

Diffraction in Millimetre Wave Compressive Imaging

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ABSTRACT

This letter examines the impact of diffraction on image reconstruction quality in millimetre wave compressive imaging. In the millimetre wave frequency range, the dimensions of coded aperture patterns are often on the order of a wavelength λ . As a result, significant diffraction occurs, unlike in typical visible-spectrum imaging systems, where the patterns are many times a wavelength. However, the impact of severe diffraction is sometimes overlooked in the millimetre wave compressive imaging literature. In this work, the mechanism of how diffraction interferes with compressive imaging systems is investigated via first principles in physics and EM simulation. Our analysis provides an illustrative yet insightful reference to the diffraction limits on millimetre wave compressive imaging.

1 | Introduction

Millimetre-wave imaging has become increasingly important in scenarios where optical imaging systems fail due to occlusions, concealment, or poor lighting conditions [1–6]. In contrast to conventional X-ray technology [7, 8], millimetre waves are non-ionising, making them particularly suitable for personnel screening and security applications [1, 4–6]. Modern commercial millimetre-wave imaging systems provide high-resolution 3D focusing capabilities achieved through sophisticated holographic imaging theory [4, 5]. The associated signal modulation requirements lead to bulky, complex, and costly systems. Passive millimetre-wave imaging offers a simpler alternative, relying solely on naturally emitted radiation intensities rather than phase or frequency information [1, 6]. Nevertheless, both active and passive approaches suffer from inherent challenges: limited resolution and high hardware costs, as even a single imaging receiver is large and difficult to integrate into dense arrays.

To circumvent the need for large sensor arrays, the single-pixel camera (SPC) method – initially developed for visible-spectrum imaging based on compressive sensing (CS) theory [9] – has been adapted for millimetre-wave imaging [10–14]. In this architecture (Figure 1), the scene is modulated by a sequence of coded

apertures, and the transmitted energy is aggregated by a lens and measured by a single detector. Following the labelling convention in Figure 1, the system resolves

$$y = Ax + z \quad (1)$$

where the noisy measurement vector $y \in \mathbb{R}^M$ is generated by the matrix-vector product of a known sensing matrix $A \in \mathbb{R}^{M \times N}$, $M \ll N$, and the unknown high-dimensional sparse input signal $x \in \mathbb{R}^N$; interference and measurement noise are denoted by $z \in \mathbb{R}^M$. Although in theory the entries of A may take any values, in practice, the entries of a standard physical CS system are often drawn independently and identically from $\{0, 1\}$ with equal probability; such pseudorandom binary patterns correspond directly to two-level (opaque/transparent) aperture pixels in SPC and retain the recovery guarantees of CS theory [9]. Compressive sensing enables reconstruction from far fewer measurements than required by a raster scan ($M = N$, $A = I_N$), reducing acquisition time and complexity while preserving essential image structure. This is particularly advantageous for millimetre and terahertz frequencies, where hardware is bulky and expensive, making large arrays difficult to realise. However, directly transferring visible-spectrum SPC models to the millimetre-wave regime introduces a critical challenge: *diffraction*, which is typically

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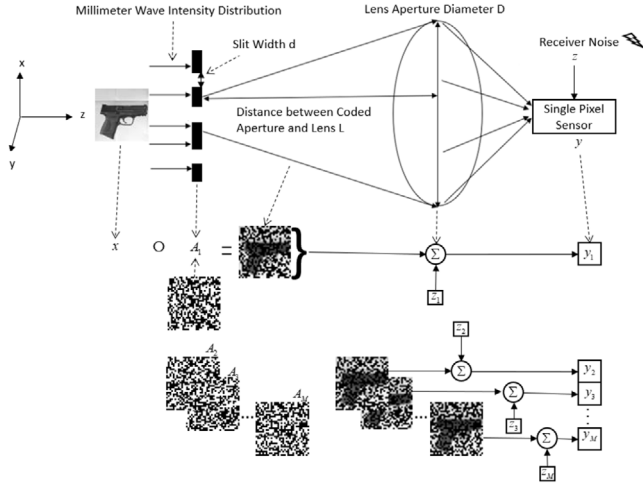


FIGURE 1 | SPC data acquisition process and hardware schematic. The symbol $\circ$ represents Hadamard products. The coded aperture for the m th measurement y_m is denoted by A_m , corresponding to the m th row of sensing matrix A in (1). Summations over both axes are denoted by Σ .

negligible at optical wavelengths but becomes significant at millimetre-wave frequencies.

We investigated the exemplar SPC architecture shown in Figure 1 to understand the limitations of diffraction in SPC-type millimetre-wave compressive imaging systems. The reconstructed image dimension is typically determined by the coded aperture size, while the resolution is dictated by the pixel size of the coded apertures. For security screening applications, the pixel size must be sufficient to capture the details needed for reliable object detection. To reliably detect small objects such as a razor blade, the coded aperture pixel size must be a fraction of the 94 GHz wavelength—yet such small pixel sizes inevitably lead to severe diffraction at this frequency band.

This phenomenon, known as pixel diffraction [15], is often overlooked in existing millimetre-wave compressive imaging designs [10, 11]. In Gopalsami et al. [12], diffraction was modelled heuristically as an effective SNR reduction, an approach that does not capture the varying degrees or spatial structure of diffraction-induced distortions. Schmitt et al. [15] studied pixel diffraction using 1D EM simulations of synthetic patterns, providing useful but limited insights, as such patterns do not represent realistic imaging conditions and lack accompanying theoretical interpretation. As a result, the underlying mechanism by which diffraction degrades CS reconstruction performance has not been fully investigated.

In this work, we systematically analyse how diffraction affects millimetre-wave compressive sensing systems. We examine the conditions under which pixel diffraction disrupts the linear modulation model (1), derive the diffraction resolution limit using both the Fraunhofer approximation and Maxwell's equations [16], and validate these findings using full-wave EM simulations (Ansys HFSS). The framework applies directly not only to millimetre-wave imaging but also to terahertz imaging systems where pixel diffraction remains relevant.

2 | Pixel Diffraction Analytical Analysis

The study starts with a first-principle analysis of the mechanism of how diffraction interferes with the SPC system. Compressive image sensing relies on a linear signal model, Equation (1), and corresponding CS algorithms [17, 18]. The validity of this linear model fundamentally relies on the assumption of linear superposition: that the total energy measured at each time is the simple sum of the energy transmitted through all open slits, i.e., the transmittances (T 's) of all open slits measured at the single-pixel receiver are uniform. Because the single-pixel receiver sums all spatial intensity into a single reading (Figure 1), if the focusing lens dimension is large spatially compared to the coded aperture/image size, pixel diffraction does not alter the single-pixel receiver measurements or the compressive imaging performance. However, if the size of the focusing lens is comparable to the image size, the power contributed from each open pixel varies drastically depending on the spatial intensity distribution diffracted from the corresponding pseudorandom pattern. The following analysis derives the theoretical pixel diffraction limit due to nonuniformity of T 's, which invalidates the CS linear model.

2.1 | Fraunhofer Diffraction Analysis

For far-field diffraction [19], the spatial intensity distribution can be modelled by the Fraunhofer equation [20]. In polar coordinates:

$$I_{2D,F}(\theta, \phi) \propto \text{sinc}^2\left(\frac{\pi d \sin \theta}{\lambda}\right) \text{sinc}^2\left(\frac{\pi d \sin \phi}{\lambda}\right), \quad (2)$$

with $\theta = \arctan(x/z)$ and $\phi = \arctan(y/z)$ in Cartesian coordinates, where (x, y, z) is the spatial location of interest, assuming a monochromatic plane wave propagating in the z direction and a diffracting square at the origin in the $(x, y, 0)$ plane.

To quantitatively understand how spatial intensity distribution varies the transmittance of each pixel, an exemplar hardware arrangement is analysed in MATLAB. The ideal 1D receiver lens is modelled as 20 mm in length and positioned 9 mm from the diffraction slit. The pixel size is set to $d = 0.5$ mm, and the wavelength λ is varied such that $n = d/\lambda \in [0.1, 1.2]$ (horizontal axis in Figure 2). For a single-pixel slit of width d , $n = 0.2$ corresponds to severe diffraction (slit width $= 0.2\lambda$), while $n = 1$ corresponds to mild diffraction (slit width $= \lambda$). This arrangement satisfies the conditions for the Fraunhofer approximation [19]. Figure 2 demonstrates the transmittance T of a single-pixel slit and a two-pixel slit for $n \in [0.1, 1.2]$, as well as the gap between the two transmittance values. Since slit width can only be integer multiples of pixel size d , T remains approximately constant when the single slit width $> n^*\lambda$, where $n^* = 0.6$ is the onset of rapidly diverging transmittance gap, implying significant nonuniformity in T due to varying slit sizes.

2.2 | Vectorised Diffraction Analysis

The Fraunhofer diffraction equation is widely used due to its simplicity and consistency with empirical far-field results

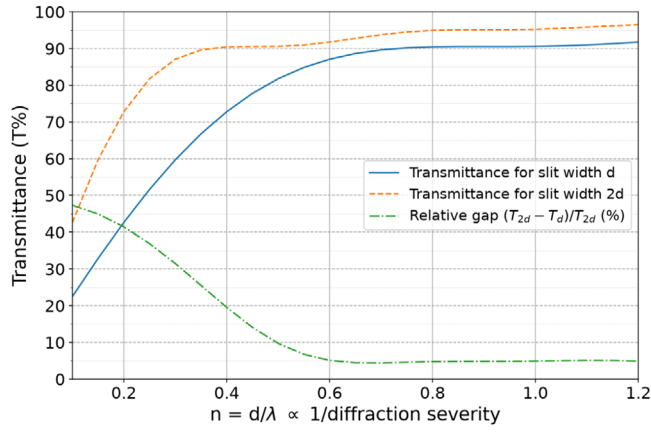


FIGURE 2 | 1D slit experiment: transmittance ($T\%$) vs. $n = d/\lambda$. Divergence in T between the two curves indicates non-uniformity that invalidates the CS model assumption.

[19, 20]. However, in the classical optics literature, it is explicitly specified or implicitly assumed that the dimensions of diffracting objects are at least $\approx \lambda$ [20]. By neglecting interactions between the scattered E and H fields, 3D Maxwell's equations may be decoupled into scalar wave equations, which converge to the Fraunhofer equation in the far field [20]. Although these approximations are naturally satisfied in conventional optical systems, their validity becomes questionable for millimetre-wave imaging systems. To validate the pixel diffraction limit at a fraction of a wavelength ($n^* = 0.6$) and for arbitrary hardware arrangements not necessarily in the far field, we resort to a numerical method based directly on Maxwell's equations [16].

The integral of the Poynting vector normal to the receiver lens plane over the lens aperture (20 mm) is taken as the single-pixel measurement: $P_{\text{rec}} = \int_{\text{lens}} (-\hat{j}) \cdot \frac{1}{2} \Re(E \times H^*) dx$, with $E = 1$ V/m assumed without loss of generality. The transmittance for a slit is then $T\% = P_{\text{rec}} / (\frac{a}{2\mu_0 c}) \cdot 100\%$, where a is the slit width. As a vectorised diffraction analysis, the diffracted field depends on the orientation of the linearly polarised field; the final field may be considered as a linear combination of the two extreme cases – s and p polarisations [16], corresponding to the source EM field being perpendicular and parallel to the slit edge, respectively. To compare the polarisation-dependent vector solution with the single scalar Fraunhofer curve, we construct an equivalent transmittance T_{eq} for a square pixel with the incident field aligned with the pixel grid; the two transverse aperture dimensions attenuate the field as the s- and p-configurations, respectively. Above the fundamental waveguide cutoff limit ($d/\lambda > 0.5$), the aperture supports propagating modes, and these orthogonal polarisation states remain approximately decoupled. Under this decoupling assumption, the total 2D pixel transmittance factorises as $T_{2D} \approx T_s \cdot T_p$. The equivalent 1D per-dimension transmittance is therefore defined by the geometric mean, $T_{\text{eq}} = \sqrt{T_s \cdot T_p}$. Because the onset of a rapid dip in the transmittance curve occurs at $n^* = d/\lambda = 0.6$ as demonstrated in Figure 3, the independent modal propagation assumption remains physically consistent at the identified limit. However, if a specific hardware geometry or lens configuration shifts the transmittance drop-off boundary deep into the sub-cutoff regime ($d/\lambda < 0.5$), the independent factorisation assumption breaks down due to severe cross-polarisation

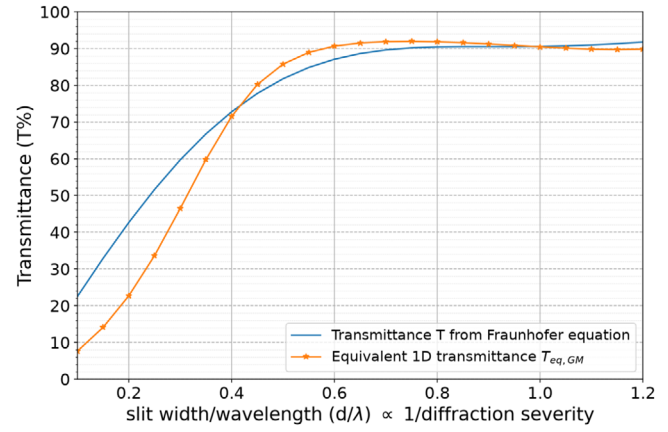


FIGURE 3 | Transmittance for slit width $a \in [0.1\lambda, 1.2\lambda]$, comparing Fraunhofer and vectorised (Maxwell's equations) analyses.

coupling. In such scenarios, EM simulation may be used to study the diffraction property of the specific arrangement.

It is interesting to note that though the diffraction model does not follow the fundamental assumptions of scalar Fraunhofer diffraction theory when the slit size falls below λ , the Fraunhofer result is impressively close to the result from this significantly more sophisticated first-principles approach – consistent with the claim [21] that scalar diffraction theory can perform satisfactorily accurately, quite often beyond its assumed limitations. In the case of SPC, this could be attributed to the uniquely measurement modality – the measurement is an integral of power density over the lens window, and hence insensitive to the spatial details in the EM waveform.

3 | Diffraction Analysis via EM Simulation

To accurately assess the impact of pixel diffraction on a full compressive image sensing system, it is crucial to separate it from other sources of uncertainty. In practice, quantitatively isolating pixel diffraction is highly challenging at the millimetre-wave band. Other distortions – such as fabrication imperfections, experimental implementation variability (noting that single-pixel measurements are carried out sequentially hundreds of times per image), and nonlinearities in electronic and optical components – interfere with the analysis. Instead, diffraction is investigated using a finite element method (FEM) simulator (Ansys HFSS) to solve Maxwell's equations and calculate the field intensity of a single-pixel CS imaging system. Before implementing the CS imaging experiment, EM simulations for slits at different diffraction severity levels were compared against analytical results [16] and validated to be consistent with the vectorised diffraction analysis. Each reconstructed image required 10–30 days of computational time on a dedicated 24-core Xeon server with 384 GB RAM.

The object feature under investigation is adopted from [10], which has demonstrated superior reconstruction quality with the TVAL3 [18, 22] CS algorithm. The detailed parameters are summarised in Table 1 and the simulation workflow is illustrated in Figure 4. MATLAB generates $M = \delta \cdot N = 0.3 \times 32^2 \approx 307$

TABLE 1 | SPC compressive imaging EM simulation parameters

EM simulation parameters	
EM frequency	94 GHz / 188 GHz
Pixel slit width d	1 mm
Character size	12×12 mm
Coded aperture	32×32 pixels
Distance L	2λ
Lens size	24×24 pixels
Meas. rate $\delta = M/N$	0.3

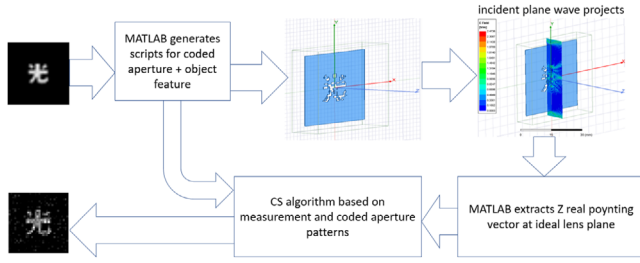


FIGURE 4 | EM simulation study of the impact of diffraction on compressive imaging performance.

coded aperture patterns; in HFSS, perfect electric conductor (PEC) coded aperture plates are merged with the planar object feature and embedded in a vacuum environment. In contrast to physical experiments where the radiation source is fixed and hardware dimensions vary, we fix the hardware and vary the radiation source between 94 GHz (pixel size $d = \lambda/3$) and 188 GHz (pixel size $d = 2\lambda/3$) to reduce reconfigurations in HFSS. The radiation source is configured as a planar incident wave propagating orthogonally to the coded aperture plane. The real Poynting vector at distance $L \approx 2\lambda$ from the coded aperture plane is integrated over the lens aperture area to represent an ideal focusing lens and receiver; the final single-pixel reading is obtained by subtracting the background field power (measured with the coded aperture and object replaced by a PEC plate with no slit holes). It is worth noting that, as demonstrated in Figure 4, the 32-by-32 mm coded aperture is further embedded in a large PEC plate, e.g. 50-by-50 mm for 94 GHz simulation. The extra margin at the boundary is to ensure the EM field due to coded aperture slits remains deep in the shadow of the background field. Based on 20 94 GHz single pixel measurement samples randomly selected, over the receiver window the background amounts to 6.2% of a typical measurement (note that this background field power is subtracted from the measurement before CS image reconstruction). As for background-slit cross-coupling interference, it is estimated from the 20 samples to be on the order of 1% of a typical measurement, and hence excluded from further analysis. For each CS imaging simulation, M HFSS projects are executed for the M coded apertures, and MATLAB then uses the resulting single-pixel measurements to execute the total variation augmented-Lagrangian alternating-direction algorithm TVAL3 [18, 22], which reconstructs $\hat{x}$ by optimising measurement consistency $\|Ax - y\|_2^2$ while subject to a total

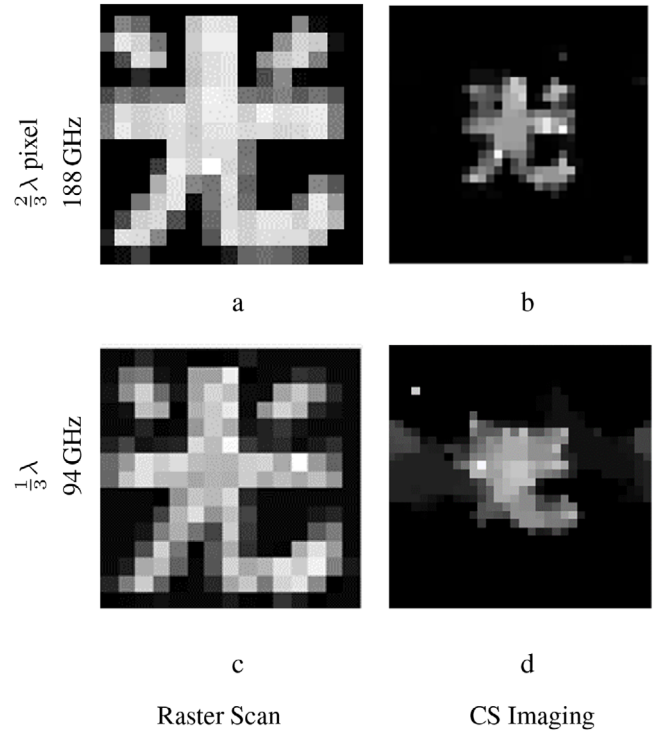


FIGURE 5 | CS reconstruction from EM simulation. (a) Raster scan 188 GHz; (b) CS reconstruction 188 GHz; (c) Raster scan 94 GHz; (d) CS reconstruction 94 GHz.

variation constraint (enforcing smoothness on the reconstructed signal), i.e., $\min_{\hat{x}} \text{TV}(\hat{x}) + \frac{\mu}{2} \|A\hat{x} - y\|_2^2$.

The results are shown in Figure 5, where the vertical direction corresponds to diffraction severity level and the horizontal direction compares the CS performance (right column) to the benchmark, i.e., the raster scan method (left column). The raster scan approach scans every image pixel sequentially; since raster scans only traverse the character feature area, reconstructed images are 12×12 pixels, whereas CS reconstructed images follow the coded aperture dimension at 32×32 pixels. The reconstruction quality matches closely for the two raster scan results (Figures 5a and 5c), indicating that the raster scan approach – where the slit pattern is always a single pixel – is insensitive to pixel diffraction except for a reduction in received power, consistent with the heuristic SNR reduction of [12]. As for compressive imaging performance, where slit patterns vary due to pseudorandom coded aperture masks, moderate pixel diffraction (pixel size $\sim 2\lambda/3$; Figure 5b) causes mild noise in the CS reconstruction yet preserves adequate detail for observing the object feature. In the case of severe diffraction (pixel size $\sim \lambda/3$; Figure 5d), the fine details are severely distorted and illegible. SSIM (11×11 Gaussian window, $\sigma = 1.5$) [23] is derived between each CS reconstruction and its raster benchmark (raster scan zero-padded to the 32×32 grid), and the numerical results are consistent with our observation, i.e., 0.44 for 188GHz (Figure 5b) vs 0.38 (Figure 5d). The findings support the proposed 0.6λ pixel diffraction limit from analytical analysis in the previous section and confirm that pseudo-random coded aperture patterns – which result in *variations* in the diffraction phenomenon – are the root cause for the pixel diffraction resolution limit.

4 | Conclusion

This letter investigated the impact of diffraction on millimetre-wave compressive imaging. In compressive imaging systems with coded apertures, such as SPC, performance is limited by diffraction. For visible-spectrum systems, pixel transmittance can typically be modelled as varying between 0% for opaque pixels and 10% for slits. As a concrete rule for the class of arrangements studied as depicted in Table 1, the coded-aperture pixel should satisfy $d \geq 0.6\lambda$ (at 94 GHz, $d \geq 1.9$ mm); finer pixels invalidate the binary linear model (1), and the designer must either enlarge the receiver aperture or adopt diffraction-aware reconstruction, which would be investigated in future work. More generally, this analysis establishes a pre-fabrication design framework for evaluating pixel diffraction: by sweeping geometric parameters using appropriate physical models – such as Fraunhofer or vectorised analysis – designers can pinpoint the onset of rapid transmittance divergence, reserving full-wave EM simulations specifically for configurations that approach this diffraction limit.

Author Contributions

Y.Z. performed all simulations and vectorized diffraction calculations. W.H. performed analysis and assisted with calculations. D.B. and D. R. supervised the research.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Supporting data for the analysis is available at <https://osf.io/qdmb8/>.

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