

Review

# Compressive Sensing in Image/Video Compression: Sampling, Coding, Reconstruction, and Codec Optimization

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**Abstract:** Compressive Sensing (CS) has emerged as a transformative technique in image compression, offering innovative solutions to challenges in efficient signal representation and acquisition. This paper provides a comprehensive exploration of the key components within the domain of CS applied to image and video compression. We delve into the fundamental principles of CS, highlighting its ability to efficiently capture and represent sparse signals. The sampling strategies employed in image compression applications are examined, emphasizing the role of CS in optimizing the acquisition of visual data. The measurement coding techniques leveraging the sparsity of signals are discussed, showcasing their impact on reducing data redundancy and storage requirements. Reconstruction algorithms play a pivotal role in CS, and this article reviews state-of-the-art methods, ensuring a high-fidelity reconstruction of visual information. Additionally, we explore the intricate optimization between the CS encoder and decoder, shedding light on advancements that enhance the efficiency and performance of compression techniques in different scenarios. Through a comprehensive analysis of these components, this review aims to provide a holistic understanding of the applications, challenges, and potential optimizations in employing CS for image and video compression tasks.

**Keywords:** compressive sensing; sampling; measurement coding; reconstruction algorithm; codec optimization

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## 1. Introduction

In the era of rapid technological advancement, the sheer volume of data generated and exchanged daily has become staggering. This influx of information, from high-resolution images to bandwidth-intensive videos, has posed unprecedented challenges to conventional methods of data transmission and storage. As we grapple with the ever-growing demand for the efficient handling of these vast datasets, a groundbreaking concept emerges—Compressive Sensing [1].

Traditionally, the Nyquist–Shannon sampling theorem [2] has governed our approach to capturing and reconstructing signals, emphasizing the need to sample at twice the rate of the signal’s bandwidth to avoid information loss. However, in the face of escalating data sizes and complexities, this theorem’s practicality is increasingly strained. Compressive Sensing, as a disruptive force, challenges the assumptions of Nyquist–Shannon by advocating for a selective and strategic sampling technique.

In general, CS is a revolutionary signal-processing technique that hinges on the idea that sparse signals can be accurately reconstructed from a significantly reduced set of measurements. The principle of CS involves capturing a compressed version of a signal, enabling efficient data acquisition and transmission. As the Figure 1 shows, in the field of image processing, numerous works have been proposed in each of various domains, exploring innovative techniques and algorithms to harness the potential of compressive imaging [3–11], efficient communication systems [12–20], pattern recognition [21–29], and video processing tasks [30–38]. The versatility and effectiveness of CS make it a compelling area of study with broad implications across different fields of signal processing and information

retrieval. Moreover, Figure 2 illustrates the annual publication count of articles related to CS in the four major domains of CS applications in image processing since 2010. It is evident that CS-related research has increasingly become a focal point of attention for researchers. Therefore, a comprehensive and integrated introduction to CS is anticipated. The main contributions of this review are as follows:

- This review emphasizes various sampling techniques, with a focus on designing measurement matrices for superior reconstruction and efficient coding.
- We explore the intricacies of measurement coding, covering approaches like intra prediction, inter prediction, and rate control.
- We provide a comprehensive analysis of CS codec optimization, including diverse reconstruction algorithms, and discuss current challenges and future prospects.

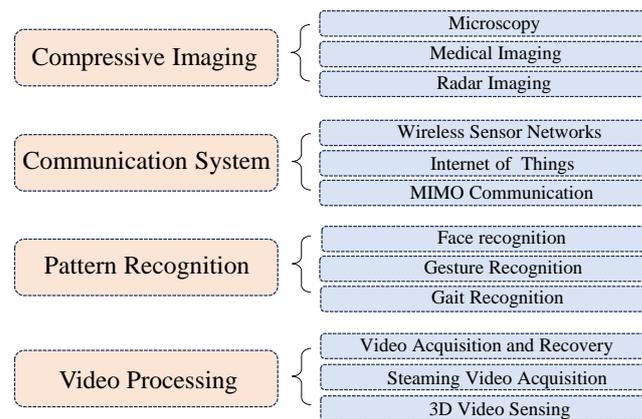


Figure 1. The applications of compressive sensing in image/video processing.

The remainder of this paper is organized as follows: Section 2 presents an overview of the principles of compressive sensing. In Section 3, we introduce algorithms for the sampling part in CS, with a particular emphasis on the measurement matrices designed for better reconstruction quality and those optimized for improved measurement coding. The methods of intra/inter prediction and rate control in measurement coding are elaborated in detail in Section 4. Corresponding to the sampling, the reconstruction methods will be discussed in Section 5, where they are from both traditional and learning-based algorithms. Section 6 provides a detailed discussion on the overall optimization of the CS codec. In Section 7, we discuss the current challenges and future scope of the CS technique. An eventual conclusion of the paper will be given in Section 8.

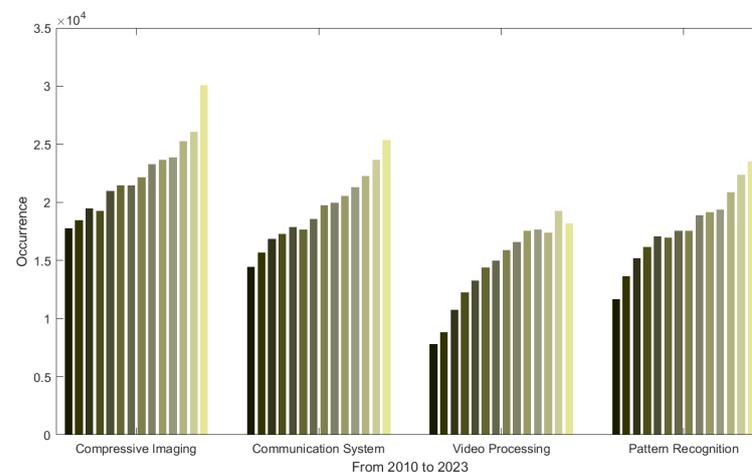


Figure 2. The paper numbers of compressive sensing research in image processing during the past decade.

## 2. Compressive Sensing Overview

Consider an original signal  $X$ , which is an  $N$ -length vector that can be sparsely represented as  $S$  in a transformed domain using a specific  $N \times N$  transform matrix  $\Psi$ , where  $K$ -sparse implies that only  $K$  elements are non-zero, and the remaining are close to or equal to zero. This relationship is expressed by the equation:

$$X_{N \times 1} = \Psi_{N \times N} S_{N \times 1}. \tag{1}$$

The sensing matrix, also known as the sampling matrix  $A$ , is derived by multiplying an  $M \times N$  measurement matrix  $\Phi$  by the transform matrix  $\Psi$ , where  $K \ll M \ll N$ :

$$A_{M \times N} = \Phi_{M \times N} \Psi_{N \times N}. \tag{2}$$

The sampling rate, or Compressed Sensing (CS) ratio, denoted as the number of measurements  $M$  divided by the signal length  $N$ , indicates the fraction of the signal that is sampled:

$$\text{Sampling Rate (CS ratio)} = \frac{M}{N}. \tag{3}$$

Finally, the measurement vector  $Y$  is obtained by multiplying the sensing matrix  $A$  with the sparse signal  $S$ :

$$Y_{M \times 1} = \Phi_{M \times N} \Psi_{N \times N} S_{N \times 1}. \tag{4}$$

Figure 3 shows the sampling procedure details of CS. We will elaborate the setting and design of the measurement matrix in Section 3.

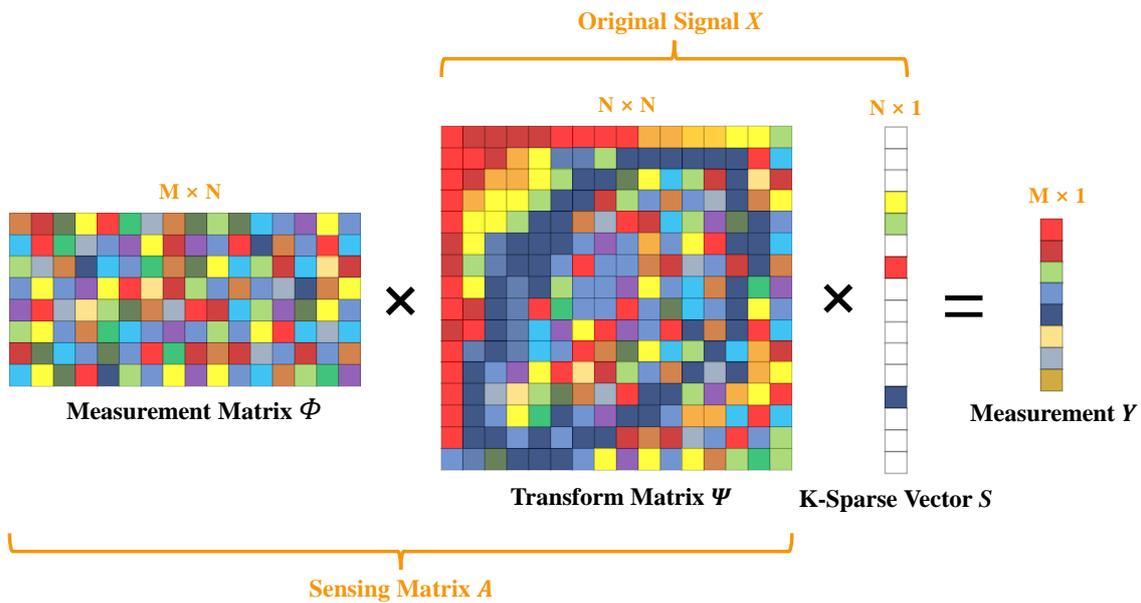


Figure 3. Procedure of compressive sensing encoder.

Since the CS reconstruction is an ill-posed problem [39], to obtain a reliable reconstruction, the conventional optimization-based CS methods commonly solve an energy function as:

$$\hat{X} = \arg \min_X \frac{1}{2} \|\Phi X - y\|_2^2 + \lambda \mathcal{R}(X), \tag{5}$$

where  $\frac{1}{2} \|\Phi X - y\|_2^2$  represents the data-fidelity term for modeling the likelihood of degradation, and the  $\lambda \mathcal{R}(X)$  indicates the prior term with a parameter of regularization of  $\lambda$ . The details for the CS reconstruction will be introduced in Section 5, later.

### 3. Sampling Algorithms

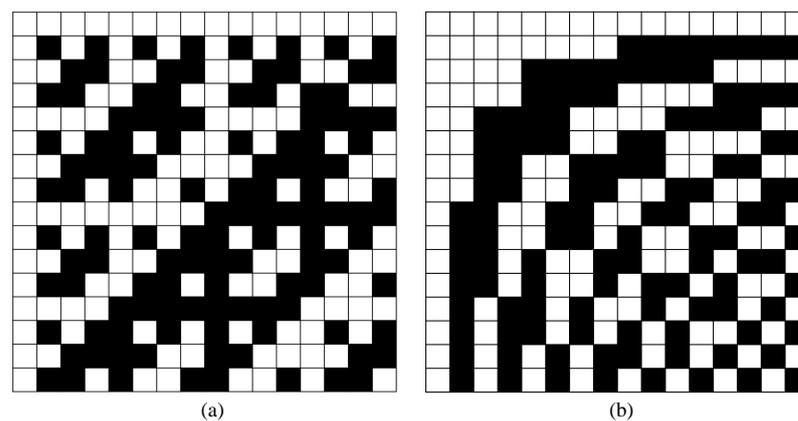
#### 3.1. Measurement Matrix for Better Reconstructions

One of the fascinating aspects of compressive sensing focuses on the development of measurement matrices. The construction of these matrices is crucial, as they need to meet specific constraints. They should align coherently with the sparsifying matrix to efficiently capture essential information from the initial signal with the least number of projections. On the other hand, the matrix needs to satisfy the restricted isometry property (RIP) to preserve the original signal's main information in the compression process. However, in the research of [40,41], they verified the possibility that maintaining sparsity levels in a compressive sensing environment does not necessarily require the presence of the RIP, and also demonstrated that it is not a mandatory requirement for adhering to the random model of a signal. Moreover, designing a measurement matrix with low complexity and hardware-friendly characteristics has become more and more crucial in the context of real-time applications and low-power requirements.

In CS-related research a decade ago, random matrices like Gaussian or Bernoulli matrices were often selected as the measurement matrices, which satisfied the RIP conditions of CS. Although these random matrices are easy to implement and contribute to improved reconstruction performance, they come with several notable disadvantages, such as the requirement for significant storage resources and the challenging recovery while dealing with large signal dimensions [42]. Therefore, the issue of the measurement matrix has been widely discussed in recent works.

##### 3.1.1. Conventional Measurement Matrix

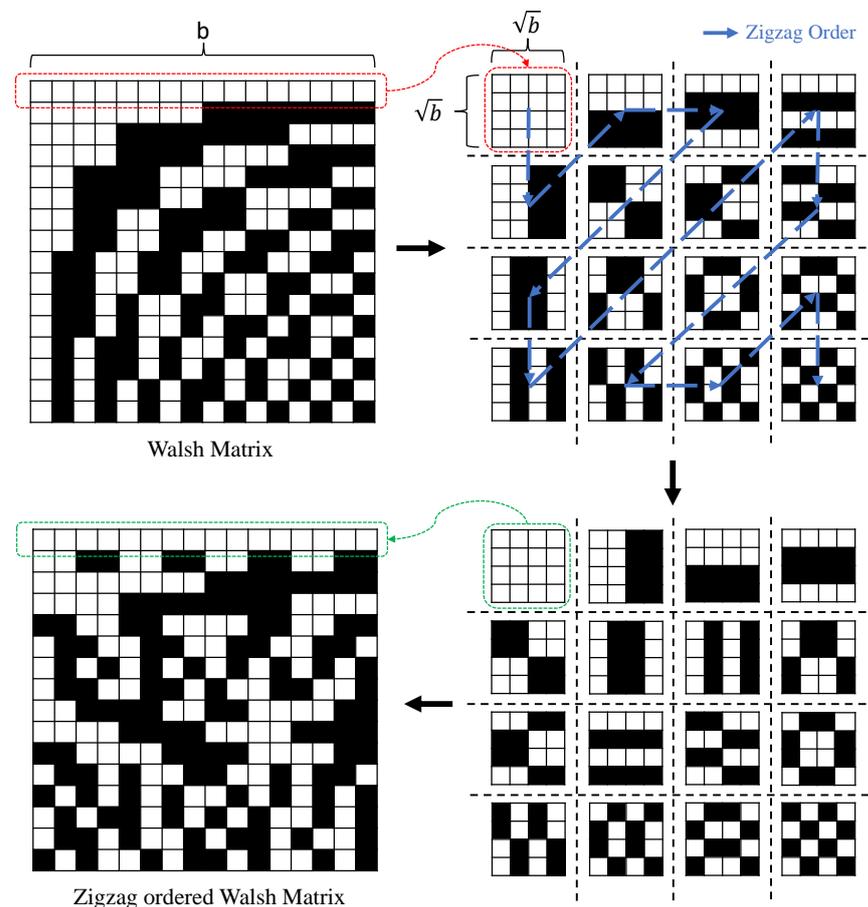
Conventional measurement matrices encompass multiple categories, ranging from random matrices to deterministic matrices, each contributing uniquely to the applications in CS. Random matrices are constructed by randomly selecting elements from a certain probability distribution, such as the random Gaussian matrix (RGM) [43] and random binary matrix (RBM) [44]. The well-known traditional deterministic matrices include the Bernoulli matrix [45], Hadamard matrix [46], Walsh matrix [47], and Toplitz matrix [48]. Figure 4 gives an example of two famous deterministic matrices.



**Figure 4.** (a) is Hadamard Matrix and (b) is Walsh Matrix.

Although these deterministic matrices have been extensively researched and successfully applied to the CS camera, because of their good sensing performance, fast reconstruction, and hardware-friendly properties, they are insupportable when applied to the ultra-low CS ratio [49]. Moreover, for instance, in the work of [44], the information of the pixel domain can be obtained by changing a few rows in the matrix, but the modified matrix results in an unacceptable reconstruction performance, posing enormous challenges for practical applications. In recent years, some studies have been carried out to investigate the effect of Hadamard and Walsh projection order selection on image reconstruction quality by reordering orthogonal matrices [50–54]. A Hadamard-based Russian-doll ordering

matrix is proposed in [50], which sorts the projection patterns by increasing the number of zero-crossing components. In the works of [51,52], the authors present a matrix, called the cake-cutting ordering of Hadamard, which can optimally reorder the deterministic Hadamard basis. More recently, the work of [54] designs a novel hardware-friendly matrix named the Zigzag-ordered Walsh (ZoW). Specifically, the ZoW matrix uses the zigzag to reorder the blocks from the Walsh matrix, and, finally, vectored them. The illustration of the process is shown in Figure 5.



**Figure 5.** The illustration of the process from Walsh matrix to ZoW matrix.

In the proposed matrix of [54], the low-frequency patterns are in the upper-left corner, and the frequency increases according to the zigzag scan order. Therefore, across different sampling rates, ZoW consistently retains the lowest frequency patterns, which are pivotal for determining the image quality. This allows ZoW to extract features effectively from low to high-frequency components.

### 3.1.2. Learning-Based Measurement Matrix

Recently, there has been a surge in the development of image CS algorithms based on deep neural networks. These algorithms aim to acquire features from training data to comprehend the underlying representation and subsequently reconstruct test data from their CS measurements. Therefore, some learning-based algorithms are developed to jointly optimize the sampling matrix and the non-linear recovery operator [55–61]. Ref. [55]’s first attempt leads into a fully connected layer as the sampling matrix for simultaneous sampling and recovery. In the works of [56,57], the authors present the idea of adopting a convolution layer to mimic the sampling process and utilize all-convolutional networks for CS reconstruction. These methods not only train the sampling and recovery stages jointly but are also non-iterative, leading to a significant reduction in time complexity compared to their optimization-based counterparts. However, only utilizing the fully

connected or repetitive convolutional layers for the joint learning of the sampling matrix and recovery operator lacks structural diversity, which can be the bottleneck for a further performance improvement. To address this drawback, Ref. [59] proposes a novel optimization-inspired deep-structured network (OPINE-Net), which includes a data-driven and adaptively learned matrix. Specifically, the measurement matrix  $\Phi \in \mathbb{R}^{M \times N}$  is a trainable parameter and is adaptively learned by the training dataset. Two constraints are applied to attain the trained matrix simultaneously. Firstly, the orthogonal constraint is designed into a loss term and then enforced into the total loss, as follows:

$$\mathcal{L}_{\text{orth}} = \frac{1}{M^2} \|\Phi\Phi^T - I\|_F^2 \tag{6}$$

where  $I$  represents the identity matrix. For the binary constraint, they introduce an element-wise operation, defined below:

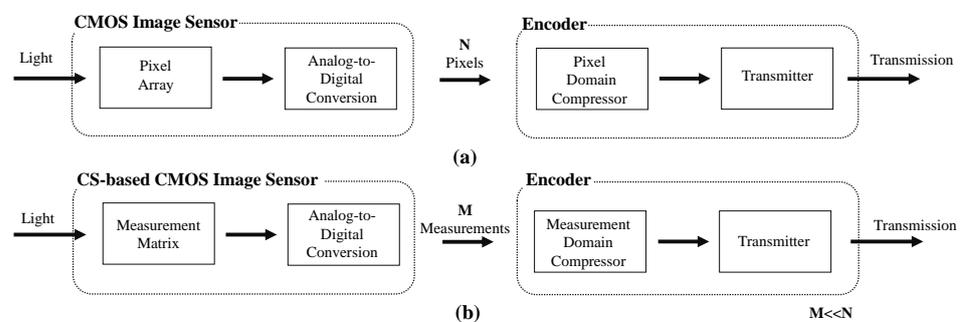
$$\text{BinarySign}(z) = 1 \text{ if } z \geq 0 \text{ or } -1 \text{ if } z < 0 \tag{7}$$

Experiments show that their proposed learnable matrix can achieve a superior reconstruction performance with constraint incorporation when compared to conventional measurement matrices.

In general, by learning the features of signals, learning-based measurement matrices can more effectively capture the sparse representation of signals. This personalized adaptability enables learning-based measurement matrices to outperform traditional construction methods in certain scenarios. Another strength of learning-based measurement matrices is their adaptability. By adjusting training data and algorithm parameters, customized measurement matrices can be generated for different types of signals and application scenarios, enhancing the applicability of compressed sensing in diverse tasks. However, obtaining these trainable matrices usually needs a substantial amount of training data and complex algorithms. We believe that the future research focus will revolve around devising more efficient approaches to acquire matrices with better adaptability.

### 3.2. Measurement Matrix for Better Measurement Coding

It is noticed that the data reduction from the original signal to CS measurement does not completely equal signal compression, and these measurements can indeed be transmitted directly, but still require a substantial bandwidth. To alleviate the transmitter’s load further, the CS-based CMOS image sensor can collaborate with a compressor to produce a compressed bitstream. However, due to the high complexity, the conventional pixel-based compressor is not suitable for CS systems aiming at reducing the computational complexity and power consumption of the encoder [1]. The difference between conventional image sensors and CS-based sensors is shown in Figure 6.



**Figure 6.** The illustration of conventional imaging system (a) and CS-based CMOS image sensor (b). The measurement coding is performed on the latter.

Therefore, to further compress measurements, several well-designed measurement matrices for better measurement coding have been recently proposed [62,63]. Wherein,

a novel framework for measurement coding is proposed in [63], and designs an adjacent pixels-based measurement matrix (APMM) to obtain measurements of each block, which contains block boundary information as a reference for intra prediction. Specifically, a set of four directional prediction modes is employed to generate prediction candidates for each block, from which the optimal prediction is selected for further processing. The residuals represent the difference between measurements and predictions and undergo quantization and Huffman coding to create a coded bit sequence for transmission. Importantly, each encoding step corresponds to a specific operation in the decoding process, ensuring a coherent and reversible transformation. Extensive experimental results show that [63] can obtain a superior trade-off between the bit-rate and reconstruction quality. Table 1 illustrates the comparison of different introduced measurement matrices that are commonly used in CS.

**Table 1.** The PSNR (dB) performance of different matrices on Set5 dataset.

Image	CS Ratio	Measurement Matrices				
		RGM [43]	Hadamard [44]	Bernoulli [45]	Toplitz [48]	APMM [63]
Lenna	30%	33.24	28.25	29.87	28.26	33.98
	40%	34.76	29.71	31.24	30.83	36.04
	50%	36.39	30.92	32.48	33.91	37.69
Clown	30%	32.15	24.59	28.36	26.85	32.79
	40%	33.52	26.94	30.49	28.93	35.17
	50%	35.46	28.03	30.67	31.42	37.08
Peppers	30%	33.59	27.78	30.24	30.40	33.83
	40%	34.82	28.03	32.18	32.75	35.50
	50%	36.14	30.17	33.52	33.35	36.74

#### 4. Measurement Coding

In addition to designing a measurement matrix to enhance measurement coding, three key aspects further contribute to refining coding advantages: intra prediction, inter prediction, and rate control. Intra prediction involves predicting pixel values within a frame, exploiting spatial correlations to enhance compression efficiency. Inter prediction extends this concept by considering the temporal correlation between consecutive frames, facilitating enhanced predictive coding. Meanwhile, effective rate control mechanisms are essential for balancing compression ratios without compromising the quality of the reconstructed signal. By addressing these aspects in tandem with a well-designed measurement matrix, a comprehensive approach is established for advancing measurement coding capabilities, thereby improving the overall system performance and resource utilization.

##### 4.1. Measurement Intra Prediction

This intra prediction approach in measurement coding aims to reduce the number of measurements needed for accurate signal representation. It is especially valuable when dealing with sparse or compressible signals, where the prediction of one block's measurements can inform and enhance the prediction accuracy of adjacent blocks.

Hence, some studies are dedicated to this aspect and propose numerous novel algorithms [63–65]. In the works of [64], the authors mainly present an angular measurement intra prediction algorithm compatible with CS-based image sensors. Specifically, they apply the idea of an H.264 intra prediction and emulate its computation. More structural rows in the random 0/1 measurement matrix are designed for embedding more precise boundary information of neighbors for intra prediction. Ref. [65] applies the Hadamard matrix instead of the random matrix to sampling and generate predictive candidates, since the pseudo-random cannot guarantee the similarity between the sender and receiver. Moreover, the features of the pixel domain are also utilized to effectively reduce the spatial redundancy in the measurement domain. However, Ref. [65] achieves a good performance

but requires high hardware resources. To address this shortcoming, the research of [66] proposes a novel near lossless predictive coding (NLPC) approach to compress block-based CS measurements, which encodes the prediction error measurement between the target CS and current measurement to attain a lower data size. Furthermore, a complete block-based CS with NLPC with scalar quantization (BCS-NLPC-SQ) is designed in [66] to explore the image quality at varying CS ratios with different blocking sizes. In the previously mentioned work of [63], the authors not only propose a novel matrix APMM for better measurement coding but also present a four-mode intra prediction strategy, which is called the measurement-domain intra prediction (MDIP). An optimal prediction mode for each block is selected from a set of candidates to minimize the difference between the prediction and the current block. Each block is predicted based on the boundary measurements from neighboring and previously encoded blocks. Comparing the sum of absolute differences of four prediction candidates for each block will be utilized to minimize the amount of information to be coded. Combined with the aforementioned APMM, the proposed measurement coding framework demonstrates a superiority in data compression.

#### 4.2. Measurement Inter Coding

Regarding the measurement coding in video-oriented CS, the spatial and temporal redundancy in measurement has become a primary concern that is necessary to further compress. Accordingly, a novel work with inter prediction is proposed to further reduce the spatial redundancy in measurements while still maintaining visual quality [67]. In [67], the authors divide the type of measurement into two portions: static measurement as the non-moving part and dynamic measurement as the moving part in the pixel domain. In general, the information of consecutive frames is similar, resulting in temporal redundancy. To further reduce the bandwidth usage, quantization is a straightforward approach, such as scalar feedback quantization (SFQ). However, the output from CS is represented in a compressed vector, in which an existing video compression algorithm could not be used. Therefore, the work of [67] designs a temporal redundancy reduction method in video CS over the communication channel, which can be shown in Figure 7.

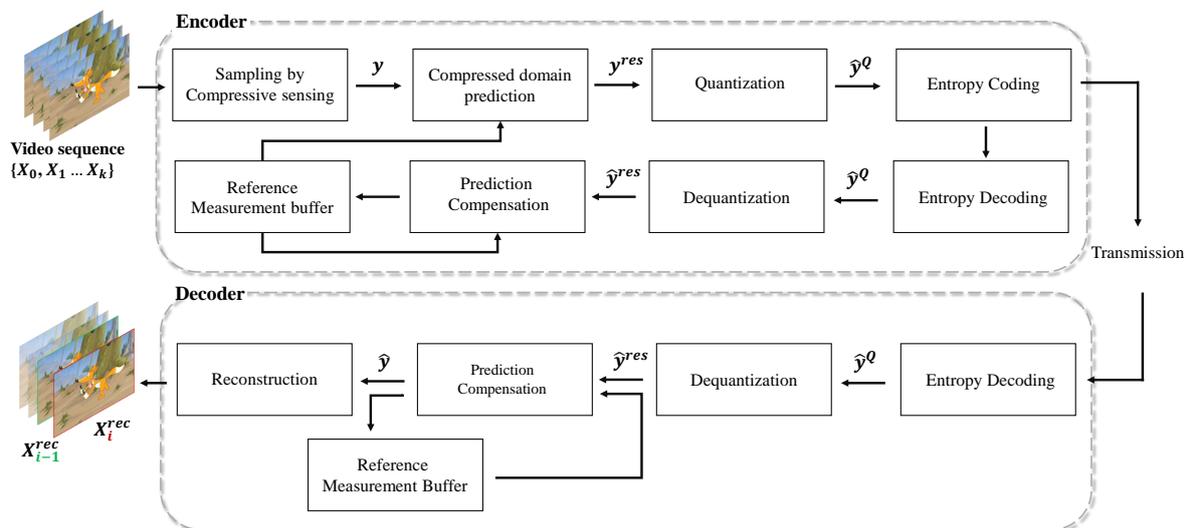


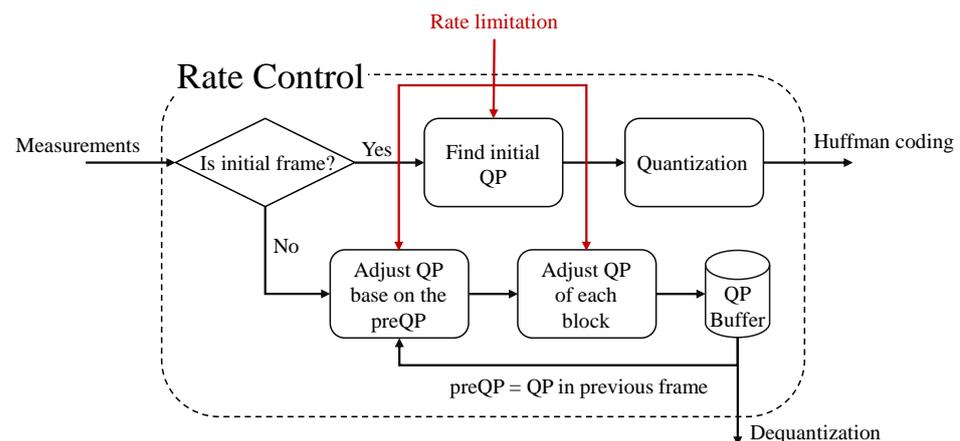
Figure 7. The intra/inter prediction of measurement coding in compressive sensing.

By utilizing the framework in Figure 7, the proposed method in [67] not only achieves a comparable estimation performance but also effectively reduces sampling costs, easing the burdens on communication and storage. As a result, this straightforward strategy offers a practical solution to mitigate the bandwidth usage.

### 4.3. Rate Control

On the other hand, the rate control is another critical strategy in CS, involving the allocation of limited measurement resources to ensure the quality of signal recovery. The rate control requires a balance between the design of the measurement matrix, the sampling rate, and the accuracy of signal reconstruction. Optimizing the bit-rate allocation allows for better signal recovery under constrained resources, especially in wireless sensor networks (WSN).

The work of [68] develops a frame adaptive rate control scheme for video CS. Figure 8 illustrates the part of rate control in their proposed framework. In a nutshell, the rate limitation will lead the first frame to find an initial value of QP by their proposed triangle threshold-based quantization method and guide the subsequent frames to adjust the QP based on the predicted QP. The paper of [69] is the extended version of [63] that was described before. In [69], the authors further propose the rate control algorithm using an iterative approach. They consider that the reconstruction quality and the encoded bit-rate mainly rely on two parameters, the CS ratio and the quantization step size. Therefore, they design a rate control algorithm to further process the residuals between measurements and predictions, in order to generate a coded bit sequence for transmitting. As a result, with a component of rate control, their proposed framework can compress the measurements and increase coding efficiency significantly with excellent reconstruction quality, leading to a smaller bandwidth required in communication systems.



**Figure 8.** The flow chart of rate control in the work of [68].

## 5. Reconstruction Approaches

In CS, reconstruction represents the method to recover the original signal from compressed measurement data. The fundamental idea behind CS reconstruction is to capture signal information with significantly fewer measurements than traditional sampling methods, enabling the efficient compression and subsequent reconstruction of the signal. The reconstruction aims to accurately restore sparse signals from a relatively small number of measurements using mathematical models and prior knowledge about the sparsity of the signal. The objective of the reconstruction approach is to minimize distortions and errors introduced during the measurement process, while preserving the structural integrity of the signal. In the following subsections, we will elaborate on reconstruction methods from both conventional reconstruction methods and deep learning-based reconstruction methods.

### 5.1. Conventional Reconstruction Methods

There are typically two types of conventional reconstruction methods based on the constraint: L1-norm-based and L0-norm-based algorithms. L1-norm-based CS reconstruction algorithms commonly use the L1-norm as a measure of sparsity. The goal of these algorithms is to find a sparse representation such that the difference between the measured values and the original signal is minimized. Some common algorithms for the L1-norm

minimization include the approximate message passing (AMP) [70], iterative shrinkage-thresholding algorithm (ISTA), Fast-ISTA [71], and L1-magic [72,73]. Correspondingly, the L0-norm refers to the number of non-zero elements in a vector, and these methods aim to find a representation with the fewest non-zero elements, essentially seeking the most sparse representation. L0-norm optimization problems are often NP-hard, practical approaches that involve approximate optimization algorithms like greedy algorithms to find an approximate solution. The common greedy algorithms utilized in CS are orthogonal matching pursuit (OMP) [74], L0 gradient minimization (LOGM) [75], and sparsity adaptive matching pursuit (SAMP) [76].

In general, for the conventional reconstruction methods, L1-norm-based algorithms are more common and easier to handle since the optimization problem associated with L1-norm has convex properties. On the other hand, L0-norm-based algorithms can be more complex and computationally challenging. In practical applications, L1-norm is often preferred due to its favorable mathematical properties and computational efficiency.

### 5.2. Deep Learning-Based Reconstruction Methods

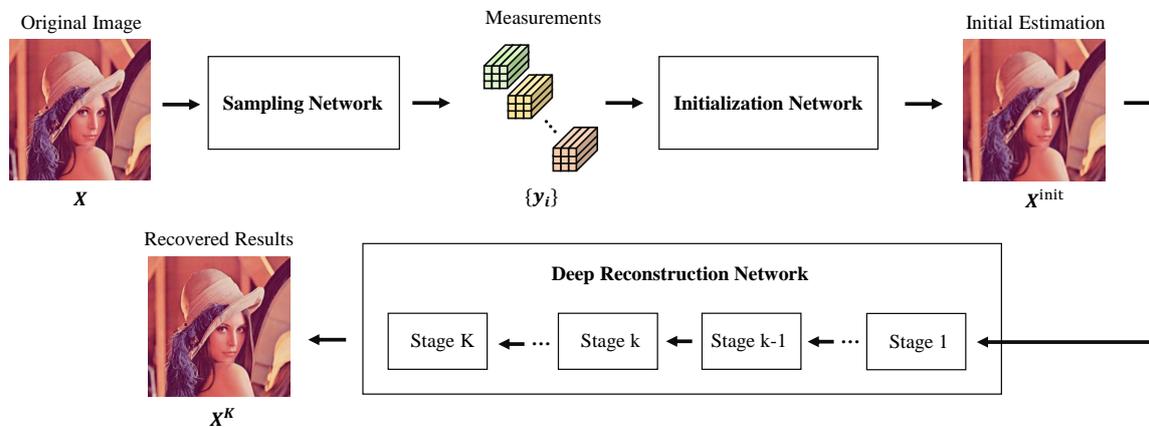
Regarding the conventional compressive sensing reconstruction algorithms, it is crucial to address their inherent limitations. Traditional methods often struggle with the reconstruction of highly complex signals and may encounter challenges in accurately capturing intricate features due to their reliance on fixed mathematical models. Moreover, these approaches typically assume sparsity as a priori information, which might not hold for all types of signals [77]. Recognizing these shortcomings, a paradigm shift has occurred in the form of deep learning-based CS reconstruction algorithms. These innovative approaches leverage the power of neural networks to adaptively learn and model complex signal structures, paving the way for more robust and versatile reconstruction capabilities.

Fueled by the robustness of convolutional neural networks (CNN), numerous learning-based CS reconstruction approaches have been developed by directly learning the inverse mapping from the measurement domain to the original signal domain [55,56,78]. The study conducted by [55] introduces a non-iterative and notably fast algorithm for image reconstruction from random CS measurements. A novel class of CNN architectures called ReconNet is introduced in their work, which takes in CS measurements of an image block as input and outputs the reconstructed image block. In [56], the authors focus on solving the problem of how to design a sampling mechanism to achieve optimal sampling efficiency, and how to perform the reconstruction to obtain the highest quality to achieve an optimal signal recovery. As a result, they design the sampling operator via a convolution layer and develop a convolutional neural network for reconstruction (CSNet+), which learns an end-to-end mapping between the measurement and target image. To preserve more texture details, a dual-path attention network for CS image reconstruction is proposed in the research of [78], which is composed of a structure path, a texture path, and a texture attention module. Specifically, the structure path is designed to reconstruct the dominant structure component of the original image, and the texture path aims to recover the remaining texture details.

Recently, to further enhance the reconstruction performance, a novel neural network structure for CS has been developed, which is called Deep Unfolding Network (DUN). The architecture of DUN is shown in Figure 9.

The conventional DUN architecture is usually divided into three parts in CS: The sampling network, initialization network, and deep reconstruction network. The sampling network aims to utilize the convolution layers to simulate the sampling operation to obtain the measurements. Before going through deep reconstruction networking, an initialization network is employed to generate the initial estimation of the target image. The image reconstructed at this phase is often of subpar quality and still requires optimization and improvement. The final recovered results will be obtained by a deep reconstruction network. The deep reconstruction network typically consists of multiple stages, each representing an iteration of the traditional iterative reconstruction algorithm. These stages are usually

connected sequentially, allowing the network to learn and refine the recovery at each stage. The advantage of deep unfolding lies in its ability to leverage the representation power of deep neural networks to capture complex patterns and dependencies in the data, surpassing the capabilities of traditional iterative methods.



**Figure 9.** The architecture of DUN.

Therefore, the DUN-based image compressive sensing algorithms with good interpretability have been extensively proposed in recent years and have gradually become mainstream [58,61,79–82]. The work of [79] proposes a cascading network with several incremental detail reconstruction modules and measurements of residual updating modules, which can be regarded as the prototype of DUN. Refs. [58,80] integrate the model-based ISTA and AMP [70] algorithms into the framework of DUN, respectively, achieving a superior performance while retaining commendable flexibility.

More recently, some researchers have started to pay attention to both the size of the network parameters and the speed of the reconstruction process, while retaining the recovered quality [61,81,82]. In general, DUN is composed of a fixed number of stages; the recovered results will be closer to the original images while increasing the unfolding iteration number. The authors from the research [82] perceive that the content of diverse images is substantially different, and it is unnecessary to process all images indiscriminately. Adhering to this perspective, they design a novel dynamic path-controllable deep unfolding network (DPC-DUN). With an elaborate path-controllable selector, their model can adaptively select a rapid and appropriate route for each image and is slimmable by regulating different performance-complexity trade-offs.

## 6. Codec Optimization of CS

Encoder optimization in the context of CS involves the elaborate selection and transformation of input signals into a compressed form. This phase is critical for capturing the essential information needed for accurate signal reconstruction while discarding non-essential components. One of the challenges lies in striking a balance between compression ratios and the preservation of crucial signal features. On the other hand, decoder optimization plays a pivotal role in the reconstruction of signals from the compressed representations generated by the encoder. The decoder must efficiently recover the original information, addressing challenges such as noise, artifacts, and inherent loss during the compression.

Recently, many researchers have been focusing on the holistic performance of CS and developed numerous optimization approaches for CS codec, which brings the gap between encoder and decoder enhancements. By concurrently refining both components, the CS codec optimization aims to achieve synergistic improvements, unlocking new possibilities for efficient data compression and signal reconstruction.

## 6.1. Scalable and Adaptive Sampling-Reconstruction

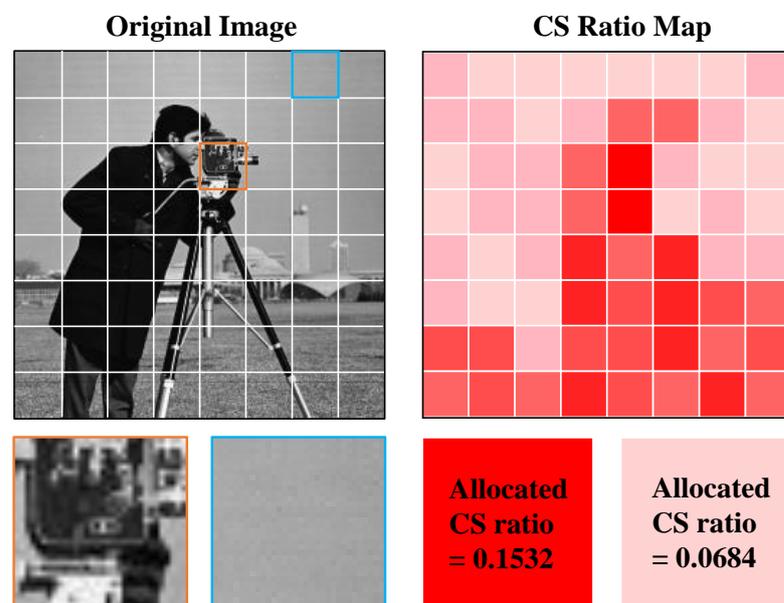
### 6.1.1. Scalable Sampling-Reconstruction

Although the learning-based algorithms have achieved excellent results, a prevalent limitation among current network-based approaches is that they treat CS sampling-reconstruction tasks separately for various sampling rates. This approach results in the development of intricate and extensive CS systems, necessitating the storage of a multitude of parameters. Such complexity proves to be economically burdensome when considering hardware implementation costs.

Several studies have been proposed to save the CS system memory cost and improve the model scalability [60,83,84]. In the work of [83], a scalable convolutional neural network (SCSNet) is proposed to achieve scalable sampling and scalable reconstruction with only one model. The SCSNet incorporates a hierarchical architecture and a heuristic greedy approach performed on an auxiliary dataset to independently acquire and organize measurement bases. Inspired by the conventional block-based CS methods, Ref. [60] develops a multi-channel deep network for the block-based image CS (DeepBCS) by exploiting inter-block correlations to achieve scalable CS ratio allocation. However, whether the training difficulty and defect of delicacy in [83], or the weak adaptability and structural inadequacy in [60]; both, to some extent, bring the inflexibility and low efficiency of the entire framework. The authors of [84] are devoted to solving the issues of arbitrary-sampling matrices by proposing a controllable network (COAST) and random projection augmentation to promote training diversity, thus realizing scalable sampling and reconstruction with high efficiency.

### 6.1.2. Adaptive Sampling-Reconstruction

Another optimization aspect of the CS codec is to improve the adaptability while processing different images [85,86]. The key idea is to exploit the saliency information of images, and then allocate more sensing resources to these salient regions but fewer to non-salient regions. Figure 10 demonstrates the illustration of adaptive sampling-reconstruction.



**Figure 10.** The illustration of adaptive sampling-reconstruction. The darker the color of the blocks, the higher the allocated CS ratio.

Given that image information is often unevenly distributed, an effective approach to enhance the restored image quality involves optimizing CS ratio allocations based on saliency distribution. The works of [86,87] define saliency as the locations exhibiting a low spatial correlation with their surroundings. As illustrated in Figure 10, the block enclosed

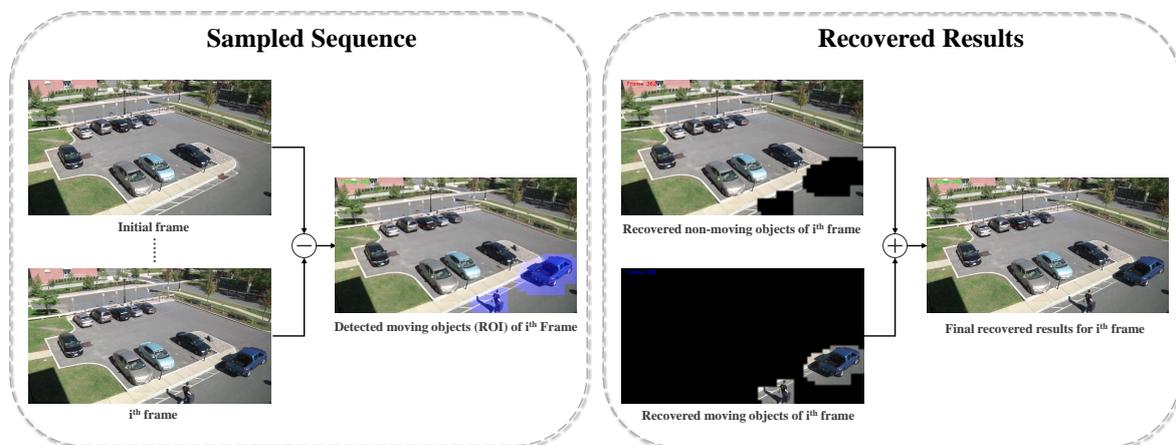
in the crimson box should be assigned a higher CS ratio than the one within the light red. This adjustment is justified by the former's intricate details and richer information content. Being equipped with the optimization-inspired recovery subnet guided by saliency information and a multi-block training scheme that prevents blocking artifacts in [86], this content-aware scalable network (CASNet) can jointly reconstruct the image blocks sampled at various CS ratios with one single model. The PSNR/SSIM and time-consuming results for various CS algorithms on Set11 [55] are shown in Table 2. The results of five CS ratios are provided to further demonstrate the different reconstruct robustness of different methods.

**Table 2.** The average PSNR (dB)/SSIM performance comparison among various CS algorithms on Set11 [55] with five different CS ratios. The average parameter and computational complexity are also provided.

Methods	CS Ratio					Parameter (M) /Time (ms)
	1%	4%	10%	30%	50%	
ReconNet [55]	17.43/0.4017	20.93/0.5897	24.38/0.7301	29.09/0.8693	32.25/0.9177	0.98/2.69
DPA-Net [78]	18.05/0.5011	23.50/0.7205	26.99/0.8354	33.35/0.9425	36.80/0.9685	65.17/36.49
CSNet+ [56]	20.67/0.5411	24.83/0.7480	28.34/0.8580	34.27/0.9492	38.47/0.9796	4.35/16.77
OPINE-Net [59]	20.15/0.5340	25.69/0.7920	29.81/0.8904	35.79/0.9541	40.19/0.9800	4.35/17.31
AMP-Net [58]	20.55/0.5638	25.14/0.7701	29.42/0.8782	35.91/0.9576	40.26/0.9786	6.08/27.38
DeepBCS [60]	20.86/0.5510	24.90/0.7531	29.42/0.8673	35.63/0.9495	39.58/0.9734	1.64/83.86
COAST [84] *	-	-	30.03/0.8946	36.35/0.9618	40.32/0.9804	1.12/45.54
CASNet [86]	21.97/0.6140	26.41/0.8153	30.36/0.9014	36.92/0.9662	40.93/0.9826	16.90/97.37

\* COAST did not provide the pre-trained models for 1% and 4% CS ratios.

The concept of adaptive sampling rates is also widely employed in surveillance video-oriented CS algorithms [88–93]. The key idea for these methods is shown in Figure 11.



**Figure 11.** The concept of adaptive sampling-reconstruction for surveillance video.

The paper of [91] first proposes a low-cost CS with multiple measurement rates for object detection (MRCS). We use another proposed MYOLO3 detector to predict the key objects, and then sample the regions of the key objects as well as other regions using multiple measurement rates to reduce the size of sampled CS measurements. However, the additional detection networking proposed in [91] will inevitably increase the parameters and the complexity of the whole framework, then bring computation and budget constraints. Moreover, the spatial and temporal correlation between successive frames of the sequence cannot be fully utilized.

Since the sampled scenes from surveillance cameras are usually fixed, some works have been developed to tackle these sequences in a straightforward method [88–90]. In [90], the first round of sampling will be conducted with a lower CS ratio for the initial frame

and the subsequent frames. By comparing the difference between the sampled measurements, thereby locating the position of the moving objects, it also can be regarded as a region-of-interest (ROI). A higher CS ratio will be allocated to these regions for sampling-reconstruction and finally combined with the region that is regarded as background to generate the recovered results. By this background subtraction method, the ROI can be detected without introducing any extra network parameters, but the poor performance in non-ROI can only be served for the video, in which the first frame is the background; this has demonstrated that there is still much room for improvement.

To solve these issues, Ref. [92] proposes a video CS with low-complexity ROI-detection in a compressed domain (VCSL). Different from the work of [90], a binary coordinate is generated after defining ROI and transmitted to the reconstruction, instead of the sampled measurement with the low CS ratio. Moreover, a novel and compact module called a reference frame renewal (RFR) is designed in this work, which states the mechanism for defining a suitable reference, thereby improving the robustness of the framework effectively. Figure 12 shows the test examples from the VIRAT [94] dataset to demonstrate the superior performance while applying [92] to the surveillance system. More recently, Ref. [93] presents an adaptive threshold of ROI detection to replace the conventional and fixed threshold setting manually, which further improves the flexibility of these video-oriented background subtraction methods.



**Figure 12.** The comparison of visual results between multi-rate VCS [90] and VCSL [92].

### 6.2. Pre-Calculation-Based CS Codec

Another aspect of optimizing the CS codec is the pre-calculation, which is developed in the research of [95]. In [95], the authors design a novel codec framework, named the compressive sensing-based image codec with a partial pre-calculation (CSCP). They perceived that in the measurement coding, encoding and decoding are time-consuming, and the quantization has a low complexity but is lossy, leading to a significant degradation of the reconstructed image quality. Therefore, after sampling by CS in the encoder of CSCP, the pre-calculation is performed by another proposal matrix multiplication-based fast reconstruction (MMFR) to attain the frequency domain data, which effectively reduces the processing time of the decoder. Moreover, unlike the existing common CS codecs [65], their proposed codec integrates quantization in the frequency domain after processing the partial pre-calculation. In addition, to simplify the complicated partial pre-calculation, they substitute the complex reconstruction with several add and shift operators relying on the sparsity of the sensing matrix they choose to further decrease the time-consumption.

As a relatively recent work, the research of [95] paves the way for a novel direction in optimizing CS codec more effectively and in help it to be more hardware-friendly. However, a limitation of this work is that the proposed approach can only be applied to a specific-sensing matrix. Developing a more universal framework for a broader range of sensing matrices is desired in the future.

### 6.3. Down-Sampling Coding-Based CS Codec

The concept of down-sampling-based coding (DBC) proposed in [96] can also be taken into account to optimize the CS codec. As shown in Figure 13, due to the limited bandwidth and storage capacity, videos and images are down-sampled at the encoder and up-sampled at the decoder, which can effectively save data in storage and transmission. The down-sampling, as observed in approaches like Bilinear and Bicubic, serves as a pre-processing step, while up-sampling methods are employed as a post-processing step.

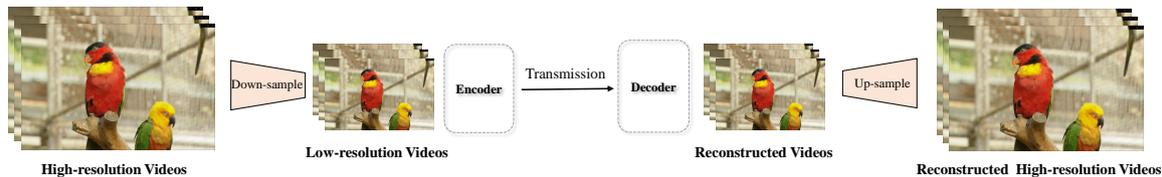


Figure 13. The concept of down-sampling-based coding.

This type of framework usually achieves a superior rate-distortion while utilizing network-based and high-quality super-resolution algorithms [97–99]. However, there are few studies that conduct this idea into CS for codec optimization. Inspired by the concept of DBC, Ref. [100] proposes a novel video compressive sensing reconstruction framework with joint in-loop reference enhancement and out-loop super-resolution, dubbed JVCSR. Specifically, two additional modules are employed to further improve the reconstruction quality: An in-loop reference enhancement module is developed to remove the artifacts and provide a superior-quality frame for motion compensation cyclically. The reconstructed outputs are fed to another proposed out-loop super-resolution module to attain a higher-resolution and higher-quality video at the lower bit-rates. The experimental results demonstrate that DBC also exhibits coding advantages in CS, especially in low bit-rate transmission. It can be anticipated that this type of method will be more widely applied to some straightforward hardware cameras and is able to provide higher-quality videos while sending the low compressed data.

Finally, Table 3 provides an exhaustive comparison to summarize the various abilities of introduced algorithms.

Table 3. The comparison of the different learning-based CS sampling-reconstruction approaches.

Methods	Matrix Learnability	Deblocking Ability	CS Ratio Scalability	CS Ratio Adaptability	Video-Oriented Enhancement
ReconNet [55]	✗	✗	✗	✗	✗
CSNet+ [56]	✓	✓	✗	✗	✗
AMP-Net [58]	✓	✓	✗	✗	✗
OPINE-Net [59]	✓	✓	✗	✗	✗
DeepBCS [60]	✓	✓	✗	✓	✗
DPA-Net [78]	✗	✓	✗	✗	✗
ISTA-Net++ [80]	✗	✓	✓	✗	✗
FSOINET [81]	✓	✓	✗	✗	✗
DPC-DUN [82]	✗	✓	✗	✗	✗
COAST [84]	✓	✓	✗	✓	✗
CASNet [86]	✓	✓	✓	✓	✗
MRVCS [90]	✗	✗	✗	✓	✓
VCSL [92]	✗	✓	✗	✓	✓
JVCSR [100]	✓	✓	✗	✗	✓

## 7. Challenges and Future Scope

The contemporary landscape in data generation is characterized by an unprecedented surge, placing substantial demands on sensing, storage, and processing devices. This

surge has led to the establishment of numerous data centers worldwide, grappling with the immense volume of data and resulting in the substantial power consumption during acquisition and processing. The escalating data production underscores the urgent need for innovative concepts in both data acquisition and processing. The emergence and growing popularity of CS have emerged as a substantial contributor to addressing this burgeoning issue, presenting a paradigm shift in how data are acquired, transmitted, and processed.

However, despite its transformative potential, CS encounters a spectrum of challenges and opportunities that warrant a closer examination. The advent of deep neural networks and transformers has given rise to a plethora of learning-based CS algorithms, aimed at achieving superior reconstruction quality. Nevertheless, a notable hurdle lies in the successful implementation of these algorithms in hardware due to the substantial size of the network models. The practical deployment of these algorithms on hardware platforms remains limited, hindering the widespread adoption.

Recent research has recognized the need to balance reconstruction quality with the size of models and processing speed, leading to the development of models that prioritize reduced parameters while maintaining high-quality reconstruction results [81,82]. These endeavors address the practical requirements for real-world applications, particularly in resource-constrained environments. The pursuit of smaller models with preserved reconstruction efficacy emerges as a pivotal research direction for the future, offering promising avenues for practical implementation. Anticipating the continued advancement of technology, the deployment of more optimized CS algorithms across diverse hardware platforms is expected to gain traction. This optimism stems from the ongoing efforts to strike a balance between computational efficiency and reconstruction quality, making CS increasingly applicable in a variety of real-world scenarios.

Beyond conventional applications, the exploration of CS in light field imaging holds immense promise [101–104]. Light field imaging, renowned for its capability to capture multiple light ray directions and intensities for each point in a scene, seamlessly aligns with the fundamental principles of compressive sensing. This harmonious integration allows for a more efficient harnessing of additional information, thereby enriching the detailed and comprehensive perception of a scene. Furthermore, the reduction in data acquisition requirements achieved through CS in light field imaging introduces significant advantages. This is particularly noteworthy in scenarios involving resource-constrained systems such as sensor networks or mobile devices. The synergy between CS and light field imaging not only enhances the overall quality of the scene perception but also contributes to addressing challenges related to limited resources, paving the way for innovative applications and advancements in these domains.

On the other hand, since the work of [105] had been proposed, several CS systems using chaos filters have been developed recently [106–108]. In general, the chaotic CS system is designed to achieve simultaneous compression and encryption. The encryption can provide many significant features, such as security analysis and statistical attack protection, and uses the parameters as the secret key in the reconstruction of the measurement matrix and masking matrix. The advantages of employing chaotic CS systems might surpass the additional algorithmic consumption, given the reduced data transmission requirements. However, the impact on performance under the scenario of a microcontroller operating at a higher frequency, and consequently exhibiting increased consumption, remains an area that requires further investigation in the future. Last but not least, CS, with its capability to substantially reduce the data representation size while preserving essential information, holds promising prospects for applications in many high-level vision tasks, such as object detection [109,110], semantic segmentation [111], and image classification [112,113]. It is imperative to underscore that the potential of CS in these domains is far from fully realized, and there exists substantial room for further advancements and breakthroughs.

## 8. Conclusions

In this paper, we provide a comprehensive overview of compressive sensing in image and video compression, elaborating it through the lenses of sampling, coding, reconstruction, and codec optimization. Our exploration begins with a detailed discussion of sampling methods, with a particular emphasis on the design of measurement matrices tailored for superior reconstruction quality and optimized for enhanced measurement coding efficiency. We delve into the intricacies of measurement coding, elucidating various approaches such as intra prediction, inter prediction, and rate control. The paper further introduces a spectrum of reconstruction algorithms, encompassing both conventional and learning-based methods. Additionally, we provide a thorough overview of the holistic optimization of the compressive sensing codec. Our discussion extends to the current challenges and future prospects of compressive sensing, offering valuable insights into the evolving landscape of this technique. We believe that this review has the potential to inspire reflection and instigate further exploration within the image and video compression research community. It lays the groundwork for future investigations and applications of compressive sensing in this field.

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