First steps towards an innovative Compressive Sampling Based-THz Imaging System for Early Crack Detection on Aereospace Plates

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***Abstract*— The paper deals with the problem of early detecting cracks in composite materials for avionic applications. In particular, the authors present a THz imaging system that exploits compressive sampling (CS) to detect submillimeter cracks with a reduced measurement burden. Traditional methods for THz imaging usually involve raster scan of the issue of interest by means of highly collimated radiations and the corresponding image is achieved by measuring the received THz power in different positions (pixels) of the desired image. As it can be expected, the higher the required resolution ,the longer the measurement time. On the contrary, two different approaches for THz imaging (namely, continuous wave and time domain spectroscopy) combined with a proper CS solution are used to assure as good results as those granted by traditional raster scan; a proper set of masks (each of which characterized by a specific random pattern) are defined to the purpose.**

A number of tests conducted on simulated data highlighted the promising performance of the proposed method thus suggesting its implementation in an actual measurement setup.

Keywords—cracks detection; nondestructive evaluation; compressive sampling THz imaging.

I. INTRODUCTION

In order to characterize or check the integrity of a particular material in the THz frequency region, raster scan-based THz imaging systems have been proposed . Typically, these systems consist of a single source generating the THz beam that illuminates the object to analyze, and a single point detector that receives radiation passed through the object. To acquire a full resolution image, with PxQ=N pixels, the object under test has to move in front of the single point receiver PxQ times, with a consequent negative effect on the capture speed [1-3]. Improving the measurement resolution dramatically increases the acquisition time, thus often making these systems unfeasible. As an example, the accurate analysis of an aerospace plate would cause a too long out-of-service period of the vehicle to which it belongs.

To fulfill the considered task, other THz solutions are indeed available, such as those based on CCD camera, Radon transform [4], interferometric imaging [5], focal plane detector array. However, lower performance is exhibited and more expensive hardware is required, thus preventing their use in many practical cases. This is the reason why very interesting attempts to reduce the acquisition time of THz imaging systems, for a given 2D resolution, can be found in the literature.

More specifically, in [6] *Chan et al.* have recently proposed an innovative THz imaging system based on a new sampling paradigm, referred to as Compressive Sampling (CS). With respect to the raster scan-based approach, the innovative idea underlying the CS is the execution of a lower number M of measurements ($M \ll N$), but sufficient to correctly reconstruct the desired image by means of CS solvers [7].

Stemming from their past experiences on topics regarding THz novel devices and imaging systems [8]-[10] and Compressive Sampling [11-13], the authors are going to look into the possible applicability of CS-based THz systems to the early crack detection on aerospace plates, an important issue to be assessed to assure safety of aerospace structures. The goal should be to improve resolution of the available systems reducing the acquisition time, with the aim of detecting in advance eventual damages, thus allowing to repair of fiber composites when it is more cost-effective.

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In the following after some theoretical background about the problem statement and CS-based THz systems, the proposed implementation is proposed and the preliminary results obtained in numerical tests are presented and discussed.

II. Problem Statement

The detection of damages for aerospace composite structures, such as cracks and delamination, is an important issue to be assessed in order to guarantee safety of aerospace structures, mainly composite plates that are located on the skin of fuselage, tail, and wing [14]. Indeed, the skin of aerospace structures is usually a component of the same aircraft structure itself, since it is designed so that it can support a certain amount of the overall stress that is provided to the whole structure in order to minimize the maximum takeoff weight. This is also due to the fact that aerodynamic forces are derived from pressures acting on surfaces that are distributed on the aircraft skin [15].

An important strategy to keep under control the damage derived from cranks and delamination is to perform Non Destructive Evaluation (NDE) in a structural component and, in particular, on a skin plate [16]. This is a main task of the Structural Health Monitoring function for an aerospace platform. This process can be accomplished by means of a twofold approach, such as:

1. Routinely, i.e. programmed inspections can be performed in order to verify if some sample plates are affected by cracks. This approach is used to detect cracks that are generated by events that can produce high stresses at local level even if they do not have a big impact on the overall structure. It is the case of impact with small crisp bodies at large velocity or the effect of bad shrinkage of rivets;
2. On purpose, i.e. special inspections can be performed in case the overall structure has been subject to an event that could have generated excessive stresses at local level. This is the case of an hard landing or impact with a large body.

Two types of functions must be performed to properly handle a damage on a skin plate, such as:

1) Damage detection: this is the case when a plate is recognized to be affected by a damage in one or more points by a certain level of confidence;
2) Damage localization: this is the case when the damage that has been detected is localized in a specific area on the plate.

Both functions must be adequately accomplished to carry out a proper damage management function. Since large areas must need inspection, several techniques have been developed to perform this task, such as:

1) Acoustic waves interferometry [17];
2) Thermal analysis by Infra Red Camera [18];
3) Digital Shearography by Visible Panchromatic Camera [19];
4) X-Ray analysis [20];
5) Terahertz waves imaging analysis [21].

In general acoustic techniques are less accurate in performing damage detection and localization but are also less demanding in terms of memory and processing resources. It depends on the intrinsic level of resolution in localization and size of damage that is usually in the order of 10^{-2}m. Alternately, imaging techniques allows for an accuracy better than 10^{-3}m thus allowing for early detection and localization of damages. Moreover, X-ray and Teraherz techniques have also the capability to penetrate the skin to detect the damage hidden by other features that are located on the top of the skin that prevent the detection by non penetrating method, i.e. methods that are not based on active energy directed on the specimen under test. Finally, imaging methods are the sole ones that are truly non-destructive, since no testing element must be attached to the plate, such as for acoustic analysis.

The technique presented in this paper is driven by the need of gathering both damage resolution and computational resources in order to satisfy all requirements needed for developing a feasible early damage detection and localization method.

III. Proposed System

A. Description of the THz imaging systems

With regard to the THz frequency region, there are presently two different approaches commonly used to perform imaging measurements: the continuous wave (CW) and the pulsed (or TD, time-domain) method [1].

The choice between these two families is usually defined on the basis of the operating frequency and emission mode. So, depending on the target application, it is possible to choose the best possible approach to optimize the imaging procedure. CW systems are basically narrow band and very low tunable, but provide very high power output and spectral resolution.

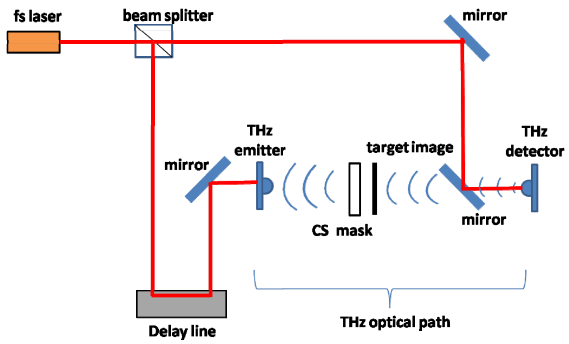

Fig. 1. Femtosecond laser emits at 1040±20 nm at a repetition rate of 50 MHz. The radiation is splitted into two parts: one used for detection and the other for generation of THz pulses. Photoconductive antennas are used forboth generation and detection and a series of parabolic mirrors are used to guide the terahertz pulsesfrom the emitter to the sample and then tothe detector. A delay stage is used to vary the arrival time of the signal with respect to the optical pulse used for detection. By scanning the delay line the THz waveform can be achieved as a function of time.

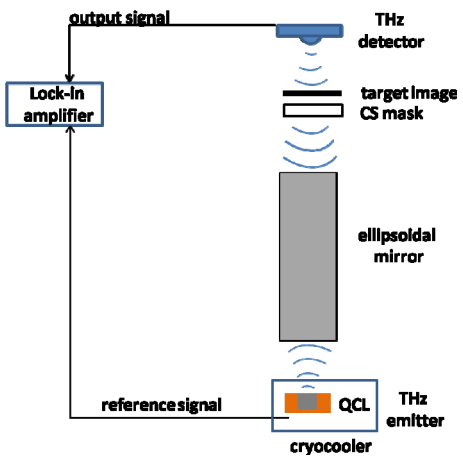

Fig. 2. Quantum Cascade Laser emits THz radiation and an ellipsoidal mirror collects the beam and focuses it on the THz detector through the CS mask and the target image. The detected signal is obtained by using a THz detector, for example a pyroelectric, connected to a lock-in amplifier.

They do not require a phase delay scan, therefore recording times are smaller than in the pulsed method. Moreover, compact and low cost systems can be easily realized.

Conversely, time domain systems are broadband in nature and emission is not continuous, so they are ideal for spectroscopic applications and for the study of ultrafast phenomena.

Such systems are based on the generation and detection of an electromagnetic transient having a duration of few picoseconds or sub-picoseconds. By Fourier transformation, frequency components in the 0.1-5 THz can be easily retrieved.

In order to have the best imaging result, the comparison between these two approaches must be the basic step, so they may be optimally applied depending on the final application.

Fig. 1 shows one of the two setups we are developing for imaging applications, a system based on Time Domain Spectroscopy (TDS). This setup relies on an optical pump-probe method: a femto-second laser output, emitting at 1040 nm with maximum output power of about 200 mW and pulse duration less than 150 fs, is splitted in two beams. The pump beam is utilized to excite the signal source, consisting of a Photo Conductive Antenna (PCA) emitting THz pulses (duration of few ps) covering a broad frequency range, approximately from 0.1 THz to 3.5 THz. The generated electromagnetic transient is guided and focused onto the target by using Off-Axis Parabolic mirrors (OAP), and then detected from a second PCA, using a transmission or reflection mode. A time delay is introduced between the pump and probe lines, by changing the length of relative path, in order to scan the THz pulse with the laser probe beam, and the signal waveform is coherently recorded in the time-domain. Using this method, the electric field (intensity and phase) passing through or reflected by the material under test can be acquired. The frequency content can be retrieved by means of a Fourier transform.

The second setup we plan to develop is based on CW imaging (see fig. 2). Here, the THz radiation is emitted by a Quantum Cascade Laser (QCL), a very compact solid state THz emitter based on intersubband transitions in quantum wells of a semiconducting heterostructure [22].

QCLs can presently cover the THz range from 2 to 5 THz with an output power in the range 2-200 mW. The main drawback in the use of a QCL is that they must work under cryogenic conditions (4-100 K is the usual temperature range of operation), which of course adds complexity to the overall imaging system.

The laser is mounted in a Gifford-McMahon cryo-cooler, and clamped on the cold head using indium on a copper holder, to enhance the thermal coupling. The THz source is placed as close as possible to a High Density Polyethylene (HDPE) window to minimize the high divergence of its radiation pattern.

A metallic ellipsoidal mirror collects and focuses the QCL radiation on the target image, and the power transmitted or reflected by the sample is detected from a pyroelectric detector, connected to a lock-in amplifier.

In both approach the target image is reconstructed starting from the intensity data and by using CS reconstruction algorithm: with raster scan we have notable limitation in measurement and acquisition speed while by using random test function we can reduce this acquisition time, until each measurement is the product of random pixel and the entire image.

B. *Theorical background*

CS assures that a signal, or image, can be reconstructed by means of a number of samples lower than that required by the traditional sampling methods, provided that there is an orthonormal basis where the signal can be represented through only few coefficients significantly different from zero. In particular, a signal or an image are defined as k-sparse, if its representation consists of at most k nonzero coefficients in the considered orthonormal basis.

$$\mathbf{z} = \mathbf{\Psi x} \tag{1}$$

where $\mathbf{z} \in \mathcal{R}^{\mathrm{Nx1}}$ is a sparse representation of the signal $\mathbf{x} \in \mathcal{R}^{\mathrm{Nx1}}$, in the orthonormal basis $\mathbf{\Psi} \in \mathcal{R}^{\mathrm{NxN}}$ [23].

In the assumption that the signal is k-sparse, signal proves to be compressible and the sparsity of the signal is a characteristic that can be use to zip its information.

With reference to the problem of to the digitizing and reconstructing an image, the CS theory furnishes a framework for reconstructing PxQ=N pixels of the unknown image, with a much smaller number of measurements M than the number of pixels in the image, $M \ll N$.

The CS acquisition strategies can be expressed as:

$$\mathbf{y} = \mathbf{\Phi x} \tag{2}$$

where $\boldsymbol{x} \in \mathcal{R}^{Nx1}$ is the ordered vector of pixels of the unknown image to be reconstructed (the vector can obtained by concatenating the rows into a single column) $\boldsymbol{y} \in \mathcal{R}^{Mx1}$ is the measurements vector, and $\mathbf{\Phi} \in \mathcal{R}^{MxN}$ is the so-called sampling matrix that models the acquisition process [24].

It is worth noting that this problem, having lower equations than unknown variables, is ill-posed since has infinite many solutions. However, according to the hypothesis that x can be described by a k-sparse vector as in (1), the equations system (2) turns into:

$$\mathbf{y} = \mathbf{\Phi\Psi^{-1}z} = \Omega\mathbf{z} \tag{3}$$

where $\mathbf{\Psi}$ is the transformation matrix representing the selected representation basis, such that the product $\mathbf{\Psi z}$ gives the image $\boldsymbol{x}$ in the spatial domain, and is Ω the so-called sensing matrix.

Surprisingly, even though the system in (3) still has infinite many solutions, it has been demonstrated that an approximated sparse solution can be obtained with high probability by minimizing the l1-norm:

$$\hat{\mathbf{z}} = \mathbf{argmin}\|\mathbf{z}\|_1 \text{ s.t. } \mathbf{y} = \mathbf{\Phi x} = \mathbf{\Phi\Psi^{-1}z} \tag{4}$$

where $\|\boldsymbol{z}\|_1 = \sum_{i=1}^{N}|\boldsymbol{z_i}|$ [25].

Therefore, in order to provide a sparse representation of image x that is a feasible solution of the system in (3), CS strategy requires that a suitable transformation matrix Ψ has to be chosen.

When measurements vector y is characterized by a non-negligible noise, the following alternative solution has to be taken into account:

$$\hat{\mathbf{z}} = \mathbf{argmin}\|\mathbf{z}\|_1 \text{ s.t } \|\mathbf{y} - \mathbf{\Phi\Psi^{-1}}\hat{\mathbf{z}}\|_2 < \boldsymbol{\varepsilon} \tag{5}$$

As later stage, the reconstructed image $\hat{\boldsymbol{x}}$ in the spatial domain is achieved by applying equations (1) to the sparse solution $\hat{\boldsymbol{z}}$:

$$\hat{\mathbf{x}} = \mathbf{\Psi^{-1}}\hat{\mathbf{z}} \tag{6}$$

The minimum number of samples, required for a reliable reconstruction of image $\boldsymbol{x}$, is provided by following equation:

$$\mathbf{M} \geq \mathbf{C} * \mathbf{K} * \boldsymbol{\mu}^2(\mathbf{\Phi}, \mathbf{\Psi}) * \mathbf{log}\,(\mathbf{N}) \tag{7}$$

where C is a certain positive constant, K is the sparsity of $\boldsymbol{x}$, N is the total number of pixels that have to be reconstructed and $\mu(\mathbf{\Phi}, \mathbf{\Psi})$ is the so-called coherence between the sampling matrix $\mathbf{\Phi}$ and the transformation matrix $\mathbf{\Psi}$:

$$\boldsymbol{\mu}(\mathbf{\Phi}, \mathbf{\Psi}) = \sqrt{\mathbf{n}} \max_{1 \leq \mathbf{i}, \mathbf{j} \leq \mathbf{n}} |< \boldsymbol{\varphi}_\mathbf{k}, \boldsymbol{\psi}_\mathbf{j} >| \tag{8}$$

where φ_i is the i-th row of sampling matrix $\mathbf{\Phi}$ and ψ_j is the j-th column of transformation matrix $\mathbf{\Psi}$ [26].

The coherence provides the maximum correlation between the two matrices. The greater its value, the greater the number of samples required for a reliable reconstruction of k-sparce vector z.

Therefore, with the aim of strongly reducing the number of measurements to be taken, a low value of coherence should be guaranteed. To minimize the coherence, a proper sampling matrix $\mathbf{\Phi}$ has to be defined, because the transformation matrix $\mathbf{\Psi}$ has been set to obtain a sparse representation of image $\boldsymbol{x}$. Fortunately, in many cases of practical interest, choosing a random matrix as sampling matrix $\mathbf{\Phi}$, assure a low value of coherence to be obtained with a wide set of orthonormal basis $\mathbf{\Psi}$ [27].

C. Measurement algorithm

The main advantage of applying a measurement protocol as the CS-based THz systems to the early crack detection on aerospace plates, is the possibility to process a number of measurements that can be even lower by several orders of magnitude than that required by a traditional raster scan mode.

Its main drawback is associated with the fact that the reconstruction process of the signal of interest is characterized by high computational load. However, the time needed for reconstruct an image THZ could considerably decrease if it is k-sparse in the spatial domain.

Let us suppose that THz image $\boldsymbol{x}$ highlight the early crack , to be reconstruct, is k-sparse in the spatial domain.

Thus, by assuming:

$$\mathbf{\Psi} = \mathbf{I_N} \tag{9}$$

where $\mathbf{I_N} = \mathbf{diag}(\mathbf{1}, \mathbf{1}, \ldots, \mathbf{1})$, the equation in (1) turns into:

$$\mathbf{z} = \mathbf{\Psi x} = \mathbf{I_N x} = \mathbf{x} \tag{10}$$

than the system (3) can be express as:

$$\mathbf{y} = \mathbf{\Phi\Psi^{-1}z} = \mathbf{\Phi I_N x} = \mathbf{\Phi x} = \Omega\mathbf{x} \tag{11}$$

As stated above, since $\boldsymbol{x}$ is k-sparse in the spatial domain than it can be directly obtained minimizing the l1-norm in system (11). The sampling matrix $\mathbf{\Phi}$ is usually realized as a random sequence of entries set to 1 or 0 otherwise, with equal probability.

The measurement set-up of a CS-based THz systems is given in [6]. In order to perform a random sampling of M measurements, useful to reconstruct an image of N pixels with M<<N, then a set of M random masks is realized. Each mask is a 2D-dimentional matrix, of $PxQ = N$ pixels having random features to transmit or block THz radiation, with equal probability.

The source generates the THz beam that first passes through the object to be analyzed, spatially modulated by inserting of a random mask between the object and the single point detector. Differently from the raster scan mode, in which the beam THz converges on a single pixel of the object to be imaged, in traditional CS-based THz system the beam THz is collimated on the whole area to be analyzed.

As a consequence, the THz the radiation detected at the receiver, is the superposition of radiation that passes through the pixels of each single random mask. By taking a snapshot of the field THz in the time-domain, in the presence of each mask, the vector of measurements $\boldsymbol{y} \in \mathcal{R}^{Mx1}$ is obtained. The complete set of masks M has been realized on a planar screen, a uniform grid on a printed-circuit board (PCB). A dual-axis

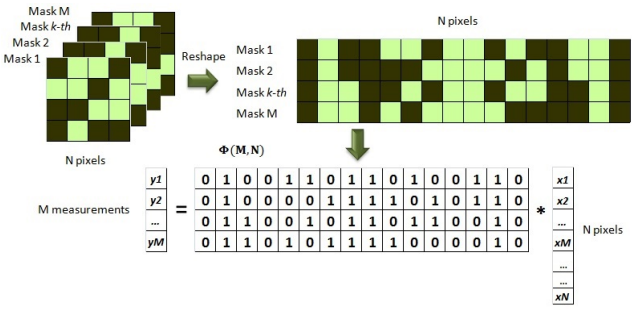

Fig. 3. Sampling matrix $\boldsymbol{\Phi}(\mathbf{M},\mathbf{N})$ with M rows and N columns obtained from a set of M random masks

linear stepper motor can be used in order to move the planar screen more rapidly.

CS approach requires only to move planar screen for M<<PxQ=N times in front of the THz receiver, while the object to be analyzed is fixed during all acquisition stage, achieving a significant decrease of total capture time. From a mathematical point of view, the sampling matrix $\boldsymbol{\Phi}$ is obtained by reshaping each of M random masks as row of $\boldsymbol{\Phi}$.

According to the feature of each pixels of the mask, the entries of each row of the sampling matrix $\boldsymbol{\Phi}$ are set equal to 1, if the correspondent pixel transmits the THz radiation, equal to 0 otherwise (Fig.3). Consequentially, a sampling matrix $\boldsymbol{\Phi}(\mathbf{M},\mathbf{N})$ with M rows and N columns is obtained.

The compression ratio of the proposed method is:

$$\boldsymbol{CR} = \left(\mathbf{1} - \frac{\boldsymbol{M}}{\boldsymbol{N}}\right) * \mathbf{100} \tag{12}$$

IV. Preliminary Results

A number of tests have been carried out by means of numerical simulations in order to preliminarily assess the performance of CS-based THz systems when applied to the early crack detection on aerospace plates.

As an example, two possible simulated defects, such as circular crack 24-sparse, and slit crack 19-sparse, have been generated, and were reconstructed varying acquisition strategy and comparing several CS solvers. The computer used in numerical experiments has a 2,20GHz CPU and 8GB RAM. To better appreciate the performance of the reconstruction process, Fig.4-5 show the original image compared to the image reconstructed by CS solvers for a value of CR equal to 80%.

For each CS solver used, the reconstructed image has been compared to the original one, assuming, as first performance indicator, the reconstruction error defined as:

$$\varepsilon = \left\| \frac{\hat{x} - x}{x} \right\| \cdot 100 \tag{13}$$

where $\hat{\boldsymbol{x}}$ is the reconstructed image and x is the original image. The computational burden in the reconstruction step very often turns out to be as high as to make the CS inapplicable. If CS, in fact, reduces the number of samples to be acquired, the number of operations needed by the reconstruction algorithm to find the desired solution considerably increases. Therefore, the CPU times required by a CS solver to find a sparse solution $\boldsymbol{x}$, is given as second performance indicator. In particular, the evolution both of reconstruction error and CPU time versus different number of M measurements has been evaluated for three different CS solvers (namely, CVX [28], TVAL3[29] and Sparsify[30]).

As it can be noticed, when the image is a circular crack, the method based on the TVAL3 algorithm provides a better estimate than that of other solvers up to a CR of 85%. By increasing the number of measurements, CVX gives a reconstructed error close to zero, also with a CR equal to 80%.

However, it has to be taken into account that increasing the number of measurements requires also to increase the number of masks used to perform the acquisition process. As a consequence, the total capture time could considerably increase, causing the loss of the main benefit of a CS-THz system.

Moreover, the CS solver Sparsify achieves a perfect reconstruction with a CR lower than 65%, but gives the better performance in term of CPU time, only 6,2 ms versus 177 ms of CVX. On the other hand, with reference to slit crack, it can be noticed that using Sparsify as CS solver, a perfect reconstruction is obtained with a CR equal to 75%. If this is combined with its best performance in term of CPU Time,

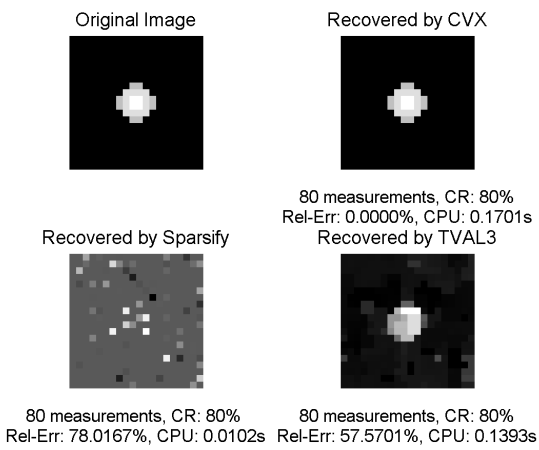

Fig. 4. Original image of a circular crack compared to the reconstructed image by CS solvers for a value of CR equal to 80%.

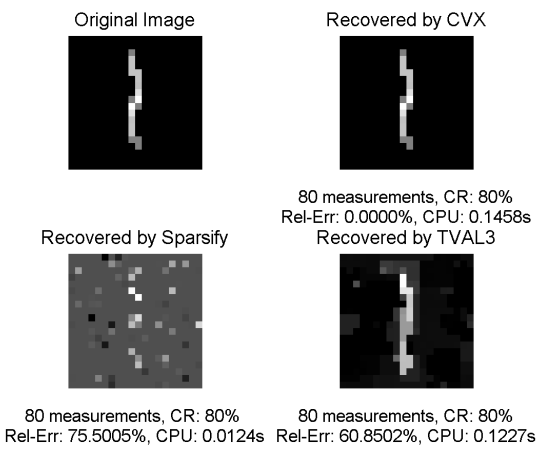

Fig. 5. Original image of a slit crack compared to the reconstructed image by CS solvers for a value of CR equal to 80%.

therefore a CS-based THz measurements setup exploiting Sparsify as CS solver should be the goal in order to improving early crack detection. Numerical tests conducted in simulations highlighted the promising performance of the proposed CS-THz imaging system custom-tailored to the detection of early crack on aereospace plates. Ongoing activities are related with the characterization of a first prototype of the whole measurement setup.

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