Compressive Sensing: Methods, Techniques, and Applications

Vivek Upadhyaya¹ and Dr. Mohammad Salim²

¹Research Scholar, Department of Electronics and Communication Engineering, Malaviya National Institute of Technology, India
²Professor, Department of Electronics and Communication Engineering, Malaviya National Institute of Technology, India

E-mail: 2018rec9028@mnit.ac.in

Abstract. According to the latest research, it is very much clear that in future we require a huge amount of data as modern advancement in communication and signal processing generates a large number of bytes some examples are 5G peak data rate about 300 Mb/sec, an image of black hole required several petabytes to store & in medical signal processing huge amount of data required. So, by these examples, we can easily understand the scarcity of storage in near future. To overcome this problem of data scarcity such type of data compression is required in which the information of the signal will not be degraded. A well-known method is Compressive Sensing which can easily tackle this problem of data compression.

1. Introduction:
We are living in an era where various types of sensing systems are developed day by day to enhance the performance, fidelity, accuracy, and capacity of the system. Sensing of the signal with its compression is the technique that is very popular nowadays because the compression is used in each & every area of data processing to its storage. By using the sensing technique, we can easily find out the information from the source of information. As we can see in the digital camera which can able to capture an image and can easily give the value of each pixel also have sensing capability. Sensing is a very important process so it requires some necessities also[1][2]. The data which we get by using the sensing has to undergo in the processing which is done using the digital system, for that processing the technique which is required is known as Nyquist theorem, this theorem is considered as the basic benchmark for the digital signal processing that can be employed to recover the compressed signals properly. As stated by the Nyquist the sampling frequency should be the twice maximum frequency component available in the signal. The bandwidth which is as per the principle of Nyquist can easily reconstruct the compressed signal and can maintain a high-level accuracy with very few noisy components. But this traditional theory having some complexity and limitations, the limitations which shows a severe problem with Nyquist is that the bandwidth or frequency which is required to reconstruct the signal is too much high than the maximum component of the original signal. This is not possible in each case because the data which is used is also large if we want to transmit that. So to overcome this problem a new approach named compressive sensing is taken into consideration. This approach can take very few samples/measurements from the original signal and reconstruct the original signal without any noise. So by using this approach we don’t have to store a large amount of data.

Recently, Donoho, Candes, Romberg, and Tao present sparse signals completely reconstructed with high accuracy from the linear, nonadaptive small measurements. Under the result, generate the chances
that the detection of a signal from the small measurement sets, which are far away in the number that’s why it is named, is compressive sensing. In whatever manner three important statements made a CS different from the other classical sampling. Firstly in the given theory of sampling, considers and understands the dimension of the continuous-time signal. So CS is a calculated theory, whose main work to measure the finite-dimensional vector with Rn. Second thing is that CS systems get the measurement values among the test signal and input the original signal at the particular time instead of sampling the signal. Actually, in the latest sampling method, we are taking advantage of the use of more linear measurement which is the same as received signals [3][4]. The design of the test function is the main focus work in the paper that we considered. At the last third statement is finding the difference among the strategy that how the scenario is deal with the recovery signal and some recovery-related problem from the few measurement samples of the original high coefficients. We use the Nyquist Shannon theory which reconstructs the signal with the help of sine interpolation. This is a mostly linear process that has little calculation and easy interpolation. In the spite of CS is a recovery sampling process is obtained by highly nonlinear methods. In this survey describe and discuss all over the brief overview of these techniques.

The high non-zero coefficient values and places used for the representation of sparse and compressible signals can be present with high reliability. This process is known as a sparse approximation. Some standards form like JPEG, JPEG2000, MPEG, and MP3 associated with sparsity and compressibility give benefits to the transform coding schemes. Transform coding is a Leveraging but compressive sensing is the new combined groundwork for signal acquisition and sensor design. CS permits to reduce the sample of the signal which we want to sparse and compressed representation and evaluation cost of the signal. The states of the Nyquist Shannon sampling theorem need a few sample measurements to perfectly recover a bandlimited signal but in the second case if the signal is sparse that’s known as a basis, we extremely deduced the measurement sample signal which we seriously needed for recovery. With the result, when a signal is sparse it can be better regarding performances [5][6]. So the compressive sensing is not used as a firstly sampled the signal at a high rate and after that compressed the data. We would like to search for a path that compressed data should be sense directly with a low sampling rate. Emmanuel Candès, Justin Romberg, and Terence Tao, and David Donoho, Who work on the CS. In their research work trying the large-scaled with sparse and compressible represented signal easily reconstructed from the small number of linear and nonadaptive measurement sets. The most challenging task in the CS field is designing the measurement method. The design of these measurement schemes and their dimension implement the practical data module and acquisition.

The basic concept of compressive sensing is Sparsity. Sparsity and compressibility are the two fundamental concepts that show a significant role in various fields of science and mathematics. Sparsity can be considered as a guide for the approximation theory which is very efficient, algorithms named shrinkage and thresholding also depend upon sparsity. This sparsity has a very good estimation as well as a compression level. The exactness of transform coding depends upon the sparsity level of the signal. The reduction of dimensions with effective modeling can also be done by sparsity. This sparsity can also be used in data acquisition; it also provides efficient protocols for data acquisition [7][8].

The rest of the sections focusing on the advanced technology which we used nowadays give a noticeable point on the result of CS and further the groundwork is to attend background material. This paper’s main target to highlight an overview of the CS techniques and focus on the important parameter of the result, most of the parts are discussed in the next section. To complete our investigation, in brief, we used some analytical models to supervise the fundamentals of low-dimension signals which are mainly used in CS, from the scenario get an advantage of the sparsity and subspace model [9]. We will give focus on the basic theory and algorithm for the reconstruction process of the finite dimension which is a sparse domain. Here in this work some lemmas and some theorems are taken into considerations and some strong results provide for that. Analysis of the theoretical aspects is also considered in this work which is based on the analysis.

The primitive attention is a must to image reconstruction with wanted high resolution in the image pixel should need the number of Fourier samples. Overall the work of this main theory of “compressive
sampling” or “compressed sensing,” hence we suggest the name, but in the real fact linearly is not correct completely. Sometimes the recovery of any kind of pixel image is accurately reconstructed from the small few measurement samples which are low resolution as compared to the needed resolution of the signal image. Compressive sampling is believable that has apart to innuendo [10]. Let us have an example, it gives all possible tips for data acquisition protocols that generally convert analog to essential digital information. Compressive sensing theory can be used for sampling as well as for compression of data. Compressive sensing is the approach that furnishes some key relations between mathematics which are used for sampling and compression and various other fields too like coding theory, statistics, and information theory.

2. Literature Review

Macro Rossi, Alexander in their work focus on object detection which is based on the Compressed Sensing RADAR [11]. In their work, they represent how to localize a target with the help of a MIMO radar array in the spatial domain for compressive sensing and offer the Multi-Branch Matching Pursuit (MBMP) algorithm, which needs the cognition of various targets. Over the MBMP algorithm, the author gives a theoretical model for target detection that has its advantage over the last method.

It has adaptive property cover all sets of the multiple measurement vectors and provides the data which produces the false alarming conditions as well as the detection probabilities. This method has an inherent advantage to tune any sensing matrix. The author used the Complex Approximate Message Passing (CAMP) model, to resolve the l1-norm problem associated with object detection within a single sensing matrix. The authors proposed a detection framework for the analysis of compressive sensing in which they used the unknown parameters.

A fast gradient-based Compressiv e sensing is proposed by Huihuang Zhao, Yaonan Wang for nosy video and image signal. They used orthogonal transformation to make it sparse, and then rebuild the transmit signal by resolution of convex optimization problem collide with a novel gradient-based method. The objective of the authors is to find out the problems with the reconstruction of noisy images and video signals. After that, they derive how to improve the computation efficiency of gradient-based compressive sensing [12]. The iteration parameter of the Lipschitz gradient, which explicates the convex optimization of the noisy signal is replaced by the Lipschitz constant with this strategy. The convergence of the fast compressive sensing (FGB_CS) is improved from O (1/K) to O (1/K^2). Hence this method is capable to accomplish better performance compared to the other several classical algorithms.

Zhenyu Wu and Chang Wen Chen proposed a W-norm-based model with compressive sensing from the partial frequency coefficient. They resolved the optimal convex problem with constraints and then reconstruct the up-sized signal. This strategy maintains and manages the efficiency of the small and large-frequency components by resolving the correlation between sampling metrics and reconstruct signals which are image and video signals. Interpolation method based integrates filters are used in highly incomplete frequency information, reconstruct from partial frequency coefficients for images/video frame up-sampling [13]. The prime motive of the method is to reduce the artifacts of the hybrid method. This paper encounters the upsampling problem from a different angle. This scheme avoids the different effects like ring effect and other contours effect which is the most problem of the hybrid DCT-wiener method. The following method obtains the meaning of full PSNR and SSIM gain against other compressive sensing method and the original hybrid method.

SRM is more capable of real-time compressive sensing applications as compared to other random metrics. In their paper, encapsulate the several approaches regarding SRM as it has fast numerical calculation satisfied the theory [14]. It supports block-based processing. Hence better approximation sensing matrix with a sparsifying basis should be essential high incoherent. In which rows component of the sensing matrix does not have any representation of sparse on the basis. The mutual coherence coefficient is used for non-coherence calculation between the sensing and basis matrix. A sub-Gaussian distribution like Gaussian or Bernoulli gives a random projection or a random variables matrix that are not famous sensing metrics. The main property of the sensing matrix is that it can sense and capture the
signal in its original domain without losing any sensing efficiency any important information. The experiment is conducted on an image signal of 512*512: Lena, Barbara & boat images.

As we know that many fields like medical, army are used radar data set which need to send one to another place these files have so much data so this data must reconstruct the original signal from a few sample signals. A Compressed signal is used in the radar image application very widely. At the receiver side, it helps to remove the need for a matched filter for the pulse and analog to digital conversion bandwidth. Along which stepped-frequency waveform acquired an ultra-wide bandwidth with the help of the simple hardware that is the sequence of single-frequency pulses. The stepped frequency waveform has some advantages that it needs simple hardware and good high resolution but along which it has few limits that require more time to transmit the signal in the application of Synthetic Aperture Radar (SAR). To overcome these drawbacks of the stepped frequency is replaced by random frequency. Our prime motive in this work to do a comparative analysis of work done by various researchers. This comparative analysis is shown in table 1 which is given below.

| Paper reference Number | Objective of Paper | Experimental Signal Used | Algorithm Used for reconstruction | Parameters which is used as outcome/Conclusion |
|------------------------|--------------------|--------------------------|-----------------------------------|-----------------------------------------------|
| [15]                   | Combining the measurements from different sensors | Satellite Image with different variations | $l_1$ | Comparison between progressive decoding and Normal Decoding with different satellite images. |
| [16]                   | Application of Compressive Sensing on audio signals | Different audio signals like a trumpet, Voiced speech, etc. | OMP | The power spectrum of different audio signals & SNR plot. |
| [17]                   | Compressive sensing on Sparsely exciting signals. | Speech Signals | Matching Pursuit & Orthogonal Matching Pursuit | Plots between SNR & Measurements, Average SNR value for different signals. |
| [18]                   | Analysis of Music Signal Processing | Piano Signal, MIDI signal “I love her” | Bass like extraction, Source Separation | Decomposing of complex music signals into different components & to improve the quality of different music signals. |
| [19]                   | Structured Compressive Sensing & its applications | Different Image Signals | CoSaMP | Here they classify basic CS frameworks that integrate basic CS framework. The algorithmic approach & theoretical approach both done for signal recovery. |
| [20]                   | Different parameter estimation for Compressive Sensing (Frequency estimation) | Different signals effected by AWGN | OMP | Justification of Isometry property is given in this paper. Connections between CRB/ZZB & Isometry are also described. |
| #  | Title                                                                 | Signal / Image                           | Method                           | Note / Analysis                                                                 |
|----|-----------------------------------------------------------------------|------------------------------------------|----------------------------------|---------------------------------------------------------------------------------|
| [21]| Learning of Gaussian Mixture Model                                    | Different image signals                  | KSVD-OMP                         | MSE and PSNR estimation of different images.                                     |
| [22]| Image compression based on Compressive sensing                       | Lena image, Baboon, Bridge               | $l_1$                            | PSNR estimation of different images.                                            |
| [23]| Compressive sensing of RADAR images                                   | SAR images                               | ROMP                             | Analysis of SNR & phase error concerning SAR.                                   |
| [24]| Recent trends and advanced theory of Speech Compressive sensing      | Voice sampled signals at different frequencies | OMP                             | Various approaches to a sparse representation of speech signals are given.       |
| [25]| To design a framework for Speech Signal using the CS technique       | Framed voice of female                   | OMP                              | Construction of basis matrix using a hybrid dictionary                          |
| [26]| Compressive Sensing with unknown parameter                            | Signal of Target Detection               | Multi-Branch Matching Pursuit[MBMP] | Finite & accurate analysis of target detection using compressive sensing        |
| [27]| To recover a noisy picture or a video by using Gradient-Based CS.    | Image (250*250) Like Lena Video signal With 48 frame | FGB-CS                           | 1) PSNR, Runtime of different Compressive sensing. 2) PSNR v/s Sample M. 3) Time v/s Sample M. 4) Quantization comparison in noised video reconstruction. |
| [28]| Recovery of Image or Video by using the CS approach with the help of lowered frequency components. | Image(512*512) Video(355*288)            | W-norm                           | 1) PSNR for video (352*288) & (1920*1080) 2) PSNR for Image (512*512)             |
| [29]| To Provide a fast CS framework by using an adaptive sensing matrix.  | Video sequence                           | AFCT-1                            | Evaluation matrix-like success rate (SR), F-score, center location error (CLE), Deviation, average Frame per second (FPS) |
| [30]| To Provide a fast CS framework by using structured random matrices.  | Image (512*512) Like Lena Barbara, Boat | AFCT-2                            | 1) Signal sparsity Vs probability of perfect Recovery. 2) PSNR Vs Sampling rate. |
| [31]| Compressive reconstruction of the speech and musical signal          | Music signal like piano & Speech Signal. | DCT domain & DST domain           | 1) Time & Frequency domain representation of the recovered signal.              |
| Reference | Title                                                                 | Signal Type                      | Methods                                                                 | Notes                                                                 |
|-----------|----------------------------------------------------------------------|----------------------------------|------------------------------------------------------------------------|----------------------------------------------------------------------|
| [32]      | Audio CS with the help of several sensors.                          | Speech signal, Music signal, Impulsive | Basic pursuit, DCT, DWT, OMP, MS-BP, MS-Idea                           | 1) SDR v/s M/N of an audio signal using basic pursuit, DCT, DWT, and orthogonal pursuit.  
            |                                                                      |                                  |                                                                        | 2) SDR Vs M/N by the 4-sensor system using Ms-BP, SOMP, BP.            |
| [33]      | Compressed Synthetic Aperture Radar                                | SAR image                        | Compressive sensing based algorithm                                    | Reconstruction of the image signal with SAR-range frequency and SAR range is taken into consideration. |
| [34]      | Measuring Structural similarity in music                           | Image with 200 frame              | DCT                                                                    | (1) Evaluate Chroma DCT reduced log pitch.  
            |                                                                      |                                  |                                                                        | (2) Chroma energy normalized statistics feature.                       |
| [35]      | CS framework for musical signal.                                    | Piano and violin                 | STFT                                                                   | (1) Frequency-based analysis & spectrogram as a resultant.  
            |                                                                      |                                  |                                                                        | (2) To draw novelty curve with the magnitude spectrogram.              |
| [36]      | Multi Hypothesis Compressed Sensing video technique                 | Video signal of News, football And foreman | MH-ST, MH-Enet, MH-TiKonov                                           | PSNR v/s sampling rate                                                |
| [37]      | To provide a CS-based framework for speech and audio signals.      | Speech and audio signal           | Compressive sensing                                                    | 1) The Power spectrum of a trumpet tone.  
            |                                                                      |                                  |                                                                        | 2) Spectrogram of the original signal, trumpet, voice signal reconstruction. |
| [38]      | Modified Lasso screening for audio word based music classification using the large-scale dictionary. | Audio word based music            | Modified LASSO Screening based SC                                      | 1) Improve the mean average precision (MAP) for various entries.  
            |                                                                      |                                  |                                                                        | 2) Efficiency of SC with or without screening.  
            |                                                                      |                                  |                                                                        | 3) Compute the MAP 10-precision, AUC, R-precision.                     |
3. Compressive Sensing Theory

3.1. Power Law
The power law is the law that is followed by a compressible signal suppose \( F \).

\[
|F|_p \leq D I^{-\gamma} \quad (1)
\]
\( |F|_L \). Holds is the highest value component for G. an assumption is considered that the value of r always greater than 1. D_t is a parameter whose value is determined by r [3]. If a signal is compressible it means that the signal has very few components that have large values and has a very large number of components that have the least value. This approach is well enough for the signals which have wavelet type of coefficients.

3.2. Sparsity Fundamental Theory of Compressive Sensing

Suppose F is a real time-domain signal which has a unique length. Our concern is to present this signal in vector representation in a real space with the number of elements N like \( F[0], F[1], \ldots, F[N] \). As per the literature this representation is incorporated by the Basis Matrices so the basis matrix can reduce the dimension of the data. Like vectors \( \{\psi_j\}_{j=1}^{N} \) and \( \{\phi_h\}_{h=1}^{N} \) are showing the column of Basis matrices which have NxN dimension.

\[
F = \sum_{j=1}^{N} S_j \psi_j \quad \text{or} \quad F = \Psi S
\]

Here \( S_j, j=1, 2, \ldots, N \) are the key contributors of the S matrix that is of Nx1 dimension. The value is calculated by

\[
S = \langle F, \psi_j \rangle = \Psi^T F
\]

The signal F is presented in the sparse domain consists of both space & time. Suppose we have a total N number of samples in a vector space and we have to consider only K samples for the representation of a signal then (N-K) samples will be discarded, this is the prime concern in compressive sensing. We have to remove the step to calculate the N-K sample due to that the efficiency of the system improves and the time required to find out N-K components overcome [44].

3.3. Measurement Matrix

As we know that in the traditional compression method the number of samples that have to be calculated is N, even the number of samples required for recovery is less (K). The measurement matrix is a very important part of the compressive sensing system. It is the component that is responsible for the compression purpose. Various random matrices can be considered as a measurement matrix-like Gaussian, exponential, etc. The measurement process is defined as the dot product of the mentioned signal & vector \( \{\phi_j\}_{j=1}^{M} \). It can be further notified as

\[
B_h = \langle F, \phi_h \rangle - \Phi^T F
\]

Where \( B_h \) is the column component of the matrix B of the order Mx1 and \( \phi_h^T \) is the rows element of \( \phi \) the matrix of order M x N.

\[
B = \Phi F = \Phi \Psi S = ES
\]

Where \( E = \Phi \Psi \) is an M x N matrix.

We have two design problem here, the first one is that we have to design a measurement matrix which is so much stable. The stable measurement matrix means that the elements of the measurement matrix will not be disturbed in any case. The second design constraint is associated with the reconstruction, the number of samples M used for reconstruction must be equal to K- sparse. The whole structure of this principle is given in Fig. 1 and Fig. 2. These two figures are used to indicate how the compression and reconstruction process takes place. We recover any signal without any corrupt elements by two properties which are given in the next sections 3.4 and 3.5.
3.4. Incoherence
The parameter that will calculate the minimum components to reconstruct the highly efficient signal is known as incoherence. Incoherence measure the value of the correlation between measurement matrix ($\Phi$) & basis matrix ($\psi$) Now let us consider that $\psi$ is orthonormal, $\Phi \in R^{M \times N}$ is a subgroup matrix of $\Phi \in R^{M \times N}$ where $M < N$. $\Phi$ is orthogonal. $\Phi^T \Phi = NI$ is an equation that is satisfied by any basis matrix, here I represent Identity. Matrix $\Phi$ represented as $\Phi = \Phi^{-1}$ here $f$ is a combination of elements based on {1, 2, ..., N}. Here $A$ can be shown as $E = \bar{E}^f$, and $E$ shows the orthogonality and follow $\bar{E}^T . \bar{E} = NI$. Let $\lambda(\bar{E})$ holds the value which is highest $\bar{E}$ [46].

$$\lambda(\bar{E}) = \max_{p,q} \left| \left< \Phi_p, \Psi_q \right> \right|$$  (6)

Equation (6) represents the mutual incoherence value between $\Phi_p$ & $\Psi_q$.

3.5. Restricted Isometry Property (RIP)
The motive of CS is to recover the compressed signal near to the actual signal with the help of very few samples at the decoder side. So the sparse signal should follow the Restricted Isometry Property. Now assume some parameters like vector Y and its equivalent as S (Parameters of F) for the non zero elements equal to K which holds the value which is small and positive.

$$(1 - \mu) \| \sigma \|_2 \leq \| E. \sigma \|_2 \leq (1 + \mu)$$  (7)
RIP property only sustains if the value of $\nu$ for $\mu > 0$ then the Euclidean distance of the signal which has K-sparse representation is maintained by $E$. Let we think about basis matrix $\Phi$ as impulse basis and sensing matrix $\Psi$ as Fourier basis that being so independent and identically distributed (I.I.D.) Gaussian random matrix $E=I \Psi=\Psi$ of the order of $M \times N$ will have a great high probability for RIP property if the condition $M \geq *D.K*K^\log(N/K) \leq N$ is satisfied where the constant value is $D$ and carry forward to reconstruct the original from the few sample signal.

### Table 2. Algorithms with Acquisition Strategy and Other Parameters

| Acquisiti on Strategy | Measurement Matrix Used | Measurement Constraints | Features | Application |
|-----------------------|--------------------------|-------------------------|----------|-------------|
| RD (Random Demodul or) | Pseudorandom matrix | $m \approx O(k \log W/k)$ | # Its architecture is Serial. # Implementation is easier. | Can be employed in Wideband Signal Acquisition [47] |
| MWC (Modulated Wideband Converter) | Pseudorandom matrix | $N \approx 4M \log(L/2M)$ | # Parallel Processing. # Multiple ADC’s. # Implementation is easier than RD and rapid processing. # Reconstruction Required solution of $l_1$ block sparsity problem periodically. | Wideband Signal Acquisition [48] |
| RMPI (Random Modulatio n Pre-Integrator) | Pseudorandom matrix | $m \geq c\mu^2 k(\log n)^5$ | # Parallel Architecture used for processing. # Multi ADC’s. # Rate of sampling can be enhanced by reducing parallelism. | UWB Signal Acquisition [49] |
| Random Filtering | Random Gaussian or Bernoulli | $m \geq ck \log(n/k)$ | # Serial Processing. # Architecture is very simple to design. | Streaming and Compressible Signal Acquisition [50] |
| Random Convolutio n | Structure d Random | $m \geq ck(\log n)^5$ | # Serial Processing Approach. # It requires prior knowledge of the signal. | Recovery is universal [51] |
| CMUX (Compress ive Multiplexe r) | Pseudorandom matrix | $N \leq B \frac{1}{K} \frac{\log B}{c(\log B)}$ | # Parallel Processing Structure. # Specific Analog to Digital Conversion. # Exploits Joint Sparsity. | Multichannel Data Acquisition [52] |
| RES | Random Position Based | $T_s = QT_s + T_s \mod T_s$ | # Serial Processing Structure. # Specific Analog to Digital Conversion. # Location of the sample is also saved in this approach. | High-frequency analog signal Acquisition [53] |
4. Some Basic Algorithms for Compressive Sensing

As we know that compressive sensing is a technique using widely nowadays in various areas. Lots of work already been done in this area. Some algorithms which are given by various researchers for the compression and recovery process are given below. The acquisition strategy which is given in the table has unique features and applications. Some of these algorithms are indicated in the Table. 2. All the algorithms have unique measurement matrices too.

As in the above table, lots of parameters are discussed. Now in the next section, we introduce the characterization of various reconstruction algorithms. The classification is inspired by 8 different categories of algorithms based on the complexity of an algorithm, efficiency of the reconstruction, etc. These 8 categories are:

- Convex Relaxation
- Orthogonal Matching Pursuit based Algorithms
- Iterative threshold-based Algorithms
- Greedy Algorithms
- Non-Convex Minimization Algorithms
- Combinational Sub-Linear Algorithms
- Message-Passing Algorithms
- Bregman Iterative Algorithms

Further classification of these algorithms is given in Figure 3 & Figure 4.

**Figure 3. Reconstruction Algorithms**
5. Applications of Compressive Sensing

There are many widespread applications of compressing sensing. If we consider the future, then seismology is an area in which we can use CS methodology. It is proved that it can change the whole process of imaging and can modify it. MRI, NMR spectroscopy, RADAR modeling, communication process & high-speed A-to-D conversion are the different examples of applications where compressive sensing can be used.

5.1. Compressive Imaging

Of course, the most important feature for which compressed sensing is used is to provide efficient & exact images. As per our interest now we are going to illustrate those images which are sparse over some distinct basis so they can be used to work with compressive sensing. Nowadays, images are captured with one sensor per pixel by digital cameras & each pixel in the image is reconstructed & after that, the data is compressed and stored. We can now see the cameras with a high Megapixel range this is because silicon is used widely. Now, an obvious question arises why we have to capture & store this large amount of data, why don’t we throw it as soon as possible? The answer is over here which is the technology of compressive imaging, dedicated sensors for each pixel are avoided and linear measurements are produced by a sensor directly. Compressive sensing technology provides a model for practically implement such an idea which includes different measurement methods & decoding algorithms. Researchers doing great work to provide such types of systems. One of them is to design a model of a “single-pixel” CS framework-based camera. This camera comprises a digital micro-meter
device (DMD), an A-to-D converter, & a single photon detector with 2 lenses. Out of two, the first one focuses the light on DMD. Each mirror that is presented over DMD is to provide a pixel in to image and can be a move towards or away from the secondary lens. We can treat this same process as a process of inner products with random vectors. After a successful collection of light by using the lenses, focussed on the photon detector where the measurement occurs. The random linear measurements of the image are calculated by an optical computer and pass it to a computer that is digital and then recovers the original image.

A photon detector is used by this camera which is so much different from the traditional camera. One very keen point which is considerable with a single-pixel camera is that it can work with a much broader range of light spectrum as compared to traditional cameras. If we consider sensors, then sensors are too much expensive for a certain light spectrum. A digital camera that can be used to take infrared images is too much costly & so much complicated if it is designed using traditional methods.

If we go through the medical imaging, then MRI processes take Fourier coefficients of an image. Then this area is also the area that can serve by using compressed sensing. These images are sparse on a different basis; like angiograms MR images which are sparse in their actual pixel representation, while some other images are sparse on different basis like wavelet Fourier basis. As we know that MRI is so much time-consuming because the speed which is used to collect the data is controlled or more specifically we can say bounded by physiological limitations. So a concept is required which can reduce the number of samples without intact with the quality of Magnetic Resonance Images. It is now an open area for research to apply compressed sensing on the MRI data. Now many researchers provided various algorithms for MRI applications [56].

5.2. Radar Signal Processing

After transmitting some kind of pulse form, a traditional radar system employs a matched filter that is used to correlate the signal which is received with transmitted pulses. Now for signal processing, the receivers after receivers apply a system that is used to compress pulses with high data rate Analog to digital converter. This formal technology is so much hard & expensive & the resolution problem also arises here because as we consider traditional RADAR systems then the resolution is limited due to the problem associated with the uncertainty concept of RADAR. The main concepts behind Compressed RADAR imaging to represent the time-frequency component into discrete format and project every scene as a matrix. The job of the grids will be sparse if the targets are few, & we can easily use the CS model to reconstruct the target scene [57].

5.3. Biology

CS is also employed for high efficiency & cost-effective biological sensing. In fact, in world war II an idea that was related to compression sensing was used for testing soldiers for syphilis. It was the application of group testing. Because of the high test/ sensing price of blood for syphilis antigen, then group testing method applied in which testing of the entire pool of blood samples was done after grouping the people. If syphilis antigen was found in a pool of samples, then further testing of the subgroups would occur. Nowadays, in the biology field for comparative DNA Microarray [58], compression sensing is used. These microarrays (DNA, protein, etc.) can detect and measure simultaneously a huge number of different genomic particles and they are affinity-based biosensors too. In general, a huge number of samples can be tested in only one experiment with the help of DNA microarrays which consists of millions of probe spots. In formal microarrays, only one data point is collected because to capture a single target, each spot is designed which consists of a huge copy of a similar probe. It is so much tedious to find out the difference between genes that are denoted by reference samples and the test samples. Thus to form the compressed microarrays, a compressive idea is used, in which copies of many different probes are held by each spot and now the number of spots is very less. One another case of compressive sensing is the study of gene expression [59].
5.4. Error Correction
CS shows a significant effect on error coding & other coding models it can be proposed as the solution of the error correction problem in real-time problems. The problem which is known as error correction is the fundamental problem in coding theory related to communication theory. Because when we send meaningful information from the transmitter to the receiver then some bits are garbled or corrupted by some unfair means or losses. Now the area of interest is how we can sort out this problem and how to correct these errors. In the real field, we can use sparse recovery to recover the signal from the corrupted encoded data because the errors generally occur in some distinct places. Error correction is the prime problem associated with communication theory and the traditional coding approaches only consider the data values which are occupied using the finite field length.

5.5. Other Important Applications
Some major application areas are discussed in the above paragraphs. But compressive sensing has huge applications nowadays.

![Diagram of Compressive Sensing Applications](image)

*Figure 5. Applications of Compressive Sensing in Imaging, Biomedical, Communication Systems, and Pattern Recognition [60-95]*
So apart from the above-discussed applications, some other specific application areas are also given in Figure 5 and Figure 6.

**Figure 6.** Applications of Compressive Sensing in Imaging, Biomedical, Communication Systems, and Pattern Recognition [90-115]

### 6. Conclusion
As per the above discussion, it is very much clear about compressive sensing that it has various advantages in various areas. We can use compressive sensing in Medical Imaging, Satellite Communication, RADAR communication, and for data security purposes too. So as we can see in the literature that day by day the use of compressive sensing technology enhances. This paper is comprised of fundamental concepts of CS methodology as well as various algorithms that are widely used in compressive sensing. Some concepts are given by various researchers also discussed in the literature. So as per the details provided by the researchers, various algorithms that have the ability for proper reconstruction as well as have reduced time complexity also mentioned in the given table.
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22