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EDITED BY

Zhi-Han Zhu,
Harbin University of Science and
Technology, China

REVIEWED BY

Zhongming Yang,
Shandong University, China
Yang Cao,
Polytechnique Montréal, Canada

*CORRESPONDENCE

Yajun Pang,
yjpang@hebut.edu.cn
Liyang Lang,
langliying@hebut.edu.cn

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Advances on terahertz single-pixel imaging

Qiao Hu^{1,2}, Xudong Wei^{1,2}, Yajun Pang^{1,2*} and Liyang Lang^{1,2*}

¹Center for Advanced Laser Technology, Hebei University of Technology, Tianjin, China, ²Hebei Key Laboratory of Advanced Laser Technology and Equipment, Tianjin, China

Single-pixel imaging is a novel imaging technique that can obtain image information through a single-pixel detector. It can effectively avoid the problem of lack of high-quality area array detectors in the terahertz band, and has attracted the attention of a large number of researchers in recent years. In this paper, the basic imaging principles, terahertz beam modulation methods and typical image reconstruction algorithms for terahertz single-pixel imaging are introduced and discussed, as well as its research progresses and developing trends.

KEYWORDS

terahertz imaging, single-pixel imaging, terahertz beam modulation, compressed sensing, reconstruction algorithm

1 Introduction

Terahertz [1] (THz) waves (0.1–10 THz, 3 mm–30 μm) have the characteristics of high penetration, low photon energy and spectral resolution, which makes terahertz imaging a widely technology used in various fields, such as nondestructive testing [2–4], safety monitoring [5–7] and medical applications [8–10].

According to different detection methods, terahertz imaging can be divided into array imaging and point-by-point scanning imaging [11]. Array imaging usually uses CCD cameras [12], CMOS cameras [13] or microbolometer cameras [14] as the detectors, which has advantages of high integration and real-time imaging. However, due to the limitation of THz array detectors, the resolution of array imaging cannot be very high. Point-by-point scanning imaging [15] scans the sample mechanically to obtain the value of every pixel, thereby realizing the imaging of the object. Its spatial resolution is higher than that of array imaging, but the scanning speed will limit the imaging efficiency. So it is impossible to realize high-speed imaging. Based on the shortcomings of the above imaging methods, some researchers applied single-pixel imaging in the field of terahertz imaging. Single-pixel imaging [16] is a new computational imaging technology, whose basic idea is to use a single-pixel detector to collect spatial intensity information of objects and then reconstruct the image using the correlation calculation of intensities between the collected light and the original light with a specific spatial distribution. Since only a single-pixel detector is needed to obtain the image of the object, the system structure can be simplified and the cost can be reduced, which provides a new method for terahertz imaging [17].

2 Basic principle

Single-pixel imaging is a computational imaging method that can be described by a mathematical model. An image can be regarded as a one-dimensional matrix I with a size of $1 \times N$. The mask pattern is P_i ($i = 1, 2, \dots, M$ represents the i -th measurement), which modulate the light source spatially. So the intensity of the detected light S_i can be expressed as $P_i \times I_i$. Using a single-pixel system for M measurements, linear equations can be obtained:

$$\mathbf{S} = \mathbf{P} \times \mathbf{I}. \quad (1)$$

Where \mathbf{P} is the measurement matrix with a size of $M \times N$, and \mathbf{S} is a one-dimensional matrix composed of M measured intensity values. By this way, the problem of reconstructing the object image is transformed into the problem of solving N independent unknowns by using M linear equations. Generally speaking, when $M = N$ and \mathbf{P} is an orthogonal matrix, the image can be reconstructed according to Eq. 2, otherwise Eq. 1 is an underdetermined equation. Image reconstruction is the process of matrix inversion:

$$\mathbf{I} = \mathbf{P}^{-1}\mathbf{S} \quad (2)$$

When the measurement matrix adopts random matrix, it takes more measurement time to recover the object image with considerable quality.

3 Development of terahertz single-pixel imaging

According to the basic principle of single-pixel imaging, the key points is the spatial modulation of the beam, the selection of modulation matrix and the reconstruction algorithm of the image. In the view of the beam modulation methods and imaging algorithms, this section introduces the development of terahertz single-pixel imaging.

3.1 Spatial modulation of terahertz wave

The existing spatial light modulators, such as digital micromirror devices and liquid crystal spatial light modulations, generally work in visible and infrared bands, which cannot directly be used to modulate terahertz waves. Therefore, studying the spatial light modulation methods in the terahertz band is a very important topic to THz single-pixel imaging. Recently, researchers have put forward a great many different solutions to this challenge.

3.1.1 Metallic masks modulation

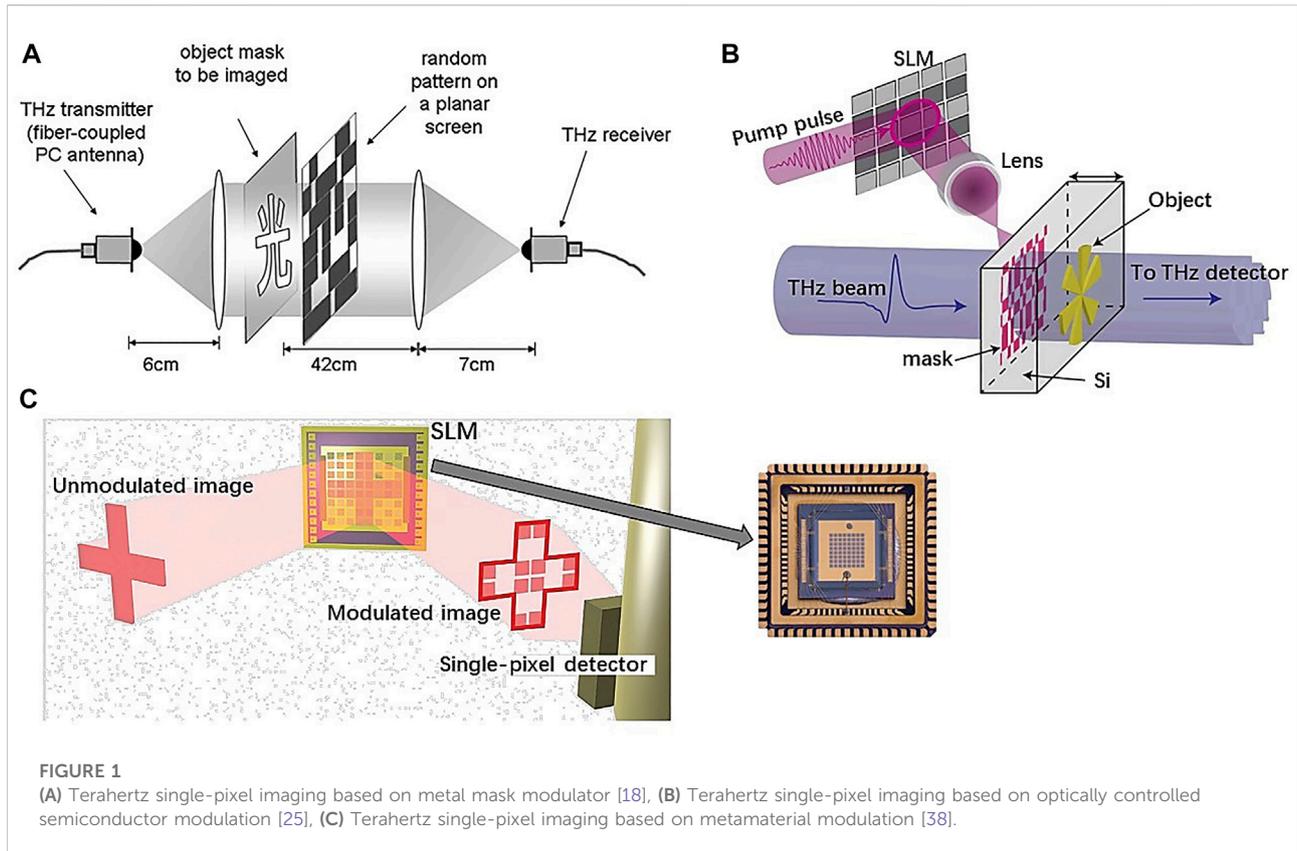
As metals have strong absorption and reflection properties for terahertz waves, it is an effective method to modulate

terahertz waves by metal masks. As shown in Figure 1A Chan et al. partially printed copper on the transparent PCB as a random mask [18] and combined it with the CS algorithm to achieve 32×32 pixels terahertz single-pixel imaging. However, making a large number of masks is cumbersome and its mechanical switching speed limits the imaging speed of the system. Duan et al. [19] proposed a metal mask structure that shares the adjacent mask matrices and used a linear motor to drive a metal plate to achieve automatic modulation of terahertz. The imaging system uses a terahertz Tunable Parametric Oscillator (TPO) as the radiation source and obtains identifiable results for hole imaging of the circular, rectangular and shape image letter "H." The sharing mode of adjacent mask matrices greatly simplifies the complicated process of making a large number of mask plates, improves the switching speed of mask matrices, and eliminates the problem of optical path alignment caused in the process of mask replacement. However, with the improvement of resolution, the length of mask will greatly increase, which makes the whole system cumbersome.

Some researchers have proposed the use of rotating masks to modulate terahertz waves. In 2012, the University of Liverpool [20] demonstrated for the first time that continuously rotating PCB circular disks with masks can be used to rapidly modulate terahertz. For terahertz imaging, 160 measurements (about 16%) can provide images with acceptable quality. Similarly, Vallés et al. [21] used metal ring with a series of direct perforation random masks to realize 2D imaging with high pixel resolution (1200×1200) in the entire terahertz frequency range (3–13 THz). Moreover, the Chinese Academy of Sciences uses the rotation of double amplitude modulation plates [22, 23] to generate reusable measurement matrices, which further improved the acquisition speed of the measurement matrix and imaging quality (7 mm resolution).

3.1.2 Optically controlled semiconductor modulation

In addition to the direct modulation of terahertz waves by metal mask, there is also photo-induced semiconductor modulation technology [23, 24] to be commonly used in recent years. As shown in Figure 1B, its modulation mechanism is that the area of the semiconductor illuminated by light will excite the internal photo-generated carriers, forming a transient region with high absorption or high reflection of terahertz waves, so that the modulation of terahertz waves is converted into modulation of the current carrier in the semiconductor. Therefore, the modulation of terahertz waves can be realized by combining traditional spatial light modulators and semiconductors. Because of its own characteristics, silicon has a band gap width suitable for laser pumping and it is the first time semiconductor material that has been proved to be used to realize optically controlled terahertz modulation devices. In



addition, materials such as germanium and gallium arsenic have also been proved to be used as modulation semiconductors.

Busch et al. applied the modulation technology of optically pumped semiconductor materials (25% modulation depth) to terahertz beam control and imaging [25], and obtain a 64×64 pixels image of a cross-shaped aluminum sheet by using a series of masks. Hendry's group [26] used spatially modulated femtosecond laser pulses to pump high-resistance Si, and achieved single-pixel imaging of terahertz with a spatial resolution of $103 \mu\text{m} \pm 7 \mu\text{m}$ ($\sim \frac{\lambda}{4}$, the central wavelength of the terahertz pulse $\lambda = 375 \mu\text{m}$) under a 115 mm thick silicon wafer. Subsequently, they also studied the effect of silicon wafer thickness at this resolution [27]. By reducing the silicon wafer thickness to $6 \mu\text{m}$, a resolution of $9 (\pm 4) \mu\text{m}$ ($\sim \frac{\lambda}{45}$) can be achieved, which is about 3 times faster than scanning imaging. In a similar way, Stantchev [28] et al. used a continuous wave source to optically excite charge carriers in high-resistance silicon to form a light-controlled terahertz modulator with depth of up to 80%. By optimizing the modulation geometry (total internal reflection TIR) and post-processing algorithm, a single-pixel fiber-coupled photo-conductive detector was used to obtain a real-time terahertz video with a resolution of 32×32 at a speed of about 6 frames per second. Besides, Zanotto et al. proposed far-field imaging based on single-pixel imaging with THz-TDS system [29]. Without mechanical grating scanning, they

reconstructed the terahertz electric field waveform in the time domain at each spatial position of the object, and obtained the time-of-flight images of high-density polyethylene samples with different thicknesses. This achievement combines the powerful functions of THz-TDS and compressed sensing, and the sampling efficiency is greatly improved.

To improve the modulation depth of silicon-based modulators, many researchers have used micro-nano structures to cover the silicon surface, such as graphene [30], metal gratings [31], and so on. Zhu et al. performed a comparative analysis of the THz imaging results between a micro-structure silicon modulator and a conventional high-resistance silicon modulator [32]. The results showed that the micro-structure greatly improved the absorption and utilization rate of silicon for laser and improved the imaging effect.

Graphene has also been proved to be useful for the modulation of terahertz waves due to its unique structure and high carrier mobility. Wen et al. designed a graphene based all-optical spatial terahertz modulator [33]. They transferred a layer of graphene on the top of doped germanium, and controlled the transmission of terahertz waves by irradiating the germanium substrate with a laser to generate carriers to diffuse into the graphene layer, thereby realizing the modulation of terahertz waves. The maximum modulation depth of the optically controlled modulator is as high as 90%. In addition, Shenzhen

TABLE 1 Comparison of modulation methods in THz single-pixel imaging.

Research units	System	Modulation mode	Modulation efficiency
Rice University [18]	Fiber-coupled antennas (100 GHz)	PCB	100%
Tianjin University [19]	Terahertz parametric oscillator	Coded sheet metal	100%
University of Liverpool [20]	IR and THz	Rotating circular disks with masks	100%
Chiba University [21]	Monochromatic terahertz source	A perforated metallic ring mask	—
Philipps-Universität Marburg [25]	fiber coupled THz-TDS system	DMD + fs laser pump high resistance silicon	25%
University of Glasgow [26]	THz-TDS system	DMD + fs laser pump high resistance silicon	>90%
Chinese University of Hong Kong [28]	CW and single-pixel photoelectricity Conductive antenna	DMD pumped triangular silicon	~80%
Institut National de la Recherche Scientifique [29]	THz-TDS system	DMD + fs laser pump Si-plate	95%
University of Electronic Science and Technology of China [33]	THz-TDS system	Germanium-based monolayer graphene	94%
Tianjin University [35]	Wideband pump probe THz-TDS system	Metal gratings are integrated into SOS	>60%
University of Science and Technology of China [36]	THz-TDS system	VO ₂	60%
Los Alamos National Laboratory [37]	THz-TDS system	Split-ring resonators	50%
Boston University [38]	Blackbody radiation (>4.6 THz)	Metamaterial THz absorber	33%

Institute of Advanced Technology used the mono-layer graphene on a high-resistance silicon substrate illuminated by a coded laser beam as a terahertz modulator to realize Fourier single-pixel terahertz imaging [34]. Though the sampling ratio is only 1.6%, the image reconstruction can be completed with a signal-to-noise ratio as large as 5.11. The modulation depth of graphene combined with semiconductor is still limited and its working frequency is narrow. Tianjin University [35] proposed to integrate sub-wavelength metallic grating into silicon on sapphire to design a high-efficiency, ultra-thin and fast THz SLM with high modulation depth (over 60% THz peak amplitude modulation depth at the pump flux of $80 \mu J/cm^2$). Besides silicon, vanadium dioxide, a phase change material, is also a common used material. The University of Science and Technology of China proposed to exploit the photo-metallic-insulating phase transition properties of the phase-changing material vanadium dioxide (VO₂) to achieve efficient spatial modulation of coherent terahertz pulses [36]. They achieved a modulation depth of 60% and the THz single-pixel imaging with a spatial resolution of $4.5 \mu m$ was realized by using VO₂ with a thickness of $180 nm$. Moreover, the spatial resolution exceeded less than one percent of the central wavelength ($\frac{\lambda_0}{133}$).

3.1.3 Metamaterial modulation

Artificial metamaterials combined with tunable semiconductor structures can realize high-speed terahertz modulators. This class of modulators mainly involves fabricating metallic metamaterial structures on semiconductor materials and controls the resonant strength of the metamaterial structure by applying a bias voltage between the metamaterial and the substrate. In 2006, Chen et al.

proposed a terahertz modulator [37] with a semiconductor metamaterial structure to obtain a modulation depth of 50% at 0.72 THz. As shown in Figure 1C, Padilla's team proposed a reconfigurable terahertz spatial light modulator based on metamaterial absorber in 2014, which uses an electronically controlled 8×8 mask. In the mask each pixel is composed of dynamic, polarization sensitive absorbers, so real-time adjustment of terahertz wave transmittance can be achieved [38].

Terahertz SLMs (Spatial Light Modulator) are widely adopted in single-pixel imaging, in Table 1, we summarize the representative results of current THz single-pixel imaging. The metal mask controllability over terahertz is not strong, which affects the quality of reconstructed images. The photo-induced carrier concentration in photo-induced semiconductor modulation will directly affect the modulation efficiency. At present, it is difficult for the existing semiconductor materials to meet the requirements of modulation speed and modulation depth at the same time. Therefore, how to improve the carrier concentration in photo-induced semiconductors is a research hotpot. Artificial metamaterial modulation can better control the transmission of terahertz waves, but the design is complex and provides very few controllable pixels.

3.2 Imaging algorithm

Another important factor that affects the imaging quality of terahertz single-pixel is the post-imaging reconstruction algorithm. With the development of single-pixel imaging, many reconstruction algorithms have been proposed to improve imaging quality and efficiency, which can be broadly classified as follows: traditional

terahertz single-pixel imaging algorithms developed from computational ghost imaging algorithms, single-pixel imaging algorithms based on compressed sensing, single-pixel imaging algorithms based on base scanning, single-pixel imaging algorithm based on deep learning, etc.

Computational ghost imaging based on spatial light modulation was proposed by Bromberg et al. [39] in 2008. In terms of imaging nature, conventional terahertz single-pixel imaging and computational ghost imaging are mathematically equivalent, as in Eq. 3, which uses an iterative approach for image reconstruction based on correlation algorithms.

$$I = \frac{1}{M} \sum_{i=1}^M (S_i - \langle S \rangle) (P_i - \langle P \rangle) \quad (3)$$

It can be seen from the formula that the reconstructed image is equivalent to a weighted sum of modulation masks, where the weight is the detection value of a single-pixel. Usually, this method can only obtain images with high SNR for a larger number of measurements ($M \gg N$). In order to improve the quality of terahertz single-pixel imaging, some researchers have proposed differential ghost imaging [40] and normalized ghost imaging [41] based on the traditional imaging algorithms. Differential ghost imaging removes noise by using the differential value of the barrel detector instead of the total light intensity value to improve the SNR of the imaging results. Normalized ghost imaging improves the noise immunity of the system by normalizing the detection value of the signal optical path with the total intensity value of the reference optical path, and this method has a similar SNR to differential ghost imaging. Although these methods further improve the imaging quality, they are still inferior to traditional imaging methods and require a very large number of samples.

In order to overcome the problems of large amount of sampled data and long time in imaging, some studies have proposed combining compressed sensing (CS) techniques with optically controllable terahertz spatial light modulators in single-pixel imaging. Compressed sensing theory [42–44] was first proposed in 2006 by Candès and Donoho et al. It breaks away from the traditional Nyquist sampling theorem by exploiting the sparsity of natural images in the orthogonal transform domain to accurately reconstruct the original target image using a small number of sampled measurements. The CS theory solves the problem of solving the uncertain inverse problem with more unknown values than the available data. In single-pixel imaging [17], this means that the number of mask patterns is less than the total number of pixels used to restore the image, which provides a new method for single-pixel imaging. After the CS theory was proposed, Rice University [45] conducted a single-pixel imaging experiment using the theory, which used a digital micromirror array to modulate visible light, combined the pre-designed observation matrix with the one-dimensional measurements obtained from the single-pixel detector, and then used the compressed sensing reconstruction algorithm to obtain the original image.

Although the introduction of CS algorithms [38, 46, 47] reduces the number of samples and effectively reduces the imaging time, it

requires a long time for computation and high computational complexity in the image reconstruction process. In addition to the random matrix modulation, terahertz single-pixel imaging can also be modulated with deterministic orthogonal bases, such as Fourier bases [34, 48, 49], Hadamard bases [50–52], discrete cosine bases [53], and wavelet transform bases [54, 55], etc. This imaging method is also known as base-scan terahertz single-pixel imaging. Since these substrate patterns are orthogonal, by determining the illumination projection of the patterns, the spatial information of the object image in the transform domain can be obtained and the corresponding inverse transformation can be performed to recover the target image. In addition, taking advantage of the sparsity of natural images in the transform domain, it is possible to reconstruct clear images using under-sampled data by measuring coefficients of larger amplitude.

Although the base-scan terahertz single-pixel imaging approach effectively solves the problem of long data acquisition time, the sampling frequency is subjectively selected in the sampling process, which leads to selective loss of image information and does not always exactly match the frequency distribution of the image. In recent years, many researchers have demonstrated the advantages of deep learning [56–63] in the field of single-pixel imaging, which is widely used in the fields of information encryption [64] and image super-resolution [65]. For single-pixel imaging, the image quality is proportional to the number of samples, and how to get effective recovery of the target image under low sampling is an important issue nowadays. Combining deep learning with single-pixel imaging and relying on the deep learning ability of the model can obtain better image quality. In 2017, Lyu et al. applied deep learning [66] to a traditional computational ghost imaging algorithm by using a large number of reconstructed low-quality images at low sampling rates as network inputs and the original images as labels for the network, and iteratively trained the network to obtain high-quality target images at 10% sampling rate. In addition, some researchers used the single-pixel detection signal sequence as the input of the neural network and the image reconstruction result as the output of the neural network to train the neural network to achieve deep learning single-pixel imaging [67]. In terahertz waves single-pixel imaging, most of the existing research uses deep learning techniques to improve the quality of imaging [68–70], and it is also a research direction to investigate how to train modulation masks suitable for terahertz single-pixel imaging to improve the imaging speed in response to the current problems.

4 Discussion and conclusion

Applying single-pixel imaging technique to THz imaging can effectively solve some problems existing in traditional method. With the continuous development of spatial modulation techniques, many terahertz single-pixel imaging techniques have been investigated as described above. This paper summarizes the initial physical metal masks to later methods based on light modulation in

semiconductors and artificial metamaterial modulation. In terms of imaging algorithms, the main imaging algorithms applied to terahertz single-pixel imaging are introduced, including the traditional terahertz single-pixel imaging algorithm developed from computational ghost imaging algorithm, single-pixel imaging algorithm based on compressed sensing, single-pixel imaging algorithm based on basic scanning and single-pixel imaging algorithm based on deep learning. At present, how to improve the sampling speed to achieve real-time imaging while ensuring the image SNR is the problem that needs to be solved for terahertz single-pixel imaging. In addition, further improvement of terahertz modulation techniques and exploration of more optimized algorithms are the two most important research directions for terahertz single-pixel imaging.

Author contributions

QH: investigation, writing—original draft. XW: investigation, writing—review and editing. YP: investigation, writing—original draft, writing—review and editing, supervision. LL: investigation, writing—review and editing.

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