Emerging Vision Technology: SPI Camera an Overview

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Emerging vision technology, particularly Single-Pixel Imaging (SPI) cameras, has garnered significant attention in recent years. This work provides an overview of the advancements and applications of this innovative imaging technique. SPI utilizes improved reconstruction algorithms, enabling the reconstruction of images from compressed measurements obtained using a single detector element. The miniaturization and integration of this technology have led to its incorporation into compact and portable devices, expanding its range of potential applications. Real-time imaging and video capture capabilities have been achieved, allowing for dynamic scene capture and analysis. Enhanced sensitivity and resolution have been achieved through novel hardware and computational techniques. Deep learning approaches have been employed to further enhance the imaging capabilities and extract meaningful information from the acquired data. Medical imaging, biophotonics, object recognition, tracking, remote sensing, Earth observation, industrial inspection, and quality control are among the diverse areas benefiting from this technology. The continuous advancements in SPI cameras hold great promise for revolutionizing various fields and unlocking new opportunities for imaging and analysis.

Evolution of Single-Pixel Imaging (SPI) Over Time

The concept of SPI originated from the idea of modulating a light field and capturing the modulated light using a single photodetector. In 1970, Decker introduced the application of the Hadamard Transform from Image Scanning [1]. Later, in 1982, Ben-Yosef and N. Sirat documented this concept in their work, suggesting the utilizationof the elastic piezoelectric optical effect in crystals for light modulation [2]. However, at that time, the construction of small and numerous crystals was not readily accessible. The authors presented a proof of concept using a few crystals to reconstruct the image of an object. Nearly 25 years later, the first Single-Pixel Camera (SPC) was proposed and successfully demonstrated at Rice University. This approach was based on the pioneering idea of Compressed Sensing (CS) introduced by Donoho in 2006, which were also independently proposed by Takhar *et al.* in the same year. The SPC used random patterns to reconstruct an image through a minimization algorithm [3].

In 2008, Duarte redefined the architecture of the SPI system in their work [2], incorporating a light source element, a spatial light modulator (SLM), and a detector element (SPD). They utilized the CS approach proposed by Donoho in 2006. In the same year, Duarte introduced the first color image processing method by using an RGB filter with a single photodiode. The method involved three consecutive measurements with different RGB filters to form a color pattern. In 2013, Welsh *et al.* improved upon Duarte's method by introducing a dichroic beam splitter, which separated white light into three outputs (red, green, blue) [2]. They placed a different photodiode at each output to capture the light, allowing the restoration of an image by combining the separate color channel outputs. SPI found various applications, including 3D imaging, video streams, hyperspectral imaging (combining infrared and visible range images), and the integration of TOF and radar systems.

Subsequent to these advancements, new methods emerged to enhance the efficiency and accuracy of image reconstruction from photodetector outputs. These methods also involved strategies to generate illumination patterns and capture them more effectively. In 2013, Sun *et al.* proposed one of the first approaches for generating 3D images based on SPI [2]. They utilized a projector to illuminate the scene with random patterns and placed four photodetectors at different angles to measure the time. In 2014, Dai *et al.* introduced an adaptive scanning strategy based on illumination patterns generated the wavelet transforms [2]. They employed the Wavelet inverse transform for image recovery, which became a reference for generating depth maps in systems utilizing TOF principles. Zhang *et al.* in 2015 were inspired by Dai work and used illumination patterns generated using the Fourier transform [2]. They employed the inverse Fourier transform on the photodetector output signals for image recovery. This concept formed the basis for subsequent video sequence generation and 3D applications using SPI. These applications utilized temporal

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redundancy to reduce the number of processing steps required for reconstructing depth maps, enabling real-time video streaming.

Recent advancements in SPI–type systems focused on approaches that eliminate the need for lenses for light structuring. For example, the developments of PicoCam and FlatCam, presented in 2017, showcased lensless imaging. Furthermore, emerging technologies such as carbon nanotubes and graphene were employed in photodetectors. In 2018, LED arrays were proposed as a cost-effective alternative to SLMs. Other developments included the application of deep learning for image recovery in 2019 and hyperspectral imaging using the SPI approach in 2020. Fig. 1a and Fig. 1b provide a timeline of various developments, including modulation technologies, sampling and processing schemes, from 1982 to 2000, used in SPI systems [2].

The Single-Pixel method marks a revolutionary shift from traditional approaches in adapting diverse wavelength bands for various applications. Unlike conventional techniques that employ arrays of pixels, the Single-Pixel method ingeniously utilizes a solitary pixel to capture and process complex spectral information. This breakthrough hinges on the concept of CS, harnessing the pixel's ability to mathematically recover intricate spectral data. This innovation proffers unparalleled

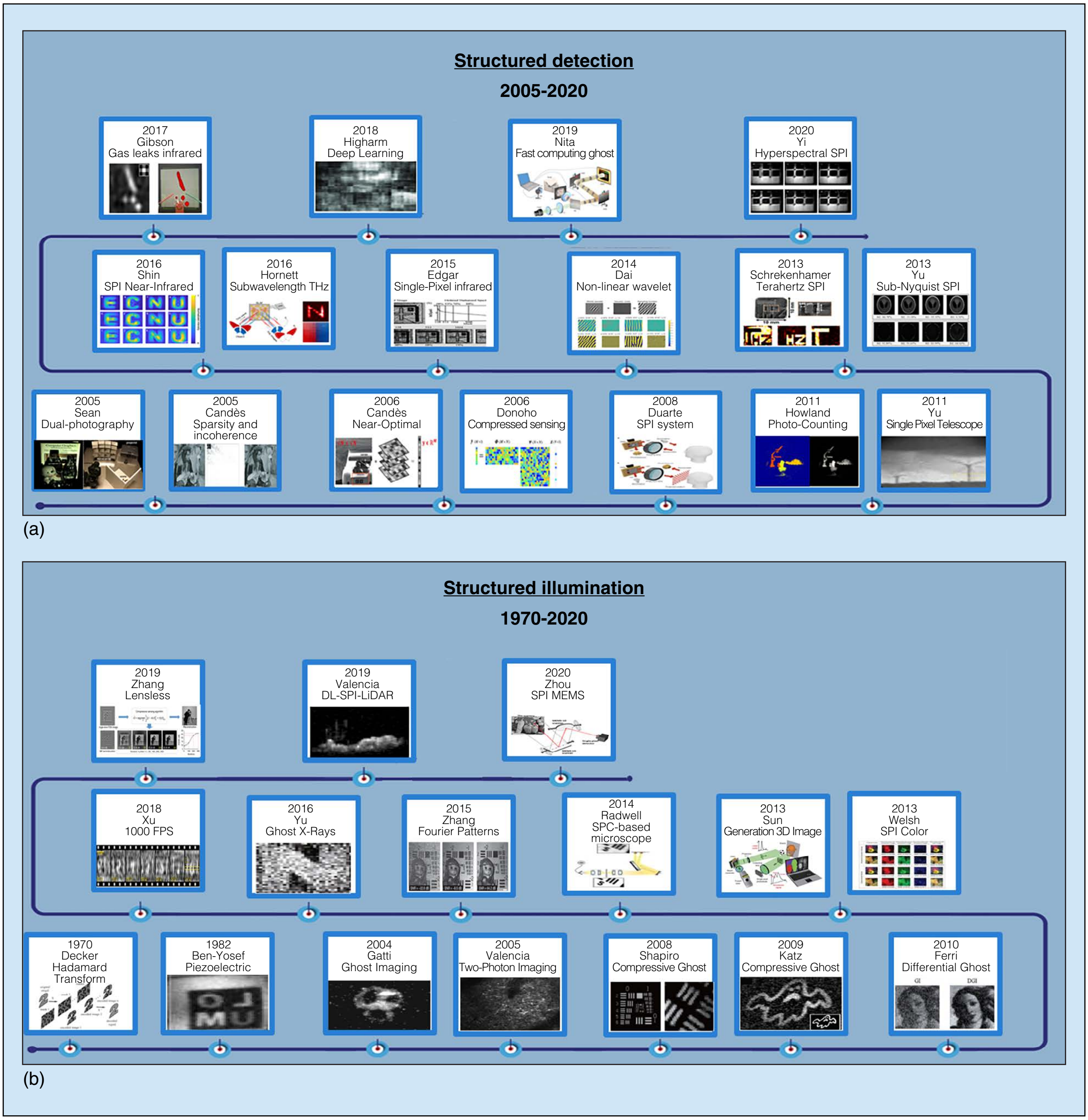

Fig. 1. Timeline showing the different developments based on single-pixel imaging. (a) Structured detection. (b) Structured illumination.

versatility and efficiency. By swiftly alternating through wavelengths, the Single Pixel maximizes resource allocation while minimizing noise and redundancy. Consequently, it excels in diverse applications such as medical imaging, remote sensing, and industrial quality control. Its adaptive nature allows seamless customization for specific wavelength requirements, eliminating the need for specialized detectors for each band. Moreover, the Single-Pixel method transcends the limitations of traditional methods, which are often cumbersome and cost-prohibitive due to intricate fabrication processes and bulky arrays. With its capacity to swiftly adapt and its potential for compact and lightweight design, this method opens doors to portable, multipurpose devices for various industries. In essence the Single-Pixel method emerges as a trailblazing technique, redefining the landscape of wavelength band adaptation.

Single-Pixel Image Reconstruction

SPI operates on the principle of spatial modulation of light, which involves projecting a series of structured illumination patterns onto the object to be imaged. These patterns are created using light modulation devices like SLM, Digital Micro Device (DMD), or similar modulators (Table 1). The modulated light reflected by the object is then detected using a lens system to focus the light onto a single photodiode. The photodiode produces an output voltage signal that corresponds to the intensity of the detected light. The relationship between the structured illumination pattern and the light signal reflected from the object, which is subsequently captured by the photodiode, can be described by (1) [4]:

$$S_i = \alpha \sum_{y=1}^{M}\sum_{x=1}^{N} O(x,y)\phi(x,y) \tag{1}$$

where (x, y) represents the spatial coordinates in the system. The reflectivity of the illuminated object is denoted by O, while ϕ_i represents the i-th structured pattern emitted in the sequence. The output of the i-th single-pixel photodetector measurement corresponding to ϕ_i is represented by S_i.

Table 1 – Summary of modulation technology [2]

Technology	Advantage	Disadvantage
LC-SLM	Grayscale modulation and programmable	Slow modulation and low power endurance
DMD	Faster than LC-SLM and programmable	Binary modulation and not fast enough
LED array	Much faster than DMD and programmable	Binary modulation and structured illumination only Random
Pseudo-Thermal	Much faster than DMD and controller	Modulation and complicated manufacturing

In addition, α is a factor that describes the optoelectronic response of the photodetector (Fig. 2). The size of the final reconstructed image is given by M × N pixels, which applies to both the object being imaged and the number of projected patterns. By utilizing the definition of each structured illumination pattern projected and the output voltage signal from the photodiode in response to these patterns reflected by the illuminated object, a virtual image of the object can be reconstructed. The reconstructed image I is directly proportional to the object reflectivity O. Therefore, the reconstructed object image can be obtained by applying (2) [4]:

$$I = \alpha \sum_{y=1}^{M}\sum_{x=1}^{N} S_i\phi(x,y) \tag{2}$$

In this context, the reconstructed image is determined image is determinate by the inner product of the output voltage signal acquired during each measurement and the corresponding structured pattern used to obtained it. SPI employs spatial light modulation and can be implemented through two distinct approaches (Table 2) [2]: structured detection scheme, illustrated in Fig. 2a, where structured illumination is applied; and a structured illumination scheme, depicted in Fig. 2b, where structured detection is employed. In the structured illumination setup, the arrangement involves positioning a light modulation device in front of the object to be captured. Typically, a white light source illuminates the SLM which generates a specific illumination pattern. This pattern is then projected onto the target object through a lens, effectively creating structured illumination stimuli. The back-scattered light reflected by the illuminated object is captured by a bucket detector.

Literature has documented six scanning and sampling strategies suggested for reconstructing single-pixel images. These strategies include: Computational Ghost Imaging (CGI), Compressive Sensing Ghost Imaging (CSGI), Hadamard Single-Pixel Imaging (HSI), Wavelet Single-Pixel Imaging (WT), Fourier Single-Pixel Imaging (FSI), and Machine Learning Single-Pixel Imaging (ML) [2].

Computational Ghost Imaging

Computational Ghost Imaging (CGI) [2] is a popular technique used to gather spatial information about an unknown target. It involves the generation of random patterns using spatial light modulation, as shown in Fig. 3a. These patterns are typically binary, allowing for high-speed generation using a DMD. CGI offers several advantages, including easy deployment, low cost, robustness against noise and scattering, wide spectral range operation, and inherent encryption of patterns [2].

Compressive Sensing Ghost Imaging

Compressive Sensing Ghost Imaging (CSGI) [2] is an innovative imaging technique that combines the principles of compressive sensing and ghost imaging to obtain high-quality images with fewer measurements (Fig. 3b). Unlike traditional imaging methods that rely on densely sampling the entire scene, CSGI leverages the concept of sparsity to

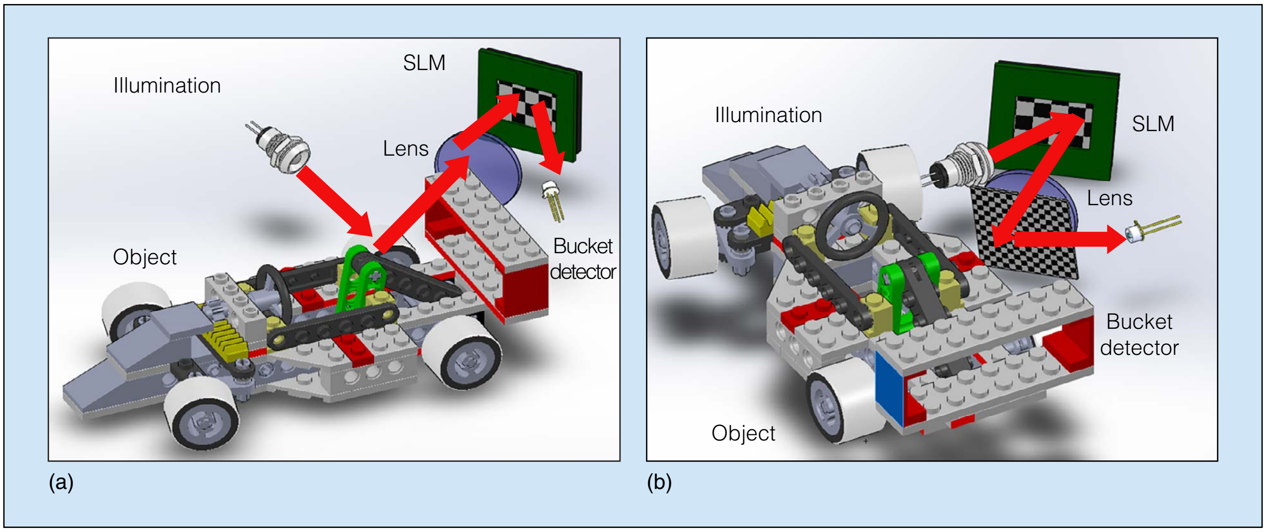

Fig. 2. Two different approaches applied to single-pixel imaging. (a) Structured detection; (b) Structured illumination.

Table 2 – Summary of single-pixel imaging system architectures [2]

Architecture	Advantage	Disadvantage
Focal plane modulation	Active or passive imaging	Limited choice on modulation
Structured light illumination	More choices for active illumination	Active imaging only
Rotating	High power endurance and cheap	Not programmable and random modulation only
Customized diffuser	High power endurance and can be customized	Not programmable and complicated manufacturing

capture images using significantly fewer measurements. In CSGI, a scene is illuminated with a random or structured light pattern, and a single-pixel detector captures the reflected or transmitted light. The detector records the intensity of the light, but not its spatial information. However, by exploiting the correlation between the illumination pattern and the recorded measurements, CSGI can reconstruct the image of the scene.

Hadamard Single-Pixel Imaging

The Hadamard pattern, known as the Wang pattern in the referenced study [2] is widely used in the re-construction SPI. Its popularity stems from its orthogonal Properties, as shown in Fig. 3c. To generate a Hadamard matrix, a square matrix is initially defined, where the elements are either +1 or –1, with two distinct rows agreeing on exactly n/2 positions and disagreeing on the remaining n/2 positions. The generated matrix, denoted as H, must satisfy the condition HHT = nI, where T represents the transposition of matrix H, I is an identity matrix, and n denotes the order of the matrix. The Hadamard matrix can be constructed using the Kronecker product [2].

Wavelet Single-Pixel Imaging

Wavelets, which are mathematical functions, are used to map data onto different frequency components with varying scale resolutions. Compared to the Fourier method, wavelet transform (WT) offers advantages when dealing with discontinuities [2]. In this context, the Haar wavelet is often chosen as it is the simplest wavelet. The Haar wavelet is characterized by a binary function and a 2D matrix. To implement the Haar wavelet, two light frequencies are used to represent the values +1 and –1. The image can be reconstructed using the inverse wavelet transform (Fig. 3d).

Fourier Single-Pixel Imaging

In the process of acquiring and reconstructing object images, FSI (Fourier Spatial Imaging) utilizes the Fourier transform, as mentioned in Zhang's study [2]. By taking the Fourier transform of the object image, FSI obtains a set of coefficients, which are depicted in Fig. 3e as Fourier coefficients. Each coefficient represents the weight assigned to a distinct Fourier basis pattern, often referred to as a "sinusoidal pattern" or "fringe pattern."

Machine Learning Single-Pixel Imaging

The most recent approach in image reconstruction is the utilization of machine learning techniques, specifically deep learning in a convolutional neural network (CNN) [2]. This method, referred to as the machine learning-based SPI, reconstructs images with fewer measurements compared to other traditional techniques like Orthogonal Sampling or the Ghost Imaging Technique. By incorporating Graphics Processing Units (GPUs) in CNN [5],[6], the computational capabilities are significantly enhanced, surpassing those of conventional computer processors. Therefore, combining CNN with the CGI approach allows for image reconstruction using minimal

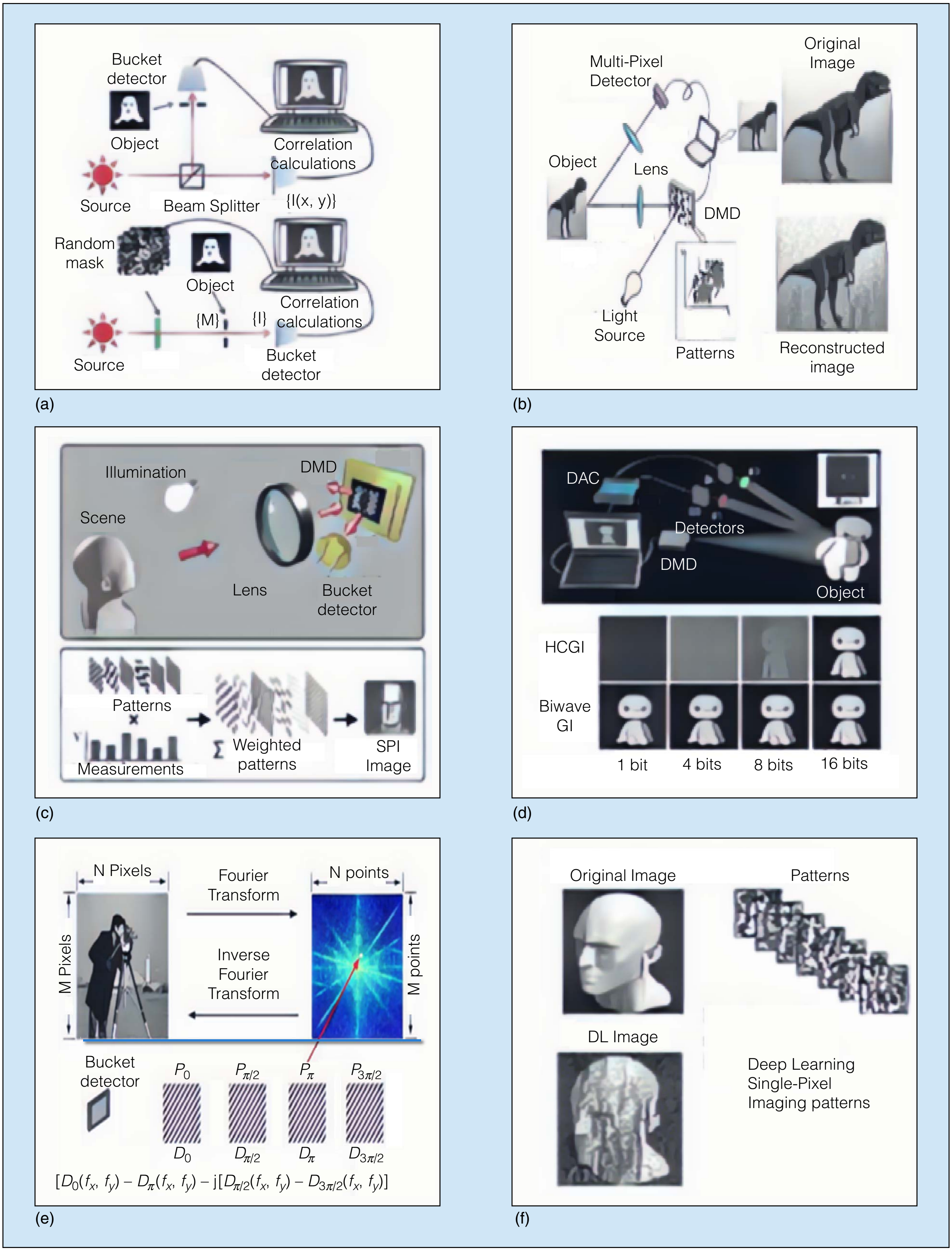

Fig. 3. Overview of the sampling and scanning strategy used for single-pixel imaging reconstruction: (a) Computational Ghost Imaging (CGI); (b) Compressive Sensing Ghost Imaging (CSGI); (c) Hadamard Single-Pixel Imaging (HSI); (d) Wavelet Single-Pixel Imaging (WT); (e) Fourier Single-Pixel Imaging (FSI); and (f) Machine Learning Single-Pixel Imaging (ML).

measurements. This approach is particularly advantageous in applications where full image reconstruction is unnecessary for object detection and classification. Additionally, SPI has the ability to identify rapidly moving objects, further highlighting its benefits. By employing a CNN, image reconstruction with reduced samples can be integrated into the control system of autonomous vehicles, enabling image-free classification sensing schemes. Fig. 3f illustrates the CNN used for image reconstruction.

Algorithms for Single-Pixel Imaging Reconstruction

In recent years, the field of SPI reconstruction has witnessed significant advancements with the utilization of deep learning methods. These methods employ neural networks to tackle the problem of SPI reconstruction, providing promising results. Fig. 4 showcases the various algorithms proposed in the literature for SPI reconstruction. These algorithms can be categorized into three main types based on their iteration approach [2]. The first category encompasses the non-iterative methods, denoted as DGI. These methods utilize deep neural networks to directly reconstruct the SPI without iterative refinement. By leveraging the power of deep learning, these algorithms are able to learn complex mappings from input data to the desired output. The second category comprises the linear iterative methods, which incorporate deep learning principles into iterative algorithms such as Gradient Descent (GD), Conjugate Gradient Descent (CGD), Poisson maximum likelihood method, and Alternating Projections (AP). This algorithm type employs both CGI and CSGI methods for its application. By integrating deep learning techniques into these traditional iterative approaches, enhanced performance and faster convergence can be achieved. Lastly, the third category encompasses the nonlinear iterative methods that methods include the sparse representation method and Total Variation (TV) and CS [2]. These algorithms are implemented in DL, WT, FSI and HSI methods. It was observed that CS and TV methods require only a small number of samples for SPI reconstruction. On the other hand, DGI, GD, and Poisson algorithms necessitate a higher sampling ratio exceeding 1. Notably, CS and TV algorithms demonstrate convergence even at a sampling rate as low as 0.8. It is important to note that during the reconstruction process, some observation artifacts and noise may be present [2]. By leveraging the representation capabilities these algorithms can effectively model the nonlinearity present in SPI reconstruction. Overall, the integration of deep learning methods into SPI reconstruction has opened up new avenues for improved accuracy and efficiency in reconstructing SPIs. These approaches have demonstrated remarkable potential in addressing the challenges posed by SPI reconstruction, showcasing the power of deep learning in this domain.

Diverse System Architectures for Assessing Single-Pixel Imaging

The evaluation of different system architectures used for generating single-pixel images reveals limitations in conventional CPU-based systems, such as long signal collection and image reconstruction times. To overcome these limitations, alternative approaches involving field-programmable gate-arrays (FPGA) and embedded GPU devices have been

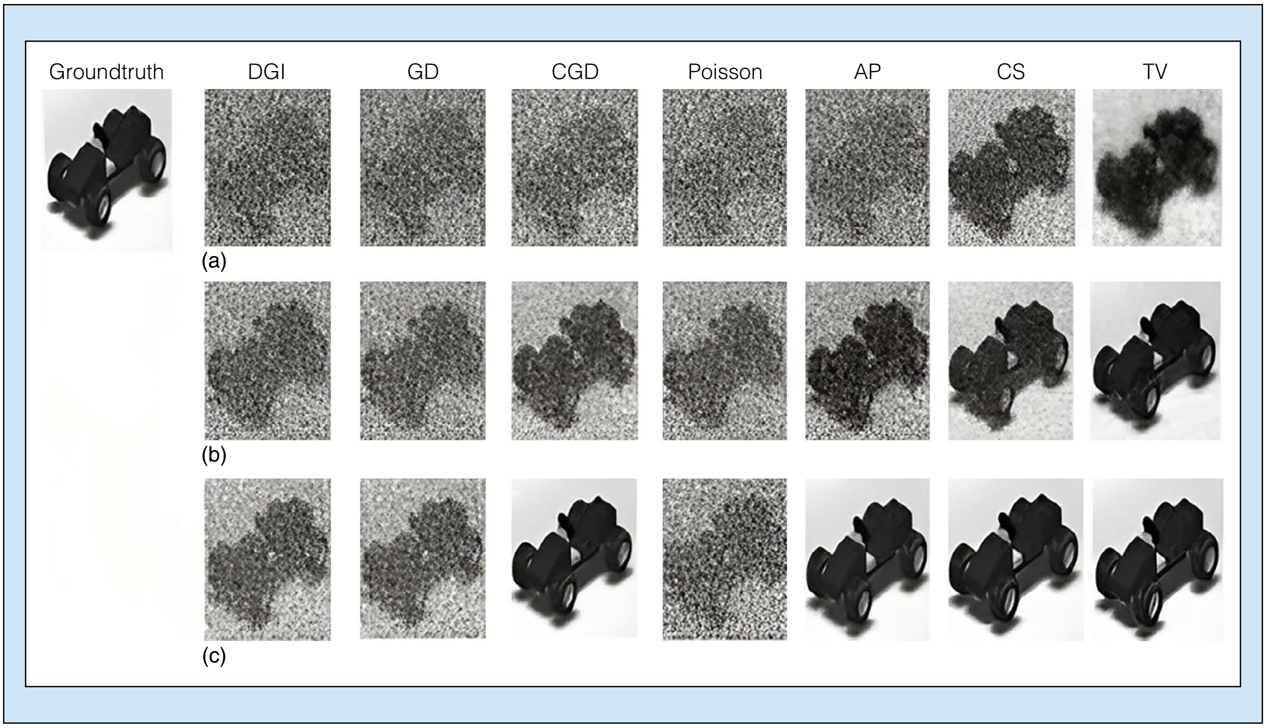

Fig. 4. The SPI simulation results for various algorithms were analyzed at different sampling ratios: (a) Sampling ratio=0.2, (b) Sampling ratio=0.8 and (c) Sampling ratio=3.

explored [2]. FPGA-based solutions improve hardware performance through efficient memory access management and pipeline architectures, while some FPGA systems utilize SDRAM for faster data transport. Computational cost is another important consideration, and algorithms like orthogonal correspondence search (e.g., Orthogonal Matching Pursuit [5]) are applied for image reconstruction but can be time-consuming. GPU platforms are well-suited for implementing compressed sensing algorithms in parallel, although bottlenecks can occur in certain modules [6]. Various techniques, including matrix-vector multiplication and matrix-inverse-update calculations, have been proposed to speed up these modules. FPGA-based architectures generally demonstrate better efficiency compared to GPU platforms for SPI reconstruction. However, GPU platforms have been utilized for machine learning approaches, albeit with low data processing efficiency compared to FPGA [2]. FPGA offers flexibility and can be reconfigured easily, making it suitable for optimized parallel architectures and matrix operation calculations. On the other hand, GPU implementations allow for kernel parallel operations and shared memory management. Both FPGA and GPU architectures have been used in conjunction, complementing each other in recent works. The efficiency of a Single-Pixel Imaging system depends on minimizing signal collection and reconstruction times, especially for real-time applications and video streaming. Improving data transport mechanisms and accelerating the generation of Single-Pixel 3D images are key focus areas for enhancing system performance [2].

Challenges Faced by Single-Pixel Imaging Technology

Over the past decade, there has been a notable surge in the advancement of various technologies such as autonomous robots, self-driving vehicles, and unmanned aerial vehicles (UAVs). Concurrently, there has been significant progress in enhancing vision systems through evolving techniques. To facilitate this development, a range of sensors, including LiDAR, RADAR, thermal sensors, and infrared (IR) cameras, have been utilized [7]. A novel approach in the realm of vision systems is the employment of the SPI system [2]. This paradigm shift enables the sensors to adapt to different wavelengths, such as visible light, near-infrared (IR), and even long-wavelengths. The inherent advantage of this adaptability is its ability to operate effectively in adverse weather conditions such as fog, rain, and situations with low visibility (Fig. 5). By simply changing the source of light without altering the SPI configuration, the system can continue to function optimally. The potential applications of SPI extend far beyond the confines of mere proof of concept, as often seen in existing literature. One such application is the development of a robust obstacle detection system specifically designed for vehicles operating under fogy or rainy conditions [7] (Fig. 5). Additionally, SPI can be integrated with LiDAR technologies to enhance

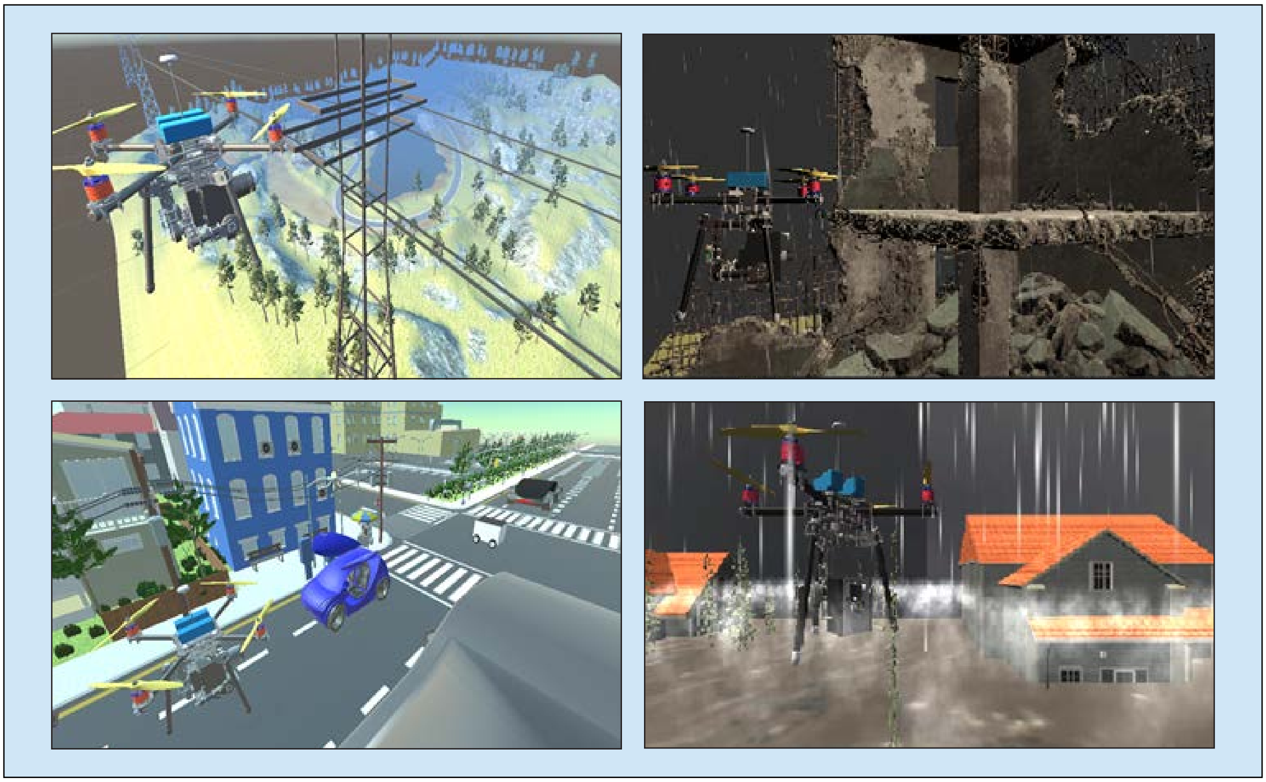

Fig. 5. Showcases an illustrative example of the potential future applications where single-pixel camera infrared technology excels by enhancing its image-capturing capabilities under various challenging lighting and scattering conditions. This advancement proves especially valuable in complex settings like urban or forest environments.

the quality of scene reconstruction. By optimizing the number of samples based on the SPI principle, a more accurate and efficient scene reconstruction process can be achieved [2].

Integrating Deep Learning Models into SPI Technology

SPI technology has emerged as a powerful technique for capturing images using a single-pixel detector and structured illumination patterns. This innovative approach has opened up new possibilities in various applications, ranging from object detection [8], segmentation to tracking [8], and depth mapping [9] (Fig. 6). Recent advancements in deep learning models have further enhanced the capabilities of SPI, enabling more accurate and efficient image reconstruction and analysis. One notable concept applied to SPI technology is the Single-Pixel Object Detection (SPOD) [8] technique. By leveraging deep learning algorithms, SPOD enables the identification and localization of objects within a scene using only SPI measurements. This approach proves especially useful in scenarios where conventional imaging methods face challenges such as low light conditions or limited hardware resources. Segmentation image SPI is another application of deep learning in SPI technology [9]. By training neural networks on segmented images reconstructed from single-pixel measurements, it becomes possible to extract precise object boundaries and generate high-quality segmented images. This enables improved object recognition and analysis in diverse fields, including medical imaging and autonomous driving [2].

Deep learning models have also made significant contributions to tracking objects using single-pixel imaging. By employing convolutional neural networks (CNNs) to learn object motion patterns from reconstructed single-pixel measurements, tracking algorithms can accurately follow objects in dynamic scenes, even under challenging conditions such as occlusions or cluttered backgrounds. This paves the way for advanced object tracking applications in surveillance, robotics, and augmented reality. Depth mapping using single-pixel imaging is another area where deep learning techniques play a vital role. By training neural networks on large datasets of single-pixel depth measurements and corresponding ground truth depth maps, it becomes possible to generate accurate depth maps from sparse measurements. This has implications for various fields, including 3D reconstruction, virtual reality, and autonomous navigation.

Integrating Deep Learning models into SPI technology extends beyond traditional imaging applications. For instance, the combination of single-pixel imaging and NeRF (Neural Radiance Fields) [10] enables the reconstruction of detailed 3D human pose estimation [11], objects, and 4D spatial-temporal data from limited measurements [12]. This advancement finds applications in fields such as virtual try-on, computer graphics, and telepresence. Furthermore, the fusion of hyperspectral imaging and high-speed video with single-pixel imaging allows the acquisition of multispectral information in dynamic scenes [13]. Deep learning algorithms can be employed to fuse the captured data, enabling improved analysis and understanding of complex scenes, such as environmental monitoring or remote sensing applications. Deep Learning models also contribute to improving the quality of SPI. By leveraging concepts such as Deep Image Prior (DIP) [14] and

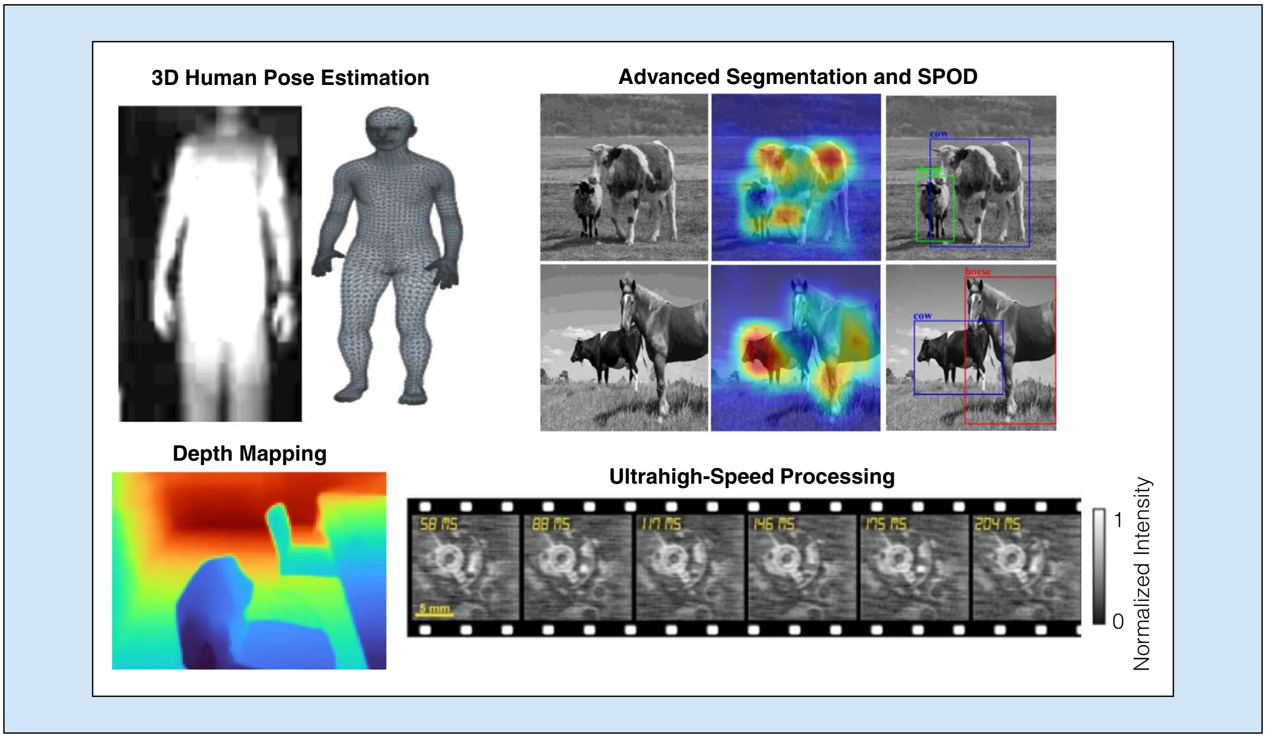

Fig. 6. Discover a new era in imaging as Deep Learning Models seamlessly merges with SPI Technology, drawing upon the insights from [8]–[9].

diffusion models [15], it becomes possible to enhance low-resolution or noisy single-pixel images. These techniques utilize learned priors or diffusion processes to effectively restore and sharpen images, providing higher fidelity results in SPI applications. The integration of deep learning models into SPI technology brings numerous advancements to the field. From single-pixel object detection and segmentation to tracking, depth mapping, and image enhancement, deep learning algorithms enable more accurate and efficient image reconstruction and analysis. These advancements expand the scope of SPI, unlocking its potential in diverse domains and paving the way for further innovations in the future.

Conclusions

The emergence of SPI cameras and their integration with deep learning algorithms has paved the way for remarkable advancements in vision technology. The combination of SPI cameras and deep learning techniques allows for enhanced image processing, object recognition, and scene analysis, leading to improved accuracy and efficiency in various applications. The future holds tremendous potential for SPI cameras and deep learning in numerous fields. Industries such as autonomous vehicles, surveillance systems, robotics, and healthcare can greatly benefit from this technology. SPI cameras offer high-speed data transfer, compact size, and low power consumption, making them suitable for integration into a wide range of devices. As deep learning algorithms continue to evolve and improve, SPI cameras will play a crucial role in enabling real-time decision-making and autonomous functionality. With the ability to capture and analyze vast amounts of visual data, SPI cameras offer a new level of precision and reliability. The ongoing advancements in emerging vision technology are set to revolutionize industries and transform the way we interact with the world around us.

References

[1] J. A. Decker, "Hadamard–transform image scanning," *Appl. Opt.* vol. 9, pp. 1392–1395, 1970.

[2] C. A. Osorio Quero, D. Durini, J. Rangel-Magdaleno, and J. Martinez-Carranza, "Single-pixel imaging: an overview of different methods to be used for 3D space reconstruction in harsh environments," *Rev. Sci. Instrum.*, vol. 92, article 111501, 2021.

[3] D. L. Donoho, "Compressed sensing," *IEEE Trans. Inform. Theory*, vol. 52, pp. 1289–1306, 2006.

[4] G. M. Gibson, S. D. Johnson, and M. J. Padgett, "Single pixel imaging 12 years on: a review," *Opt. Express*, vol. 28, pp. 28190–28208, 2020.

[5] C. O. Quero, D. Durini, R. Ramos-Garcia, J. Rangel-Magdaleno, and J. Martinez-Carranza, "Hardware parallel architecture proposed to accelerate the orthogonal matching pursuit compressive sensing reconstruction," in *Proc. of the Computational Imaging V*, Int. Soc. Optics and Photonics, vol. 11396, pp. 56–63, 2020.

[6] F. Wang, C. Wang, C. Deng, S. Han, and G. Situ, "Single-pixel imaging using physics enhanced deep learning," *Photon. Res.*, vol. 10, pp. 104–110, 2022.

[7] C. Osorio Quero, D. Durini, J. Rangel-Magdaleno, J. Martinez-Carranza, and R. Ramos-Garcia, "Single-pixel near-infrared 3D image reconstruction in outdoor conditions," *Micromachines*, vol. 13, 2022.

[8] Z. Yang *et al.*, "SP-ILC: concurrent single-pixel imaging, object location, and classification by deep learning," *Photonics*, vol. 8, 2021.

[9] L. Peng *et al.*, "Image-free single-pixel object detection," *Opt. Lett.*, vol. 48, pp. 2527–2530, 2023.

[10] R. Martin-Brualla *et al.*, "NeRF in the wild: neural radiance fields for unconstrained photo collections," in *Proc. 2021 IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, pp. 7206–7215, 2021.

[11] X.-Y. Liu *et al.*, "3D human pose and shape estimation from video," in *Proc. 2022 IEEE Int. Conf. on Internet of Things (iThings), IEEE Green Computing & Communications (GreenCom), IEEE Cyber, Physical & Social Computing (CPSCom), IEEE Smart Data (SmartData), and IEEE Congress on Cybermatics (Cybermatics)*, pp. 617–624, 2022.

[12] C. Choy, J. Gwak and S. Savarese, "4D spatio-temporal ConvNets: Minkowski Convolutional Neural Networks," in *Proc. 2019 IEEE/ Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3070–3079, 2019.

[13] P. Kilcullen, T. Ozaki, and J. Liang, "Compressed ultrahigh-speed single-pixel imaging by swept aggregate patterns," *Nat. Commun.*, vol. 13, 2022.

[14] Z. Sun, F. Latorre, T. Sanchez and V. Cevher, "A plug-and-play deep image prior," in *Proc. 2021 IEEE Int. Conf. Acoustics, Speech and Signal Processing (ICASSP)*, pp. 8103–8107, 2021.

[15] C. Osorio Quero, D. Durini, J. Rangel-Magdaleno, J. Martinez-Carranza, and R. Ramos-Garcia, "Deep-learning blurring correction of images obtained from NIR single-pixel imaging," *J. Opt. Soc. Am. A*, vol. 40, no. 7, pp. 1491–1499, 2023.

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