Scaling the Effectiveness of Existing Compressive Sensing in Multimedia Contents

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ABSTRACT
Compression has always played a crucial role in storage and transmission of heavier multimedia files. The existences of compression algorithms are more than two decade old. The normal compression algorithms are sometimes not required to process a signal in many cases where the signals are sparse. In such cases, compressive sensing highly contributes and compensates the issues of conventional compression algorithms as it performs sampling as well as compression at a same time. The concept of compressive sensing is quite new and is not much in matured stage. Our findings reported in this paper is a result of observation being carried out on all major research journals, which states that there are little amount of studies being done on compressive sensing and reconstruction of multimedia contents. The paper also discusses about the significant research gap and evaluates teh effectiveness of existing techniques.

Keywords
Compressive Sensing, Compressive Sampling, Compression, Multimedia, Lossless.

1. INTRODUCTION
With the advancement of networking and communication system, users finds it much accessible to sharing process of various digital contents. Out of all the digital contents, multimedia contents are something which are massively high in use by the users. Usually, multimedia files are quite heavier and it consists of image, video, and signals in its domain of study. As multimedia files are heavier, it is essential that the signals should be captured effectively as well as it should be compressed effectively. In the traditional image processing, an image is usually sampled first at maximum rate and then the conventional compression techniques (e.g. DCT) is applied through JPEG standards in order to ensure optimal storage [1]. However, such principles find it quite challenging in presence of imaging devices with poor resolution as well as constraint energy availability and computational potentials. Hence, the area of compressive sensing has come as a boon to solve this problem. This technique of compressive sensing is mainly investigated for its unique capabilities of performing compression and sampling at a same time [2]. Various theories till date have claimed that in order to perform reconstruction of a signal, a minimal set of measurement is required. The principle of compressive sensing furnishes the optimal minimization of the rate of sampling, complexities pertaining to computation, and energy dissipation. Fig.1 shows the process of compressed sensing where the signal is compressed and sensed together. Summation of voltages of arbitrarily selected pixels are done with sparsity matrix. The process only performs a summed value to be digitized which makes the compressed image. However, the process is not that Easy as it seems like as till date majority of the existing research work focusing on compressive sensing is more or less a hypothetical study with less scope of applicability in real-time applications. There are some of the potential pitfalls of the compressive sensing as there is lack of minimal structures in the image that is reconstructed as well as poor resolution of degraded image [3]. Existing techniques of using total variation that is found frequently to be adopted in compressive sensing needs less number of iterations.

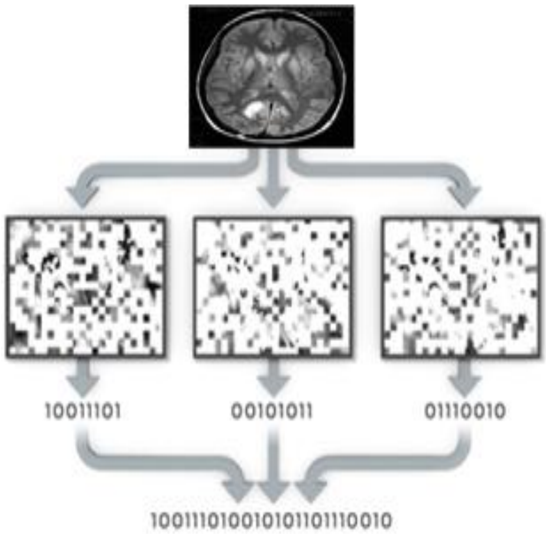

Figure.1. Process of Compressive Sensing

The area of compressive sensing is used in applied mathematics as well as majorly in signal processing. It has been also used in image processing especially in radar images, medical images, and aerial images. The prime contribution of this paper is to perform review of existing survey papers and majorly into existing research techniques in compressive sensing. The paper tries to find research gap in the existing system. Section 2 discusses about the essentials of the compressed sensing followed by existing survey on Section 3. Section 4 enlists about the existing techniques for performing compressive sensing in image, video, and speech. Section 5 discusses about the research gap followed by Section 6 that discusses about conclusion.

2. COMPRESSED SENSING ESSENTIALS
In the area of signal processing, compressed sensing is considered as one of the significant technique for extracting and reconstructing a signal by exploring the solution to underdetermine significant linear systems. The theory of compressive sensing has evolved owing to the issues in

imaging speed that is specifically important in applications related to medical signal processing (Fig.3). There are various physiological as well as physical constraints that significantly affects the process of data collecting in medical signal processing applications. Therefore, it is important that an efficient technique be explored that can minimize the amount of extracted data without any significant impact on quality of a signal. Therefore, owing to under-sampled k-space, the criterion of Nyquist's is violated and moreover there are increasing evidences of artifacts in Fourier reconstruction process.

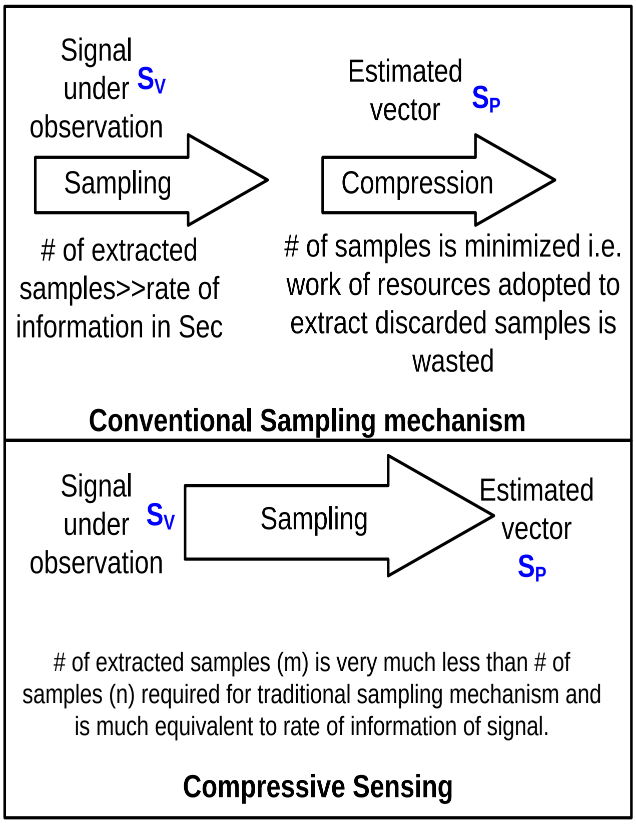

Figure.2. Conventional Sampling and Compressing Sensing

Fig.2 exhibits the conventional sampling of data as well as compressing sensing. Hence, the theory states that it is possible to extract a signal from minimal samples; however, the extraction of the signal can be 100% successful if the signal is being captured a minimal rate of information. This concept foretells that the signal is originally a sparse or belongs to some other form of transform domain. Hence, certain definitions are important to be highlighted to understand compressive sensing as:

- **Sparsity:** Various conventional forms of signals (image, audio, seismic data etc.) are reposited in compressed mode on the basis of suitability or the projection. It was found that after selecting the basis, a maximal quantity of the projection coefficients are usually found to be zero or very small values that are usually neglected. Hence, the theory states that if the signal has n-number of non-zero coefficient, that signal is said to be n-sparse. The theory also states that if maximal quantities of the coefficient of projection are minimal enough to be neglected, then only the signal can be subjected to compression algorithms.

- **Incoherence:** It is a statistical quantity that evaluates the highest correlation between any two elements from two different matrices. If θ is considered to be square matrix of size n with θ1, θ2, ….θn columns and Ω is a non-square matrix of size m x n with Ω1, Ω2, …. Ωm as rows, than the mathematical interpretation of coherence σ is:

$$\sigma(\Omega,\theta)=\sqrt{n}.\max|\Omega_k,\theta_j| \quad (1)$$

Where the value of j lies between 1 to n and value of k lies between 1 and m. Hence, according to linearity principle, the formulates:

$$1\le\sigma(\Omega,\theta)\le\sqrt{n} \quad (2)$$

Therefore, from the domain viewpoint of compressive sensing, the focus is much on the matrix incoherence factor adopted in sampled or in sensed signal Ω as well as the matrix that represents the basis where there is a sparse signal of interest θ.

- **Signal Extraction:** The process of extracting the signal in compressive sensing is quite equivalent to traditional one. The mathematical interpretation can be laid for the process of sensing SP considering S as signal,

$$S_P=\Omega.S \quad (3)$$

The signal S and signal process SP are usually represented by real number of dimension n and m respectively. The traditional sensing concepts says that m should be equivalent to n in case certain levels of presence of sparse signals or compressible signals. The minimal value of m is permissible for the sensing matrices that are found to be more incoherent within the original domain (or even in transform domain) where the signal is quite sparse. Hence, traditional sensing concepts uses Dirac delta functions while the problems is resisted by using Compressive sensing that considers random functions to speed up the process of signal extraction.

- **Signal Reconstruction:** Majority of the existing concepts uses non-linear techniques to reconstruct the original signals in compressive sensing that is dependent on knowledge of basis of representation with a possibility of either compressible or sparse signals. Hence, the basis of representation of signal S is,

$$\theta S_v=S \quad (4)$$

In the above equation, Sv is the sparse vector that represents coefficient of project of S and θ. The vector for measurement SP can be now represented as,

$$S_P=\gamma S_v \quad (5)$$

The above equation shows γ as matrix of reconstructed signal which is equivalent to Ω.θ and is of size m x n.

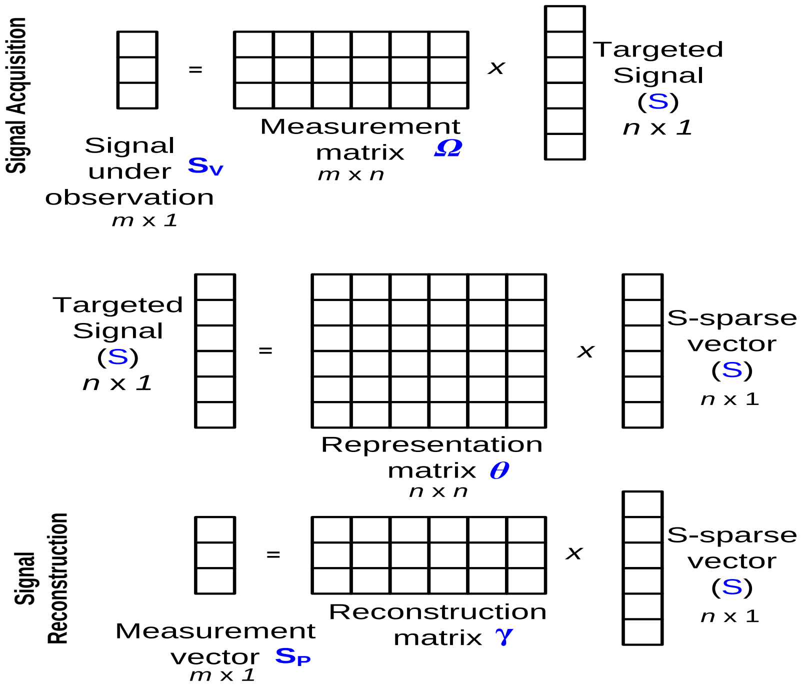

Figure.3. Signal Extraction and Reconstruction techniques in Compressive Sensing

3. EXISTING SURVEY

As the proposed study is mainly focused on reviewing the existing techniques and contributory studies discussed by prior literatures, it is very important for investigation that what is the existing status in the same domain? The adoption of compressive sensing is not new and it has been already adopted in the prior studies. There are various researchers who have used this technique on various problems domains of signal processing. Let us take a closer look into the existing status of the research paper, its year of publications, and the name of the publishers. So, we review the existing number of research papers and explored the effectiveness in them.

Table.1. Papers on Compressive Sensing techniques

Name of Journals	From	To	Journals Published
IEEE Xplore	2006	2014	201
Elsevier	2005	2015	81
Springer	2006	2014	54
Hindawi	2005	2015	48
IJCER	2006	2014	42
IJSER	2006	2014	25
IJARCCE	2012	2014	16
IJERA	2011	2015	42

Table.2. Papers on Lossless Compression techniques

Name of Journals	From	To	Journals Published
IEEE Xplore	2006	2015	235
Elsevier	2005	2015	387
Springer	2006	2014	470
Hindawi	2005	2015	29
IJCER	2006	2014	32
IJSER	2005	2015	200
IJARCCE	2012	2014	34
IJERA	2011	2015	88

Table 1 and Table 2 show the total number of the implemented research papers towards usual and lossless compression techniques. For generalized view, we choose to select the cumulative research papers from all the available journal publishers who support publication of compression techniques in signal processing domain. Table 1 shows that both the techniques have approximately more than 200 implementation papers on algorithms during the year 2006-2014. However, things are quite different in Elsevier, which was seen with 387 implementation papers on lossless compression techniques whereas there are only 81 implementation papers on compressive sensing techniques in 2005-2015. Almost the similar type of trends is observed for other journals too, which showcase that there are comparatively less implementation papers on compressive sensing till date. A simple and cumulative calculation for number of implementation papers for lossless compression scheme shows (235+387+470+29=) 1121 number of papers published during 2005-2015 (Table.2), while cumulative calculations for number of implementation papers for compressing sensing are found to be only (201+81+54+48=) 384 (Table 1). The calculations are done for only ISI indexed journals like IEEEXplore, Elsevier, Springer, and Hindawi only. This simple calculations itself shows that there are only 384 research papers in ISI index journals on compressive sensing while there exists 1121 journals on lossless compression techniques.

Table.3. Total Survey papers on Compressive Sensing techniques

Name of Journals	Year	Published Papers
IEEE Xplore	2007-2014	12
IJCER	2008-2014	3
IJSER	2011-2014	9
IJARCCE	2011-2014	4
IJERA	2011-2014	6
Hindawi	2011-2014	3
ISRN	2011-2014	2
IJEIAE	2011-2014	1
IJESIT	2012-2014	1
IJCSA	2012-2014	1
IJSRP	2012-2014	1
RJASET	2012-2014	1
IJCA	2012-2014	1
Total		45

Table 3 shows the total number of survey papers published from 2007 to till date. As survey paper on compressive sensing beyond 2006 is very much insignificant and hence ignored. Our investigation shows that there are total of 45 survey papers on compressive sensing, while ISI index Journals like IEEE and Hindawi are found to have only 12 and 3 survey papers till date. Next, we filter the 16 most significant papers out of these 45 total published survey papers and attempted to find the effectiveness of the existing survey papers. In the year 2010, Berger et.al [4] have published a survey paper towards compressive sensing exclusively focusing on the sparse channel estimation. Along with the theory, the author has discussed the conventional algorithms e.g. convex and greedy type towards sparse multipath channels. Similar type of study has also being done by Gilbert and Indyk [5] in same year. A unique survey study was found in same year by Potter et.al [6] who have investigated the techniques of sparse reconstruction towards radar imaging. Tropp and Wright [7] have also investigated the sparse approximation techniques. The authors have discussed the conventional algorithms e.g. convex relaxation, greedy pursuits, Bayesian, brute force etc., and also discussed various algorithms of pursuits. Patel and Chellappa [8] have presented a discussion paper towards compressive sensing and spare representation.

In 2011, Wang [9] have presented an editorial for compressive sensing with an exclusive focus on medical image processing. In 2012, Dias and Bandewar [10] have published a survey paper on compressive sensing and discusses the existing trends in it with respect to signal processing. In same year Mammeriet. al. [11] have presented a review paper on image compression techniques exclusively considering sensor networks. The authors have discussed various compression schemes and finally discussed on effective principles on compression for sensor networks.

In 2013, Hayashi et al. [12] have presented a survey paper with focus on design and development of sensing matrix and sparsity aspects in compressed sensing. In same year, Kaur et. al. [13] have presented a review paper on reconstruction techniques. However, the study didn’t significantly yield any potential findings towards compressive sensing. Ender [14] have performed a study, which is almost similar to review work done by Potter et. al. [6]. Pudlewski and Melodia [15] have discussed on various impediments towards multimedia transmission with respect to compressive sensing. Qaisar et. al. [16] have presented a discussion on pathway of compressive sensing from hypothetical approach to practical approach. Subban et. al. [17] have investigated the algorithms for sparse representation and compressed tracking. In 2014, Zhou and Zhou [18] have presented an article on compressive sensing that are adaptable in multimedia coding. Same year, Ali [AR] have surveyed some of the techniques of compressive sensing pertaining to localization.

Hence, it can be seen that in last decade there are 45 sets of survey work being published, out of which, we choose to discuss 16 survey papers. Table 4 will summarize these 16 surveypapers.

Table 4 existing Survey on Compression techniques

Authors	Problem Focused	Informative factor	Limitation
Berger [4]-2010	Algorithms for sparse channel estimation	Discussion on empirical aspects	No discussion of prior research attempts
Gilbert [5]-2010	Sparse recovery using sparse random matrices.	Techniques for-each guarantee	Performance effectiveness at techniques not discusses.
Potter [6]-2010	sparse reconstruction towards radar imaging	Algorithms for sparse reconstruction	Only theoretical illustrations.

Tropp [7]-2010	Sparse approximations.	Algorithms on pursuit techniques	No comparative evaluation being conducted
Patel [8]-2011	Compressive sensing for Pattern recognition	Dictionary methods	Practically reviewed only 5 implementation work
Wang [9]-2011	Compressive sensing for medical imaging.	Existing studies on compressive sensing	No comparative evaluation being conducted
Dias [10]-2012	Compressive sensing	Usage of transform techniques	Practically reviewed only 4 implementation work.
Mammeri [11]-2012	Image compression techniques in sensor networks	Discussed on compression algorithms	No discussion on Research gap, less focus on CS
Hayashi [12]-2013	Compressed sensing in signals	Discussion algorithms e.g. FISTA (Fast Iterative Shrinkage-Thresholding Algorithms), NESTA (Nesterov's Algorithm)	Only theoretical illustrations.
Kaur [13]-2013	Reconstruction techniques	Simplified techniques of compressive sensing	Practically reviewed only 5 implementation work
Ender [14]-2013	Compressed sensing in Radar imaging	Enriched theoretical discussion on domains	Only theoretical illustrations.
Pudlewski [15]-2013	Challenges in compressive imaging	Discussed various techniques reconstruction in compressive techniques	No discussion on Research gap
Qaisar [16]-2013	Compressive Sensing and reconstruction algorithms	Reconstruction techniques	Studied complexity of 11 implementation studies.
Subban [17]-2014	Real time compressive tracking methods.	Sparse representation techniques	No discussion on Research gap, Only theoretical illustrations.
Zhou [18]-2014	Brief overview of CS video coding.	Applications, literature review.	Performance effectiveness at techniques not discusses.
Ali [19]-2015	Discuss different present techniques for localization of user through CS.	Literature review, comparison between CS and DS, graphs. Different techniques with issue and parameters.	Less Significant discussion on effectiveness of compressive sensing

4. EXISTING TECHNIQUES FOR COMPRESSIVE SENSING

In last decade there are various studies that have been focusing on implementing the compressive sensing towards various kinds of multimedia contents. Hence, from total of 384 studies, we have filtered it to study more specifically. We siphoned out 11 implementation papers each toward compressive sensing on images, videos, and speech respectively. Performing compression on image is completely different as compared to video or speech. The signaling properties of image, video, as well as speech are completely different; however, there are some similarities too. Although compressing an image is no more a novel idea in research community, but performing compressive sensing of an image is quite less. All the techniques discussed in Table 5 uses the common step of compressive sensing e.g. i) developing a signal with sparse matrix, ii) designing an algorithm for compressing a sparse signal, and iii) finally performing reconstruction of the compressed signal. The common cases under consideration in existing techniques are presence of noise (especially Gaussian) during transmission effecting the compressed signals. All the techniques are more or less focuses on effective reconstruction process using the signal that is compressed. Similarly video compression mainly aims to minimize the data redundancy by integrating time-based motion compensation with distance based image compression. The adoption of source coding is very high in video compression but adoption of compressive sensing in video contents results in drastic degradation of video quality during reconstruction process. Hence, reconstructing a video file is quite challenging as compared to image file. However, adoption of compressive sensing also results in promising resiliency to channel errors. Such techniques uses both time and distance based correlation factor between the frames and coding is performed. Similarly performing compression of speech data has completely different complexity as compared to image and video. There is a various range of complexity in performing compressive sensing on speech signals, which is majorly sparse type. As human speech discontinues so it can be considered as sparse signals. However, there is a very less focus or research attempts being done in performing compressive sensing on speech signals. However, majority of the techniques adopted till date considers compressive sensing as a best mechanism to mitigate sparsity in signals as well as noise. In discussion of the sparsity, majority of the techniques tabulated in this section considers approximation in sparsity. However, specifically in video, compressive sensing is implemented as a part of encoder. Table 5, Table 6, and Table 7 discusses about the existing techniques of compressive sensing on image, video and speech. The discussion has been carried out with respect to problems that the researchers have focused, techniques that the researchers have used to mitigate the problems, and inference of the study is made with an aid of performance parameters too. Hence, out of 384 research papers, we have filtered out the best 33 papers, where the research contribution is found to be comparatively better than rest of the papers and it is tabulated.

Table.5. Summary of CS Techniques of Prior Researchers on Images

Authors	Problem Focused	Techniques	Perform Param	Limitation
Han [20]-2008	To remove dense & sparse components, to get better reconstruction of image	Compressive sensing (CS), Projection onto convex set (POCS)	Rate distortion, PSNR, Total error.	Computationally complex.
Ma [21]-2008	To get better reconstruction, minimize non-smooth functions on large data sets	Total Variation (TV), L1-minimization, Wavelets.	SNR, Relative error.	Need better quality of image, less Storage.
Nagesh [22]-2009	To recognize & recover the expression of invariant faces with feature extraction.	Compressive sensing.	Less storage space, recognition rate.	Need to use multiple views of the scene.
Schulz [23]-2009	Signal acquisition & compression and perform analysis of rate-distortion.	L1-norm minimization using (TV, SVD).	PSNR, reducing quantization step, approximation error.	Outcome not benchmarked
Wright [24]-2009	Automatically to recognize human faces with invariant expression from frontal views & illumination, as well as occlusion & disguise.	Sparse Representation via L1-minimization techniques.	Recognition rates, Sparsity Concentration Index (SCI).	Need object detection in addition to recognitions.
Yang [25]-2010	To perform fast signal reconstruction using Fourier data.	RecPF-Reconstruction from Partial Fourier data	Highly stable, efficient and robust. Relative error, objection function.	Computationally complex, outcomes not benchmarked
Sen [26]-2011	To reduce rendering rate by using CS to find values of unrendered pixels.	Compressive rendering	MSE, high quality of images, accurate reconstruction.	Needs at extremely low sampling densities. (<5% of pixel samples), outcomes not benchmarked
Chen [27]-2012	To detect & track objects in motion with minimum number of data samples. (for Video-surveillance)	A real time CS L1 tracking, random Gaussian or Toeplitz phase. Motion detection algorithms.	High resolution, less storage, better reconstruction. Fast tracking.	Outcomes not benchmarked
Sermwuthisarn [28]-2012	To remove the effect of Gaussian noise and get better reconstruction of images.	OMP-PKS+RS based on Compressing sensing.	PSNR, better Visual quality, low measurements.	Need to improve reconstruction for both impulsive and Gaussian noise.
Hemalatha [29]-2013	To analyze the energy consumption to transmitting image using CS with rate distortions analysis.	BinDCT + Noiselet based on CS.	PSNR, reduced bit rate (<0.5bpp), compression ratio, Energy consumed.	Still need to reduce energy consumption
Liu [30]-2013	To recover signals from sub-Nyquist samples with CS for Multiple structures of biomedical signals.	L1-TV, TV-minimization, Nuclear norm minimization.	Mean L1 error, better reconstruction accuracy.	Outcomes not benchmarked

Multimedia compressive sensing (CS), another use of CS, has as of late been researched to catch rapid features at low edge rate by method for time-based compression. A shared trait of these multimedia CS frameworks is the utilization of every pixel adjustment amid one coordination time-period, to conquer the spatio-fleeting determination exchange off in feature catch. As an outcome of dynamic and inactive pixel level coding systems, it is conceivable to interestingly adjust a few transient edges of a consistent feature stream inside the Time-scale of a solitary incorporation time of the camcorder (utilizing an ordinary cam). This allows these novel imaging architectures to keep up high determination in both the spatial and the fleeting areas. Each one low-speed presentation caught by such CS cams is a direct blend of the hidden coded rapid feature outlines. After obtaining, fast features are reproduced by different CS reversal calculations. These hardware based frameworks were initially intended for uniform time based compression ratio. Table 6 showcase video CS techniques.

Table.6. Summary of CS Techniques of Prior Researchers on Video

Authors	Problem Focused	Techniques	Perform Param	Limitation
Pudlewski [31]-2010	To investigate the limits & outlines of video parameters on the received video of CS streams over multi-hop WSN.	Adaptive Parity based Channel coding.	SSIM, BER, Quantization rate, image quality, low degradation.	Enhanced quality of reconstructed signal, Outcomes not benchmarked
Chaozhu [32]-2011	To reduce System computational complexity & compression efficiency.	Distributed video coding based on CS, L1-minimization.	PSNR, quality, less computational, compression ratio.	Not much significant novelty
Pudlewski [33]-2011	To investigate rate of video transmissions, low complexity with limited budget of available energy.	CS video encoder (CVS).	SSIM, BER, SNR, Encoded Video Rate, Total Energy Budget.	Mainly inclined on using H.264
Mansour [34]-2012	estimate to focus the measurements on the large valued coefficients of a compressible signal	adaptive CS scheme, weighted L1 minimization	SNR, QCIF	Less extensive outcomes analysis
Sankaranarayanan [35]-2012	CS for Spatial-Multiplexing Cameras	CS multi-scale video, Sensing and recovery framework for SMCs, L1-norm recovery	Relative speed, frame rate.	Outcomes not benchmarked
Chen [36]-2013	To decrease signal power for better transmissions, high loss rate & noise for heterogeneous receiver.	Enhanced compressed-sensing-based wireless video multicast	PSNR, low complexity encoding, better transmission.	Visual perceptibility is less
Pudlewski-[37]-2013	To achieve better video quality transmission and to required transmission power at the multimedia sensor node.	Relay Assisted Compressed Video Sensing	SNR, MSE, SSIM, good video quality.	Minor enhancement in PSNR only.
Pudlewski [38]-2013	To reduce energy, lack of resilience to channel errors and high computational complexity.	CVS, H.264AVC intra, MJPEG.	SSIM, good quality of video, low energy consumption per frame, BER.	Mainly focused on H.264 and MJPEG encoders, outcomes were not found benchmarked.
Yuan [39]-2013	To estimate the motion of the objects within the scene, to adapt the compression ratio for effective video capture.	adaptive temporal compressive sensing (CS) for video, block-matching algorithm	PSNR, compression ratio,	seek to embed this real-time Framework into the hardware prototype.
Liu [40]-2013	a video system where acquisition is carried out in the form of direct compressive sampling (CS) with no other	Karhunen–Loeve bases (KLT), K-SVD	PSNR, reconstruction quality.	Doesn't support efficient encoding and decoding scheme, doesn't

	form of sophisticated encoding.			considered much on recovery algorithms
Iliadis [41]-2013	Video compressive sensing (CS) framework based on the Single Pixel Camera (SPC).	Multiple Measurement Vectors (MMV), SMV.	PSNR, Visual quality.	Minor enhancement in PSNR only, should have evaluated with other datasets too.

Table.7. Summary of CS Techniques of Prior Researchers on Speech

Authors	Problem Focused	Techniques	Perform Param	Limitation
Giacobello [42]-2008	Retrieving sparse patterns using CS framework for speech.	CS, L0 normalization.	Good perceptual quality, normalized error,	Time and space complexity not discussed
Christensen [43]-2009	To sparse decompositions based on dictionaries comprised of windowed complex exponentials.	CS method.	SNR, Power spectrum, sparsity,	Numerical outcomes not benchmarked
Masiero-[44]-2010	To estimate source radiation pattern of sound sources with a reduced number of sensors.	L1 minimization method based on CS.	SNR, better quality of audio signals.	No effective benchmarking
Griffin [45]-2010	Speaker identification using sparsely excited speech signals.	Least Absolute Shrinkage and Selection Operator	SNR, power gain,	Signal quality not optimized
Asaei [46]-2011	speech recognition from distance	L1 minimization, Line Orientation Separation Technique	SNR, BSS-MSR.	Less extent of outcome discussion
Tan [47]-2011	Speech recognition from anterior end	Least Angle Regression for exploiting characteristics of collinear dictionary	SNR, degree of sparsity, accuracy,	Effect of dimensionality minimization was not focused
Wang [48]-2011	Synthesizing speech signal synthesis	Orthogonal matching pursuits algorithm, L0 norm minimization.	SSNR, high compression ratio, perceptual quality.	No comparative analysis
Feng [49]-2012	To enhance the signal quality of speech	adaptive compressive sensing method	SNR, better reconstruction,	Less effective benchmarking
Hashim [50]-2012	To achieve better reconstruction of sparse audio signals.	CS, L1 and L2 in sparse domain.	Quality of audio, better reconstruction of audio signals.	Outcomes not benchmarking
Lin [51]-2013	Compressed sensing of speech signals in IPTV	An acoustic echo cancellation with compressive sensing	SNR, compression ratio, better reconstruction.	Less effective benchmarking
Zhou [52]-2013	Compressed sensing of speech signals	K-Singular Value Decomposition, orthogonal matching pursuits	SNR, Perception evaluation of speech quality, mean opinion score	Less effective benchmarking

5. RESEARCH GAP

From the previous section, it can be seen that existing studies towards implementing compressive sensing on signal processing do exists with advantages as well as limitations too. However, a closer look into the studies being performed till date was found with an obvious research gap. Brief discussions of some of them are:

- **Less Effective Survey work**: Our investigation shows that there are 45 survey papers in the area of compressive sensing, where we choose to review the best 16 papers. It was found that majority of the survey paper are more inclined towards discussing the theoretical aspects, which are highly repetitive in all the other survey papers too. Another issue we came across is the survey papers till date has very less discussion of prior research contribution and an attempt to excavate its effectiveness by exploring either comparative analysis or by exploring research gap.

- **Less focus on Reconstruction**: All the experimental based research papers have emphasized on implementing compressive sensing and quite less focus on its outcome with respect to complexities associated with reconstructed signals. Although reconstruction phenomenon is well defined in image signals, but importance of it is found few in video and speech signals. A closer look into the tabulated information will show that frequently used algorithms are projection-based, orthogonal matching pursuits, least absolute shrinkage and selection operator etc. However, the researchers have overlooked that although such techniques sometimes yield faster processing, but none of the above discussed technique can be wisely adopted for reconstruction of a video signal.
- **Ambiguity in implementing Sparsity matrix**: Majority of the studies till date have considered sparsity as the image size, which will mean that when the image is divided into smaller sizes (like sub-images), the quantity of the samples will be required to be higher in size for the purpose of performing reconstruction of an image. However, adoption of such techniques drastically minimizes the probability of adopting compressive sensing with present definition of sparsity matrix in real-time.
- **Clear tradeoff in image and video:** As discussed earlier in this paper that as the signal properties of image, video, and speech quite differs from each other, so a generalized algorithm for compressive sensing cannot be directly applied to all of these signals. One of the significant problems in implementing compressive sensing and its encoding standards on the image signal is less effective compression which is quite poor when compared with video compression techniques.
- **Less Focus on networking aspects**: The area of compression arises from networking itself, particularly the wireless one. Although there are some of the research papers which has considered choosing to investigate compressive sensing in wireless sensor network, but such studies have not focused on original network parameters e.g. number of nodes, node ID, transmission region, channel state information (scattering, fading, interference, noise), mobility aspects, signal attenuation, physical configurations of the nodes etc. It is much required to study compressive sensing from networking viewpoint as it gives better applicability in real-time.

6. CONCLUSION

The present paper have studied about the effectiveness of existing compressive sensing algorithms that has been seen to have maximized interest in most recent times in signal processing. The phenomenon of compressive sensing works in completely different way as compared to Nyquist principle. The study of compressive sensing must be more encouraged although there are some studies being done. We propose the justification for this fact as – in real time, there are many situations where the sampling rate of the data is highly limited either owing to information capturing devices to slow processing of the signals. Hence, the applications of compressive sensing can be highly adopted in such scenario. For ensuring the information content of this article, we have adopted only the ISI index manuscript to showcase the extent and effectiveness of the studies being done till date. However, we can say that studies towards compressive sensing on speech signals are quite less as there is no ISI index journal to discuss about it, we have come across non-ISI indexed journals to discuss about speech signals. Hence, it can be said that studies towards compressive sensing is quite less and more should be encouraged to enhance the applicability of the studies towards compression. Our future work will be to address the research gap and limitations that are explored in the existing studies towards compressive sensing. Our future direction of the study will be to evolve up with a transmitter and receiver node with establishment of wireless signaling properties of wireless network and perform analysis of the compressive sensing in the present of various real time networking constraints as well as various impediments towards successful compressive sensing and reconstruction, and also in order to obtain lossless kind of reconstruction even to the neighbor region to diagnostically important region, an approach of compressed sensing is assumed to be considered as the next work towards having image compression and transmission through highly resource constraints TCP/IP and other networks.

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