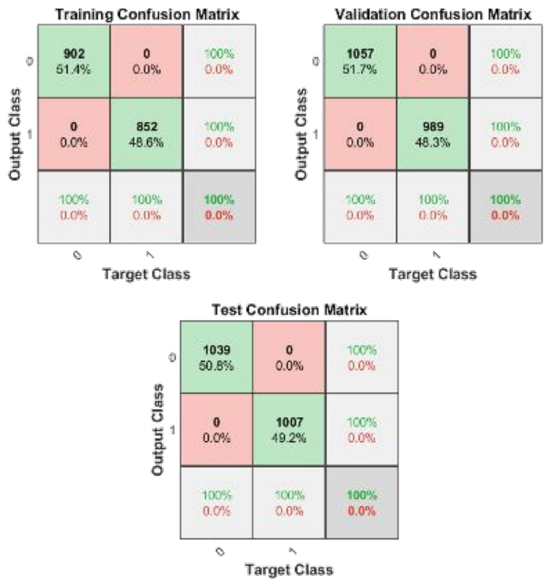

Fig. 7. Confusion matrices obtained by employing all acquired frequencies; the 30% of the total amount of measurements is used to train the neural network, 35% to validate and a further 35% to test; architecture composed by 2 hidden layers.

instead of 70%, 15%, and 15%. Still, even reducing the training size, the classifier works perfectly, keeping 100% precision in classification. This means that it is possible to reduce the training phase, limiting the complexity of the device fine-tuning, important feature in an industrial implementation.

Finally, in Fig. 8, another test, to further reduce the complexity of the device, is run by keeping a single point

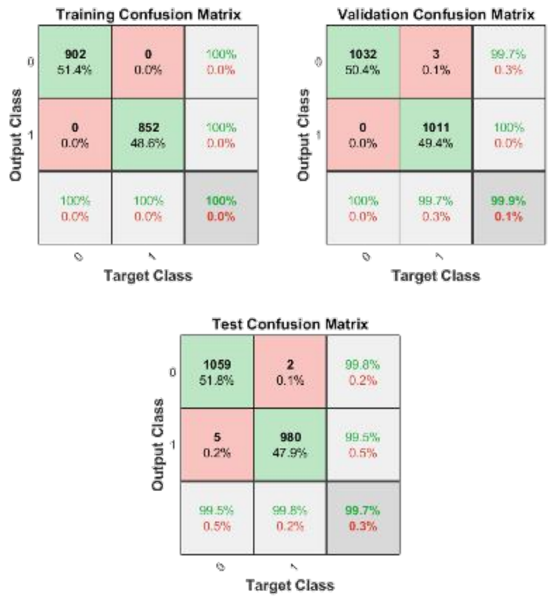

Fig. 8. Confusion matrices obtained by employing a single central frequency only (10 GHz); the 30% of the total amount of measurements is used to train the neural network, 35% to validate and 35% to test; architecture composed by 8 hidden layers.

in frequency to build the neural network, but, at the same time, improving the classifier functionalities by employing 8 hidden layers instead of 2. Again, the percentage of the training set is kept low, as in the previous case (30% of the total samples to train, and 35% both for validating and testing). In this case, some misclassifications appear, but still with very high classification accuracy, at 99.7% in the test set.

IV. Conclusion and Perspectives

This work shows the feasibility of a microwave-based device combined with a neural pattern recognition network to monitor in-line food products. It is tested and assessed in a industrial environment, with excellent classification results for millimetric-sized intrusions which are unlikely to be detected by any other existing inspection device.

The next step is an extension of the prototype to other categories of food/beverage products. This goal can be achieved by adjusting the working frequency, depending on the item to be analyzed nature, to sufficiently penetrate the food to be inspected. A 3-D image reconstruction of the target, obtained with data measured while the objects move along the line, is also under study.

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.”

References

[1] (2019) The rapid alert system for food and feed. [Online]. Available: https://op.europa.eu/en/publication-detail/-/publication/2c5c7729-0c31-11eb-bc07-01aa75ed71a1/language-en/format-PDF/source-174742448

[2] Mekitec for Safe Food. Plastic detection with x-ray inspection. [Online]. Available: https://www.mekitec.com/plastic-detection-in-food/

[3] R. Haff and N. Toyofuku, “X-ray detection of defects and contaminants in the food industry,” *Sensing and Instrumentation for Food Quality and Safety*, vol. 2, 12 2008.

[4] F. Zidane, J. Lanteri, J. Marot, L. Brochier, N. Joachimowicz, H. Roussel, and C. Migliaccio, “Nondestructive control of fruit quality via millimeter waves and classification techniques: Investigations in the automated health monitoring of fruits,” *IEEE Antennas and Propagation Magazine*, vol. 62, no. 5, pp. 43–54, 2020.

[5] J. LoVetri, M. Asefi, C. Gilmore, and I. Jeffrey, “Innovations in electromagnetic imaging technology: The stored-grain-monitoring case,” *IEEE Antennas and Propagation Magazine*, vol. 62, no. 5, pp. 33–42, 2020.

[6] M. Ricci, L. Crocco, and F. Vipiana, “Microwave tomography for food contamination monitoring,” in *15th European Conference on Antennas and Propagation, EuCAP 2021*, 2021.

[7] J. A. Tobon Vasquez, R. Scapaticci, G. Turvani, M. Ricci, L. Farina, A. Litman, M. R. Casu, L. Crocco, and F. Vipiana, “Noninvasive inline food inspection via microwave imaging technology: An application example in the food industry,” *IEEE Antennas and Propagation Magazine*, vol. 62, no. 5, pp. 18–32, 2020.

[8] M. Ricci, B. Stitic, L. Urbinati, G. D. Guglielmo, J. A. T. Vasquez, L. P. Carloni, F. Vipiana, and M. R. Casu, “Machine-learning based microwave sensing: A case study for the food industry,” *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 11, no. 3, p. 503–514, 2021.

[9] Keysight Technologies, “M980xA Series PXIe Vector Network Analyzer,” *Data Sheet*, 2020.

[10] B. D. Ripley and N. L. Hjort, *Pattern Recognition and Neural Networks*, 1st ed. USA: Cambridge University Press, 1995.