Numerical evaluation of a muon tomography system for imaging defects in concrete structures

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Abstract Among numerous applications of muon tomography, deployment in civil structures has caught attraction of many recently. In this work, the appropriateness of muon scattering tomography to detect defects in concrete structures has been studied numerically. A few basic concrete structures that are frequently used in civil construction have been considered as test cases. A simulation has been performed on Geant4 platform where an imaging setup built with several layers of gaseous ionization detectors, having a specific spatial resolution for tracking the muons, has been modeled. The images of the test cases with and without the defect have been simulated for variable exposure of cosmic muons on the basis of their scattering from the composite concrete structures. The images have been compared using t-test to evaluate the performance of the imaging setup in identifying the defects. Further processing of the images has been done with a pattern recognition method proposed in our earlier work to examine the credibility of the method of defect identification in civil works. The efficacy of the said method has been evaluated in terms of the PRM-score devised in this work. The limitation and advantages of the present application of the muon scattering tomography encompassing the imaging and image processing technique in nondestructive evaluation of concrete structures have been discussed.

1 Introduction

Cosmic-ray muons are high-energy charged particles with deep penetration power. Their invasive nature and omnipresent property inspire to utilize the scattering of the muons for imaging applications. Muon scattering tomography (MST) works on the basis of deviation of cosmic muons from their path due to their interaction with atomic nuclei and electrons of the target material. These particles with their large rest mass ($\approx 105 \text{ MeV}/\text{c}^2$) and momentum (mean $\approx 4 \text{ GeV}/\text{c}$) pass through the whole atmosphere with minor deviations [1]. A large section of muons is even capable of traversing through rocks, civil structures, etc. The deviation and energy loss of muons occur due to physical processes like multiple Coulomb scattering (mcs) and ionization. The distribution of the mcs angle projected onto a plane for

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muons of momentum $p$ is considered as a Gaussian distribution [2,3] with width $\sigma$ given by Eq. 1.

$$\sigma = \frac{13.6 \text{ MeV}}{\beta cp} \sqrt{\frac{L}{X_0}} \left(1 + 0.038 ln \frac{L}{X_0}\right)$$ (1)

$$X_0 = \frac{716.4 (\text{g/cm}^2)}{\rho} \frac{A}{Z(Z + 1)ln(287/\sqrt{Z})}$$ (2)

Here, $\beta = v/c$ is the ratio of the speed of muon, $v$, to that of light, $c$. The term, $L/X_0$, is the thickness of the scattering medium in terms of its radiation length, $X_0$. As shown in Eq. 2, $X_0$ is related to the atomic weight, $A$, atomic number, $Z$, and density, $\rho$ of the medium. Equations 1 and 2 suggest that the magnitude of deviation of muons significantly depends on $Z$ and $\rho$. Therefore, while traversing through high-$Z$ and dense matter, for example, lead, uranium, muons undergo larger deviations. On the other hand, low-$Z$ and lighter materials, like concrete, aluminum, can only cause feeble deviation in their tracks. We have shown in our previous work [4] that on the basis of scattering property of muons, high-$Z$, mid-$Z$ and low-$Z$ materials can be distinguished convincingly with the imaging setup and image processing technique based on a pattern recognition method (PRM).

The cosmic-ray muon radiography has been established as a noninvasive imaging technique since last couple of decades. It has been considered for many crucial applications, such as identifying fissile materials [5,6], scanning cargo containers [7–11], monitoring nuclear-waste containers [12,13], investigation inside geological structures [14–17], water towers [18] and scrap metal inspection in foundries [19]. It has been observed that for carrying out imaging of large concrete structures, muon transmission radiography is the preferred option [16,17,20] by which images of the targets are produced on the basis of absorption of muons inside the target. For discriminating or imaging high-$Z$ materials, MST has been used conveniently as the scattering angle becomes larger with increase in $Z$ and $\rho$ which makes its measurement executable. Apart from imaging based on scattering and stopping of muons, there has been example of devising a new method for imaging very low-$Z$ and extremely light material using muon-induced secondary radiations. A unique application of the said process in imaging of organic soft tissue, polymethyl methacrylate and water can be found in [21] which would be impractical to achieve using MST.

The imaging of civil structures has turned out to be a necessity of modern age to maintain various civil constructions, like buildings, bridges, highways, tunnels, dams, etc. Several standard nondestructive evaluation (NDE) techniques to mention are, namely ultrasonic tomography [22,23], infrared (IR) tomography [24,25], ground penetrating radar (GPR) [26], impact-echo [27], etc., which have been practiced widely for many decades to address diverse issues of imaging. For example, the ultrasound technology has been found very fruitful in identifying delamination of concrete bridge decks and corrosion of steel rebars [28], but it is difficult for ultrasonic waves to penetrate attenuating materials, like steel- and fiber-reinforced plastic [29] which are used as outer layers of composite elements in civil structures. Similarly, IR thermography is successful in scanning bridges, roads and airport pavements [30,31]. However, there are some limitations as well, such as requirement of a large amount of heat to image non-conducting materials (active thermography), interference of environmental parameters, like sunlight intensity (passive thermography), shadow of other bodies, wind, etc. [24] The radiological imaging methods using X-ray and gamma-ray are very effective but not preferred due to their potential of biological hazards. On the contrary, the minimum-interacting property leading to high-penetration and biologically non-hazardous nature of cosmic muons along with their abundant availability gives the muon transmission or scatter-
ing tomography an edge over other imaging techniques. In [32], MST has been advocated to be used as a NDE technique for its application in civil imaging with critical comparison to others.

Although the application of MST for imaging concrete-like light materials can be non-trivial, there have been several applications of imaging iron bars inside reinforced cement concrete (RCC) structures [32–34]. The promising outcomes of these investigations are encouraging for using MST in imaging civil structures. In the present work, an attempt has been made to go one step beyond and investigate the credibility of MST in identifying defects in concrete structures using images produced by a given MST setup. A few cases of defects, such as air voids and corrosion of metallic components, that appear frequently in civil structures, have been opted as test cases in this work. Each of these problems is unique in nature and possesses different kinds of challenges for imaging. These defective structures have been imaged using a MST setup constructed in Geant4 [35] simulation framework. The flexibility in design, low-cost fabrication along with suitable spatial and temporal resolutions make the gaseous ionization detectors one of the most suitable options to be used for muon tomography applications [18,36]. So, the present setup has been designed with a generic parallel plate micro-pattern gaseous detector (MPGD) with very good position resolution for tracking the incident and scattered trajectories of the muons. The simulated images have been further processed and analyzed with the t-statistics and PRM to study efficacy and limitation of the present method of MST for its application in imaging of civil works.

The content of this article has been organized in the following way. Details of the imaging setup, detector dimensions, and their placement, target specification, etc., have been described in Sect. 2. The algorithm for defect identification and evaluation of degree of discrimination has been narrated in Sect. 3. The imaging results and their analysis can be found in Sect. 4 and the conclusive statements in Sect. 5.

### 2 Simulation scenarios

The MST setup constructed in Geant4 for imaging several test cases is shown in Fig. 1 along with an instance of a target. Two sets of three tracking detectors have been placed in

![Fig. 1 MST imaging setup as modelled in Geant4. The muon-hits on the tracking detectors have been marked with stars](image-url)
| Specification          | Rusted Rebar in RCC | Void in CFST | Void in Concrete Deck |
|------------------------|---------------------|--------------|-----------------------|
| Detector Area          | 60×60 cm²           | 70×70 cm²    | 140×140 cm²           |
| Target                 | Concrete Volume: 25×10×10 cm³ | CFST Length: 30 cm | Concrete Volume: 80×80×15 cm³ |
|                        | Rebar Length: 24 cm  | CFST Dia: 16 cm       | Steel Thickness: 5 mm |
|                        | Rebar Dia: 3 cm      |                       |                       |
| Defect                 | Rust Thickness: 4.5, 2.25 mm | Void Thickness: 10, 7 mm (side-on), 10 mm (bottom) | Spherical Void Dia: 6.74, 5.64 cm |
|                        | 30%, 15%            | 12.5%, 8.75%, 6.25% | 40%, 33.33%          |

parallel on either sides of the region of interest (ROI) where the targets are to be placed. The separation between the detectors is 7 cm. The detectors, each having a gas thickness of 2 mm, have acted as trackers in order to record two-dimensional (2D) position information of the muon-hits (marked in red star). A spatial resolution of 200 μm of the detectors has been implemented by introducing a random uncertainty to the \( X \) and \( Y \) coordinates of the respective muon-hits. The corresponding angular resolution of the setup has been found to be 1.16 mrad. The area of the detectors governs the solid angle acceptance of the setup and hence has to be optimized for uniform exposure across the ROI. Thus, for each test case, it has been varied according to the target size as mentioned in Table 1. The muon events have been generated using cosmic-ray library (CRY) [37]. A variable cosmic-ray exposure equivalent to 3–90 days has been used for imaging the test cases.

Three examples of typical defects commonly found in concrete structures [23,24,38] have been considered as test cases in the present work. For each case, a variation of defect dimension has been simulated to validate consistency of the imaging technique and study its limitation as well. The percentage of defects along the \( Z \)-direction (the direction of cosmic muon exposure) has been furnished for all the cases in Table 1. The gap between the upper and lower detector layers has been kept 50 cm for all three cases. However, the \( XY \)-plane stretch has been decided according to the length of the target to ensure hit uniformity. A brief description of each of the test cases has been provided in the following subsections.

### 2.1 Rusted rebar in RCC

RCC structures with steel rebars have been used for a long time to build civil structures. The most common problem in such structures is the rusting followed by corrosion of rebars which is caused by their exposure to the atmosphere, rainfall, concrete–metal contacts, etc. [39]. Various NDE techniques have been implemented to identify the rusted region in rebars, such as half-potential method [40] and thermal imaging [38,41]. In [38], a quantitative measurement of corrosion has been done by thermography using electromagnetic induction. A similar structure but with multiple corroded regions has been constructed in Geant4 for the present work. Three different views of the geometry are shown in Fig. 2 where all the materials, namely the concrete (in light gray), steel (in red) and rust (in dark gray), have been marked. The RCC volume with the steel rebar embedded at its center has been placed at the middle of the ROI with its central axis lying along the \( X \)-direction. In the simulation model,
Fig. 2  Three different views of the geometry of the rusted rebar in RCC as constructed in Geant4. The concrete block (in light gray), steel rebar (in red) and rust (in dark gray) have been marked. The target is placed at the center of the ROI with its central axis lying along the $X$-direction

Fe$_2$O$_3$ composition has been used as rust with density 5.25 g/cc, while steel and concrete have been simulated with densities 7.87 g/cc and 2.3 g/cc, respectively. The thickness of the rusted ring has been varied following two different values as mentioned in Table 1.

2.2 Void in CFST

Concrete-filled steel tube (CFST) is a cost-effective solution for implementing in large numbers in constructing truss elements and columns in high-rise buildings. The comprehensive strength of concrete and confinement along with the rigidity of steel can make the combination carry more load than individual elements [42]. However, voids and de-bonding ring gaps can occur between concrete and steel due to fluidity before initial setting or dry shrinking during use [43]. These types of defects reduce the load carrying capacity of the CFST which is considered as a critical problem in civil engineering. Due to shielding effect, high density and low radiation length of steel, imaging of defects in CFSTs is a difficult task for traditional NDE techniques such as electromagnetic waves, impact echo technique, X-ray and gamma-ray [44]. Several experimental works have been done to identify and image the de-bonding occurring in CFSTs [23,45,46]. Similar to one of the specimen structures described in [23], a test case has been constructed in Geant4 with 50% circumferential void near the steel edge. Three different views of the geometry are shown in Fig. 3 where the steel tube (in light brown), concrete (in light gray) and void (in white) have been marked in $YZ$-plane view. The CFST has been placed at the center of the ROI with its central axis lying in the $X$-direction. Unlike the previous example of defective rebar, the CFST defect is not symmetric to the rotation in $YZ$-plane. Therefore, to allow maximum exposure of the muons to the void region, the CFST has been placed such that it faces one side ($Y$-direction), shown as ‘side-on’ in the $YZ$ and $XY$-planes. To test the robustness of the imaging setup, another orientation of the CFST where the void region faces the bottom detector layers has also been simulated, shown as ‘bottom’ in the $YZ$ and $XY$-planes. Two thicknesses of the circumferential void which are 7 and 10 mm and two orientations of 10 mm void which are bottom and side-on have been considered, as mentioned in Table 1.

2.3 Voids in concrete deck

Another common problem found in concrete structures is subsurface voids and delaminations in concrete decks. These defects make the bridge decks structurally deficient. Different NDE
techniques, such as IR thermography and GPR, have been used to identify the delaminations and voids in concrete decks [47,48]. The detection of these subsurface defects depends upon their size and position inside the concrete deck. In some research works carried out to identify such defect [24,25], it has been reported that the amount of concrete covering has a substantial impact on imaging the defects. Therefore, it would be easier to image defects if they are not buried deep inside. In [24], IR imaging has been used to detect shallow defects inside concrete decks where a few bridge decks have been constructed with several voids and delaminations. In this work, a similar kind of geometry has been constructed in Geant4 with some voids. Three different views of the geometry are shown in Fig. 4 where the concrete deck (in dark gray) and voids (in red) have been marked in the $XY$-plane view. The voids in each row have been placed at three different depths (4, 8 and 12 cm from the top) to consider the effect of randomness in concrete cover. In reality, however, defects are not expected to follow any such defined pattern. In order to maintain arbitrariness in the nature of the voids, two different shapes of voids (spherical and cubical) have been implemented. The cross section of the voids has been made comparable to receive similar muon exposure. Therefore, for length of the cubical void, $a$, and the diameter, $d$ of the spherical void, their cross section remains the same ($\pi d^2 / 4 = a^2$). Two different dimensions of the voids have been used as mentioned in Table 1.

3 Detection methodology

In MST, the incoming and outgoing tracks of cosmic muons are used to find scattering vertices in the ROI and determine the scattering angle ($\theta$). In the literature, various algorithms can be found to identify the scattering vertices [9,10,49,50]. The point of closest approach (PoCA) [49,51,52] is a reasonably accurate and relatively simpler algorithm among them which determines a single scattering vertex from the intersection or the closest approach of the extrapolated incoming and outgoing tracks. Although the mcs process is not considered in this algorithm, it is widely used due to its fast computation and fairly precise performance [17,53]. In the present work, the PoCA algorithm has been implemented to determine scattering vertices and scattering angle using C++ with links to ROOT [54] for data handling and plotting. While doing the reconstruction, a couple of selection criteria has been implemented:
Fig. 4  Three different views of the geometry of the defective concrete deck as considered in Geant4. The concrete deck (in dark gray) and spherical and cubical voids (in red) have been marked. The deck has been positioned in the \( XY \)-plane at the center of ROI. The placement of the voids at different depths (4, 8 and 12 cm from the top) has been shown in the \( XZ \)-plane view.

(i) The track should have registered hits in all six detectors, and (ii) the PoCA reconstructed point should fall inside the ROI.

The vertices obtained with small scattering make it difficult to distinguish targets from the empty space filled with air which we would refer to as background. As the concerned test cases are mostly concrete-based, the expected scattering angles are much smaller in comparison with other applications of MST involving high-Z materials which inflates the background perplexity. Hence, it is necessary to use a threshold of the scattering angle, \( \theta_{th} \), to filter the background which actually depends on the target to be identified. In context of the present work, a simulation has been performed with three cubical targets each of side 7 cm, constructed from steel, concrete and rust which are commonly found in any civil structure. Figure 5 shows the images obtained on the basis of projected scattering vertices for a muon exposure of half-an-hour following the method described in [4] and further filtered with three different \( \theta_{th} \) values. It is evident from the images that the target-to-background (signal-to-noise) ratio improves with the increase in \( \theta_{th} \). As a result, the threshold, \( \theta_{th} = 10 \) mrad, has been opted for the present numerical work to filter the background or the noise. The scattering vertices have been then projected to the central \( XY \)-plane of the ROI to obtain a 2D map. It has been further pixeled with a definite size, and each pixel has been weighted by a parameter \( S \) as defined in Eq. 3.
\[ S = \sum_{k=1}^{\rho_c} \theta_k, \]  
\[ \theta_k = \sqrt{\theta_{xz}^2 + \theta_{yz}^2} \]

Here, \( \rho_c \) represents the number of scattering vertices and \( \theta_k \) is the scattering angle at the \( k \)-th vertex. \( \theta_k \) has been calculated using the deviation angles projected on the orthogonal planes which are \( \theta_{xz} \) and \( \theta_{yz} \). The pixel size for each test case has been optimized for target area and horizontal (\( XY \)-plane) stretch of the defects. The pixel sizes are 2.5 mm, 4 mm and 8 mm for the cases of rusted rebar in RCC, void in CFST and void in concrete deck, respectively.

It can be followed from Eq. 3 that the parameter \( S \) is the sum of the scattering angles at all scattering vertices in the given pixel that passes through the filter, \( \theta_{th} \), and is measured in units of radian. This weighted 2D scattering map (we would refer to as \( S \)-map henceforth) has been subjected to further analysis.

The discrimination of the defective targets from the perfect targets (without any defect) has been done following a statistical test as well as the PRM technique applied on the \( S \)-maps obtained for different test cases.

### 3.1 Discrimination significance by t-statistics

The t-statistics is a widely accepted analysis tool for comparing the mean of a test distribution to that of a reference to determine whether there is a significant difference between them. It is quantified by the t-value which measures the difference relative to the variation of the reference distribution. The larger the magnitude of t-value, the greater is the departure from the null hypothesis that considers both the distributions to be identical [55]. In this present work, the t-test has been used for comparing the \( S \)-maps of the target with and without defects in each of the test cases. The pixels with nonzero entries in the \( S \)-map of perfect target (without any defect) constitute the reference distribution, and the same pixels in \( S \)-map of defective target (they may contain zero or nonzero values) form the test distribution. This way both the distributions are independent and approximately normal. \( \mu_1 \) and \( s_1 \) are the mean and standard deviation, respectively, of the reference distribution, while \( \mu_2 \) and \( s_2 \) are the corresponding parameters of the test distribution. Both the distributions are constituted for same number of pixels (\( n \)). The t-value has been calculated in each case using Eq. 4.

\[ t = \frac{\mu_1 - \mu_2}{s_v \sqrt{\left[ \frac{1}{n_1} + \frac{1}{n_2} \right]}} \]

\[ \text{with } s_v = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}} \]

For the distributions with same size, \( n_1 = n_2 = n \),

\[ t = \frac{\mu_1 - \mu_2}{\sqrt{\frac{s_1^2 + s_2^2}{n}}} \]

(4)

The \( p \)-value which is the probability of finding the observed t-value or more extreme given that the null hypothesis is true (the \( S \)-maps of the perfect and defective targets are identical) has been estimated. From the \( p \)-value, the statistical significance of the discrimination has
been determined. The significance of $2\sigma$ has been considered as the threshold for identifying the defects in test data.

### 3.2 Discrimination capability using PRM-score

In [4], the basics of processing images with PRM have been explained in detail. The PRM is a step-wise algorithm which learns the physical properties ($Z$ and $\rho$) of the reference target and scans the test targets for similar features. From the $S$-map of the reference/perfect target ($S_p$), a filter sub-matrix $‘K’$ has been constructed which represents constituent materials in terms of $S$-parameter. Then, convolution between $K$ and $S_d$ ($S$-map of the defective/test target) has been performed to examine the regions with common features of the test target. In relation to the present work, the method has been explained on the basis of the example of ‘Void in CFST’ as shown in Fig. 6. From the CFST without any defect, $K$ is formed from arbitrary location as shown in Fig. 6(a). While choosing $K$, several conditions are checked, for example: (i) There should not be any regional bias, which implies that $K$ should neither be chosen from the edge nor from the central region, (ii) it should not be chosen from the location of the defects known a priori, and (iii) it should be chosen from a portion of $S_p$ that has dimensions larger than that of $K$.

The pixels in the regions of the $S$-map which have lower value of $S$-parameter than the filter sub-matrix have been rejected by PRM and are called PRM-rejected pixels. The rest areas which have similar or larger values than the filtering $S$-parameter have been passed, and the constituent pixels are called PRM-approved pixels. It is imperative that if PRM is performed on test objects with features same/higher to the reference, the highest number of PRM-approved pixels will be found. However, for test objects with increased amount of defects, the PRM-approved pixels will be reduced. This technique, seemingly equivalent to a high-pass filter, has been found capable to identify multiple targets in the same ROI. It performs reasonably well in complex scenarios, such as when the target is submerged inside background or when there are different shapes of the target.

In the present work, to numerically quantify the degree of discrimination, a metric, namely PRM-score, has been introduced which evaluates the similarity between the reference and test targets as well as the capability of discriminating them. To put it in a simple way, the
PRM-score specifies the difference between images reconstructed after PRM-processing of the reference and the test target measured in the units of $\delta n$, which is the random error arising out of repeated measurement of PRM on the reference target. A higher value of PRM-score indicates that the PRM-reconstructed image of the test target is less likely to be identical to that of the reference image, whereas PRM-score $< \delta n$ implies that they are not distinguishable. To identify the defect in the concrete structures, $2 \delta n$ has been set as the threshold PRM-score. The procedure of determining the PRM-score can be followed from the example shown in Fig. 7. The PRM-reconstructed image for the perfect (reference) target is shown in Fig. 7a, while that of the defective (test) target can be found in Fig. 7b. The PRM-score of the given example has been expressed in Eq. 5 which can be simplified to Eq. 6. The PRM-score for each of the three test cases considered in the present work has been calculated following Eq. 6. The algorithm to obtain PRM-score has been described below.

$$\text{PRM-score} = \frac{\text{No. of pixels in}'R_p'(n) - \text{No. of pixels in}'R_d'(n - m)}{\text{No. of pixels in}'R_p'(n)} \times \frac{1}{\delta n}$$  \hspace{1cm} (5)$$

After simplifying,

$$\text{PRM-score} = \frac{m}{n \times \delta n}$$  \hspace{1cm} (6)$$

Algorithm of PRM-score:

- **Input:** Matrices of $S$-parameter for 2D $S$-map of reference, $S_p$, and test, $S_d$.
- **Step-1:** The filter sub-matrix ‘$K$’ is chosen randomly from un-biased location of the target region of $S_p$ as shown in Fig. 6.
- **Step-2:** ‘$K$’ is convoluted to mother matrix, ‘$S_p$’ and the number of approved PRM-approved pixels is calculated (say ‘$n$’).
- **Step-3:** The random error which may arise if ‘Step-2’ is repeated is considered to be $\delta n = \frac{1}{\sqrt{n}}$ according to Poisson statistics.
- **Step-4:** ‘$K$’ is convoluted to test matrix, ‘$S_d$’ and the number of PRM-approved pixels is calculated (say ‘$n - m$’). Here, ‘$m$’ is the number of pixels in the non-approved region (defective region).
- **Step-5:** The PRM-score is calculated using Eq. 6.
- **Output:** The PRM-score for the test case is returned in the units of $\delta n$. Comments on similarity or difference between reference and test is provided.
4 Results

The $S$-maps of the test cases as obtained from the Geant4 simulation have been furnished below along with PRM-reconstructed images. The statistical significance obtained from the t-test and the PRM-score is listed in Table 2.

4.1 Detection of targets and defects

Figure 8 shows a collection of $S$-maps and PRM-reconstructed images of three different states of steel rebar (perfect, 15% and 30% rust). The left-hand side plots show the $S$-maps of the aforementioned three states as produced by the Geant4 simulation, while the PRM-reconstructed images of the same have been depicted on the right-hand side. The color axis in the $S$-maps shows the $S$-parameter accumulated in different pixels. In the PRM-reconstructed images, the pixels approved by the PRM have been shown in red, while the rejected ones are in gray. It can be noted from Fig. 8a and b, depicting the cases of perfect rebar in RCC, that the concrete volume is clearly segregated from the background and the steel rebar has been discriminated from the concrete volume. In Fig. 8c and e, the defective (rusted) parts can be seen with low $S$-parameter in comparison with the steel section. It can be noted that the clarity has improved with the defect percentage, i.e., for the case of 30% rust, shown in Fig. 8e and f, the defect is much clearer than the case of 15% as shown in Fig. 8c and d. The same observation can be made from the plots displayed in Table 2. It can be observed from the plots in Fig. 8 that the PRM technique can perform reasonably well in identifying the defect although it is not very efficient in determining its shape. For the case of 15% defect, rust thickness becomes 2.25 mm which is smaller than the image pixel size (2.5 mm) and this sets up the lower limit of the technique. The same can be concluded from the statistical significance of 2.29 which is barely above $2\sigma$ and the PRM-score 1.48 which is also less than the discrimination threshold $2\delta n$.

Figure 9 displays the $S$-maps and corresponding PRM-reconstructed images for the perfect and defective cases of CFST. Figure 9a, b displays the CFST without any defect, while images of the CFST with 7 mm and 10 mm wide circumferential voids in the side-on orientation are shown in Fig. 9c–d, respectively. Figure 9g, h shows the results of 10 mm wide void facing towards the bottom detectors. It can be noted that the voids have been identified in all the cases of the CFST. Significant concrete cover and outer steel layers are the main causes of uncertainty in reconstruction in this example. Therefore, the void detection is better in the

| Target type     | Defect dimension (mm) | Statistical significance | PRM-score |
|-----------------|-----------------------|--------------------------|-----------|
| Rebar in RCC    | 2.25                  | 2.29                     | 1.48      |
|                 | 4.5                   | 4.75                     | 4.45      |
| CFST            | 7 (side-on)           | 5.85                     | 5.52      |
|                 | 10 (side-on)          | 8.10                     | 7.94      |
|                 | 10 (bottom)           | 7.22                     | 7.50      |
| Concrete deck   | 50                    | 4.2                      | 5.62      |
|                 | 60                    | 4.89                     | 7.98      |
Fig. 8  a, b $S$-map and PRM-reconstructed image for the perfect steel rebar in RCC.  c, d and  e, f same for rebar with 15% and 30% thicknesses rusted, respectively. The parameter $S$ (in rad) has been shown in the color axis for each image. The PRM-approved pixels are shown in red and the rejected ones in gray.
Fig. 9  a, b S-map and PRM-reconstructed image for the CFST without defect.  c, d and e, f same with 7 mm (8.75%) and 10 mm (12.5%) void, respectively, in the side-on position.  g, h show CFST with 10 mm void facing towards the bottom sets of detectors. The parameter $S$ (in rad) has been shown in the color axis for each image. The PRM-approved pixels are shown in red and the rejected ones in gray.
‘side-on’ orientation than the ‘bottom’ orientation. It can be seen from Table 2 that the void in all the cases has been identified with more than $5\delta n$ PRM-score and $5\sigma$ in t-test.

The $S$-maps and PRM-reconstructed images for all the three states of concrete deck (perfect, $\sim 33\%$ and $40\%$ defects) are depicted in Fig. 10. As this problem deals with discrimination between only two types of materials (concrete and void), this test case seems comparatively simpler than the previous ones. However, the low density of concrete makes the image reconstruction challenging. From these plots, it can be noted that the images of larger voids are clearer with better shape detection. As described in Sect. 2.3, the voids have been placed at different depths inside the concrete deck. Evidently, the subsurface voids (at 4 cm from top) have turned out more palpable than the deep ones. Nevertheless, MST has been successful in identifying the defects at different depths which is considered to be very difficult while using other NDE techniques, like IR thermography and ultrasound tomography [24,32,38,56]. From Table 2, it can be noted that the concrete decks with voids have been distinguished from the no-void case with more than $4\sigma$ significance as per t-statistics and it has also crossed more than $5\delta n$ PRM-score.

### 4.2 Variation with defect thickness, muon exposure and scattering threshold ($\theta_{th}$)

The limit of discrimination capability of the present MST system in imaging concrete structures has been studied with the case of ‘Rusted rebar in RCC’ in more detail. The particular test case has been chosen due to its composite geometry with three different materials, concrete, rust and steel, which can offer a considerable variation in $Z$ and $\rho$. The study has been carried out as a function of variation of defect thickness and muon exposure received by the system. The thickness of the rusted part of the rebar has been varied from $15\%$ to $50\%$ for 30 days of cosmic exposure. In each case, the images of the defective target have been compared to the perfect target using t-statistics and PRM-processing. The results are shown in Fig. 11a. The effect of amount of muon exposure on imaging has been studied on rusted rebar with $30\%$ defect. The study has been conducted for five different values of exposure, that is, 3, 7, 15, 30 and 90 days. However, for reduced exposure periods, like 3 or 7 days, the event statistics is very low ($\sim 10^4$). To compensate this, the cut described in Sect. 2, $\theta_{th}$, has been removed. The obtained results are shown in Fig. 11b. The thresholds for identifying the defects with both t-test and PRM-technique have been marked in the plots. From figure (a), it can be observed that the $15\%$ and $20\%$ defects with PRM-score $< 2\delta n$ are hardly distinguishable, whereas they have been discriminated with marginally higher than $2\sigma$ significance in terms of t-statistics. From figure (b), it is evident that results for 3 days exposure are less than $2\delta n$ and $2\sigma$, and it has been observed that for this exposure among the cases considered here, only the case of $50\%$ defect could be identified with good significance.

As described in Sect. 3, $\theta_{th}$ was introduced to improve signal-to-background ratio. For cosmic exposure of 30 days, the event statistics recorded for $\theta_{th} = 0$ mrad (no-cut) is $4.9 \times 10^8$, whereas for $\theta_{th} = 10$ mrad it is $1.3 \times 10^5$. Although the event statistics has reduced significantly due to the cut $\theta_{th}$, it does not affect the ability to identify defects. For example, statistical significance obtained for rusted rebar with $30\%$ defect is 4.75 for $\theta_{th} = 10$ mrad and 4.74 for $\theta_{th} = 0$ mrad. Thus, for long exposures like 30 days, increased statistics does not improve the discrimination rather adds to the background. However, for shorter duration like cosmic exposure of 7 days, the statistical significance obtained for $\theta_{th} = 10$ mrad is 2.82 and for $\theta_{th} = 0$ mrad is 3.12. This is resulted due to the huge decline in the event statistics. Consequently, the choice of $\theta_{th}$ depends on the problem at hand. For instance, given a thinner defect it is advisable to use a substantial threshold for sharp edge detection.
Fig. 10  a, b $S$-map and PRM-reconstructed image for the concrete deck without defect. c, d and e, f same with 5 cm (33.33%) and 6 cm (40%) voids, respectively. The parameter $S$ (in rad) has been shown in the color axis for each image. The PRM-approved pixels are shown in red and the rejected ones in gray. The voids at 4 cm depth are at the extreme right, and depth increases from right to left in steps of 4 cm. Instead of showing the plots for the whole ROI, a magnified view has been shown for all three states of the concrete deck. This way, the voids are more noticeable.
and to avoid excess noise. On the contrary, a sizeable defect can be identified within a shorter period of time (~7 days) with a small value or no threshold.

4.3 Systematic uncertainties

The image formation and identification of defects are based on the $S$-parameter, which in turn depends on scattering angle and clustering density. Measurement of these quantities relies on several parameters, such as gap between the detectors, area of the detectors, detector spatial resolution, additional support materials for the MST system, alignment and stability of the detector [57]. Moreover, gaseous detectors are known to display uncertainties due to atmospheric parameters, like temperature, pressure and relative humidity. The systematic uncertainty involving detectors has been assumed to be $\sigma_{det} \approx 10\%$. Similarly, the cosmic muon flux has certain uncertainties due to geographical parameters, such as altitude and latitude of the place where the test setup is situated, variation in atmospheric density due to solar activity, cloud coverage, meteorological parameters, such as temperature and pressure [58, 59]. According to [59], the uncertainty in muon flux measurement has been found to be $\sigma_{flux} \approx 2.4\%$. These uncertainties will affect the estimation of the $S$-parameter. For making the imaging technique more robust, a cumulative uncertainty, $\sigma_{cum}$, has been added to the calculation of statistical significance and PRM-score according to Eq. 7. The data in the $S$-map of the reference distribution have been kept constant, and each pixel content of the test distribution has been individually varied with a Gaussian uncertainty of $\sigma_{cum} = 10.5\%$ and the t-test as well as the PRM analysis has been carried out.

$$\sigma_{cum} = \sqrt{\sigma_{det}^2 + \sigma_{flux}^2} \approx 10.5\%$$  \hspace{1cm} (7)

This process has been repeated 1000 times, and each time the statistical significance and PRM-score have been calculated. The result follows a Gaussian distribution. Taking the uncertainty into account, for the test case of 30% rusted rebar with 30 days of cosmic exposure and $\theta_{th} = 10$ mrad, the statistical significance and PRM-score turn out to be $4.67 \pm 0.22$ and

![Fig. 11 a](image-url) The statistical significance and PRM-score of different rust thickness (15–50%) obtained with 30 days of cosmic exposure and $\theta_{th} = 10$ mrad. b Variation of same metrics with different muon exposure (3, 7, 15, 30 and 90 days) for the case of 30% rust and $\theta_{th} = 0$ mrad. The threshold for identifying the defects, $2\sigma$ for t-statistics and $2\delta_n$ for PRM-score have been marked.
4.18 ± 0.45, respectively. Similarly, for the same test case with 7 days of cosmic exposure and θth = 0 mrad, the statistical significance and PRM-score turn out to be 3.05 ± 0.23 and 3.63 ± 0.60, respectively. From these values, the experimenter gets an idea about the error in the obtained final results. Moreover, some of the uncertainties related to operational conditions of the detector can be taken care of using methods like temperature–pressure correction mechanism [60,61].

5 Conclusion

In this work, a numerical study has been carried out to investigate the capability of a MST system in identifying defects of civil structures. The study has been performed in Geant4, assuming an imaging setup consisting of parallel plate gaseous ionization detectors. Three test cases have been considered: steel rebar in RCC, CFST and concrete deck with some commonly occurring defects. Each test case is unique in its structure and composition and known to be pretty challenging for other NDE techniques. Two different dimensions of defects have been studied in each test case. The identification of the defects has been carried out by analyzing 2D scattering images (S-maps) obtained for the test cases. The S-maps have been processed with a pattern recognition method to improve defect identification. The images obtained for defective cases have been compared to perfect cases, and the efficacy of the MST system has been expressed in terms of statistical significance obtained from t-statistics and a metric devised in this work, namely the PRM-score. The present MST system has been found to be able to quantify defects reasonably well. It has been able to identify defects with more than 2σ precision following t-statistics in all the test cases. Similarly, defects in all the test cases have been confirmed with more than 2δn PRM-score except for the case of 15% defect in steel rebar. Thus, for a given muon exposure of a month, the limit of detection capability is found to be 2.25 mm (15% of the thickness of rebar). Moreover, rebars with rust equivalent to 15% and 30% thickness could be distinguished from each other with more than 2σ confidence and more than 3δn PRM-score. In the same manner, de-bonding gaps of about 8% and 12% thickness of CFST could be distinguished from each other with more than 2σ confidence and more than 1δn PRM-score. The identification of voids of spherical and cubical shape at different depths in the concrete deck has also been achieved with the present MST setup. It has also been shown that with increased exposure, the precision of defect identification improves. All things considered, the authors conclude that using cosmic muons and detectors with a decent spatial resolution (200 μm), MST can be used to identify critical defects in different types of concrete structures with a nominal exposure of around ∼ 7 days. However, a muon exposure of around 30 days is required to identify finer defects with significant precision.

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