INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 16 No. 9 (2024) 294-301
https://publisher.uthm.edu.my/ojs/index.php/ijie

Performance Evaluation of DCT, FFT and DWT Basis Compressive Sensing for Guided Wave Ultrasonic Testing

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DOI: https://doi.org/10.30880/ijie.2024.16.09.024

Article Info

Received: 11 June 2024
Accepted: 24 November 2024
Available online: 29 December 2024

Keywords

Signal basis, transform domain, guided wave, guided wave ultrasonic testing, compressive sensing

Abstract

Guided wave ultrasonic testing (GWUT) is among the optimum method that has been broadly utilised for structural health monitoring (SHM) applications. With the rapid development of wireless and real-time in SHM fields, the implementation of compressive sensing (CS) for GWUT has received attention for better signal-processing compression techniques. Instead of the traditional compression method, an efficient CS promises a compression method that can sample signals lower than the Nyquist sampling rate. In CS, the signal basis is an important parameter to be investigated that will influence the compression performance. This study transforms the GWUT input signal into three (3) types of familiar signal basis, such as discrete cosine transform (DCT), fast Fourier transform (FFT) and discrete wavelet transform (DWT), and the compression performance using the CS method is examined and compared. The results reveal that among these three (3) signals basis, considered the trade-off between quality and compressed performance, the DCT is the best basis and the sparsest transform signal for GWUT with excellent compressed ability and quality of reconstruction. It was recorded that 50 to 80 percent of the M/N sampling ratio was the best sampling ratio for DCT, with SNR values ranging from 37dB to 44 dB.

1. Introduction

Guided wave ultrasonic testing (GWUT) has been used recently in structural health monitoring (SHM). It allows inspections that can cover a large area, detect defect location and, most importantly, analyse the structural integrity and provide preventive maintenance reports. These features make GWUT has been used in many structural integrity concern areas, such as pipeline inspection [1–5], aerospace [6] and composite materials [7]. GWUT uses the pulse-echo method and frequently operates at a low-frequency range of 20–100 kHz [8]. This technique is widely used in the industry to detect corrosion and other forms of degradation.

In signal processing applications, compression techniques are crucial, especially for remotely located areas. Consequently, for GWUT in SHM, it is desirable to use data compression techniques to reduce data while maintaining signal integrity. Hence, the ultrasonic signals can be transferred efficiently through wireless or wired communication channels for analysis.

Compression is a necessary step in signal processing because it extracts important and eliminates redundant information from the sampled data. Traditionally, a signal is sampled using the Shannon sampling theorem [9] to ensure data recovery in the reconstruction or decompression process. Candès *et al.* [10], Donoho [11] and Candes and Tao [12] have established a mathematical foundation of compressive sensing (CS) that opens a new path of research to be explored in the field of signal processing.

A signal will be sparsed, either in the original domain or in other transform domains, for example, the cosine, Fourier or wavelet transform [13]. Based on the sparsity of the signals, CS can attain and precisely reconstruct the signals with significantly fewer samples than the traditional Nyquist sampling. This benefit makes CS has drawn substantial attention in numerous fields, such as reconstruction, digital multimedia signal, radar imaging, signal/image processing, biomedical, cognitive radio network, geophysics, remote sensing and the Internet of Things (IoT) [14–19].

This paper discussed CS compression performance using three (3) types of transform domains: discrete cosine transform (DCT), fast Fourier transform (FFT) and discrete wavelet transform (DWT) signal basis. The best basis for GWUT using CS performance among the signal basis is evaluated based on the trade-off between the quality of decompression or reconstruction of the signal and data reduction of the compressed signal.

The remaining structure of this paper is organised as follows. A general equation of CS and the concept of best-basis is explained in section 2. Simulation-based experimental setup and performance evaluation results are discussed in sections 3 and 4, respectively. Lastly, the conclusion is outlined in section 5.

2. Best-basis Compressive Sensing

The term best-basis refers to the best performance signal transform of the CS for GWUT, which is evaluated in this paper. In the theory of CS, the general equation is described as $y = \Theta x$, with y as a measured signal, Θ as a measurement matrix and x as the input signal, as shown in Equation (1). This equation can be elaborated and explained in much detail in Equations (2) to (5):

$$y = \Theta x \tag{1}$$

$$x = \sum_{i=1}^{n} s_i \psi_i = \psi s \tag{2}$$

$$x = \psi s \tag{3}$$

$$y = \Theta \psi s \tag{4}$$

$$y = As \tag{5}$$

The CS reconstruction model, as depicted in Fig. 1, shows that the input signal x can be recovered by utilising the measurement vector y (compressed signal that being transmit) and reconstruction matrix A, where $A = \Theta \times \psi$ (Θ is the measurement matrix and ψ is the sparsifying basis of the signal x). The signal x can be represented as a linear combination of ψ columns or the basis vectors as $x = \psi s$, where s is the sparse coefficient of the input signal. The CS method can beat the Nyquist theorem because the input signal can be sparse in some transform domains. In this study, the transform domain ψ of well-known DCT, FFT, and DWT basis for the ultrasonic input signal were investigated to identify the most suitable transform domain for the GWUT input signal. Haar transform has been used in this research work as the simplest and the fastest wavelet transform [20].

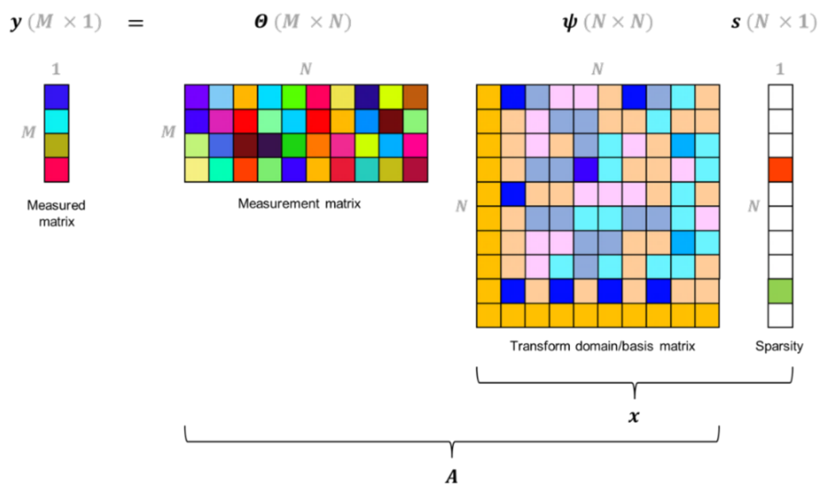


Fig. 1 *CS reconstruction model*

Instead of the transform domain, the measurement matrix Θ also plays a significant role in this experiment, as the sampling process of the CS method is based on the M/N sampling ratio. Several percentages of the M/N sampling ratio are tested and the lowest possible sampling data with excellent signal reconstruction quality is determined.

3. Experimental Setup

The experiment is simulation-based using MATLAB software. For this simulation, the input GWUT signal (.mat format) was imported from the Institute for Aerospace Technology and The Composites Research Group, The University of Nottingham and the Department of Mechanical Engineering, the University of Bristol, which are online open sources resources [21, 22]. In this experiment, the guided wave signal is generated using piezoelectric disc transducers with a frequency of 50kHz.

This experiment was conducted on the Intel (R) Core (TM) i7-5600U CPU processor @ 2.60GHz, with 8.00GB RAM and a 64-bit operating system. The guided wave signal compress using CS operation was developed using C programming in MATLAB with different types of transform domains (DCT, FFT and DWT) and the percentage of samples by M/N ratio (10% to 90%). The various percentages of the M/N sampling ratio are used to identify the best ranges of sampling ratio results. The CS reconstruction method approached in this implementation using the l1-minimization method [23].

The performance compression using CS with different transform domains is evaluated with two (2) parameters: reconstruction quality and data reduction of the compressed signal. The quality of the reconstruction signal is assessed using mean squared error (MSE) and signal-to-noise power ratio (SNR) as in equation (6) and equation (7). MSE calculates the average square error difference between the original and recovered signals at various measurement points. In contrast, SNR measures signal integrity by comparing and finding the similarity between the original and reconstructed signal [24].

$$MSE(o,r) = \frac{1}{N}\sum_{i=1}^{N}(o_i - r_i)^2 \tag{6}$$

$$SNR = 10 * \frac{log_{10}(\sum_{i=1}^{N}(o_i)^2)}{\sum_{i=1}^{N}(o_i - r_i)^2} dB \tag{7}$$

where o = original input signal, r = recovered signal and N = total number of data.

4. Performance Evaluation Setup

The CS performance of the guided wave for different transform domains can be compared as shown in Table 1, Fig. 2 and Fig. 3. The results obtained have been evaluated regarding the quality of reconstruction using MSE and SNR formulation and compressed signal for different percentages of M/N ratio from the original signal.

Fig. 2 and Fig. 3 show the MSE and SNR trends of the reconstruction signal of CS between different type of transform domain which is DCT, FFT and DWT, including no transform (NT). MSE and SNR values obtained for different transform domains are plotted against the various percentages of M/N sampling ratios from the original signal ranging from 10 to 90 percent.

Between MSE and SNR, the trends of the results will be reversed, which means decreasing the MSE will increase the SNR values. As shown in Fig. 2 and Fig. 3, quite consistently, it can be observed that the MSE values decrease and SNR values increase with the increasing percentage of M/N sampling ratio no matter the types of the transform domain.

However, in terms of performance, it can be observed that the error corresponding to DWT and NT has the highest MSE value, followed by FFT, and the minor error is for the DCT basis. These trends also make the results for SNR inversely proportional to MSE, where DCT is the best transform domain for the quality of signal reconstruction, followed by FFT and DWT and NT as the least quality.

There are two (2) main parameters that contribute to the performance of CS in this simulation, which are types of transform domain and percentage of M/N sampling ratio. From the hypothesis, a signal will be sparse in the original or some transform domain. The sparsity is an inherent characteristic of signals which enables the signal to be stored in far few samples or a smaller number of significant data. This sparsity represents the compression of the signal. Based on the results, signal transform using the DCT domain is the sparsest signal.

In terms of sampling ratio, the sparsest the signal, less number of samples requires. For example, DCT requires almost double or less percentage of the M/N sampling ratio compared to another transform domain. From the plotted graph, we can also spot that the best sampling ratio for DCT is from 50 to 80 percent of the M/N sampling ratio, as the MSE and SNR values remain almost consistent.

Fig. 4 compares the compressed signal (kB) of CS computation between transform domains for different percentages of the M/N sampling ratio. DWT was reported as the highest compression performance, DCT as the intermediate and FFT as the least memory reduction. If we compared for 50 percent M/N sampling ratio, from 36kB original signal, DWT compressed signal from 36kB to 8kB (77 % memory reduction), DCT compressed signal from 36kB to 15kB (58% memory reduction) and FFT compressed signal from 36kB to 29kB (19% memory reduction). NT compressed signal is the same as DCT as the DCT algorithm does not change matrix dimension. The exact size dimension created the same amount of compressed signal but a different quality of reconstruction.

Table 1 *Transform domain reconstruction signal performance*

Transform domain	M/N ratio (%)	MSE	SNR	Original signal (kB)	Compressed signal (kB)
DCT	10	9.87E-07	4.4249	36	4
	20	7.44E-08	15.6532	36	6
	30	1.70E-09	32.0724	36	9
	40	7.27E-10	35.7547	36	12
	50	4.40E-10	37.9325	36	15
	60	2.79E-10	39.9107	36	18
	70	1.90E-10	41.569	36	21
	80	1.18E-10	43.6526	36	24
	90	5.84E-11	46.7017	36	27
FFT	10	2.12E-06	2.5908	36	6
	20	1.81E-06	4.2112	36	12
	30	8.74E-07	10.0026	36	18
	40	1.94E-07	18.6679	36	24
	50	8.73E-08	19.3398	36	29
	60	7.36E-08	26.7512	36	35
	70	7.39E-08	29.8581	36	41
	80	1.05E-08	35.7336	36	47
	90	1.50E-09	46.0269	36	53
DWT	10	3.04E-06	0.2132	36	2
	20	2.60E-06	0.2249	36	4
	30	2.07E-06	1.2097	36	5
	40	1.43E-06	2.8145	36	6
	50	1.19E-06	3.6119	36	8
	60	8.69E-07	4.9782	36	9
	70	5.92E-07	6.6428	36	11
	80	3.14E-07	9.3938	36	12
	90	1.34E-07	13.0855	36	14

NT	10	3.09E-06	0.2561	36	4
	20	2.45E-06	0.4765	36	6
	30	1.85E-06	1.6939	36	9
	40	1.47E-06	2.6962	36	12
	50	1.18E-06	3.6436	36	15
	60	8.17E-07	5.2438	36	18
	70	4.99E-07	7.3842	36	21
	80	3.46E-07	8.9803	36	24
	90	1.44E-07	12.7809	36	27

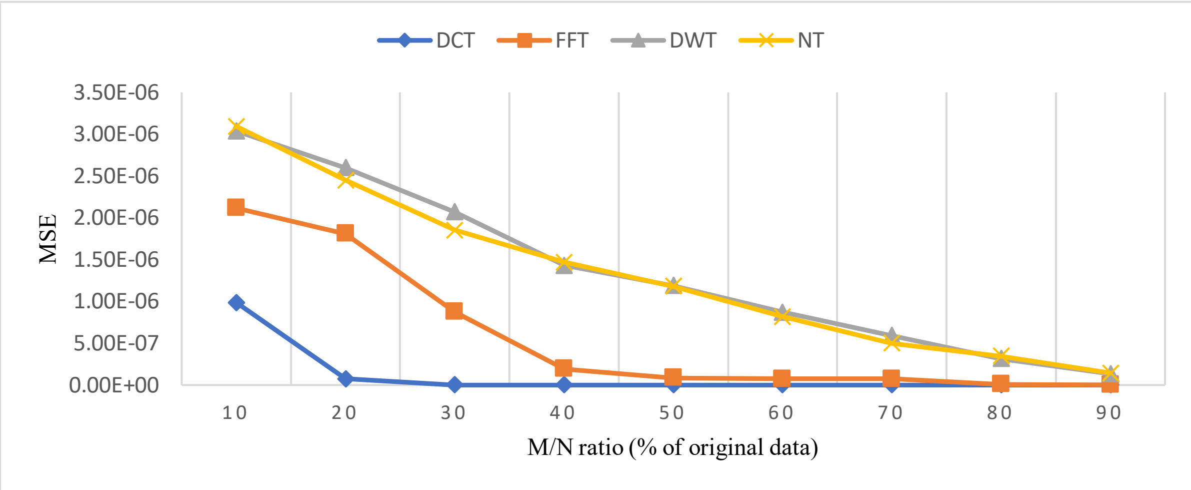


Fig. 2 *Comparison of MSE vs M/N sampling ratio for different types of transform domain*

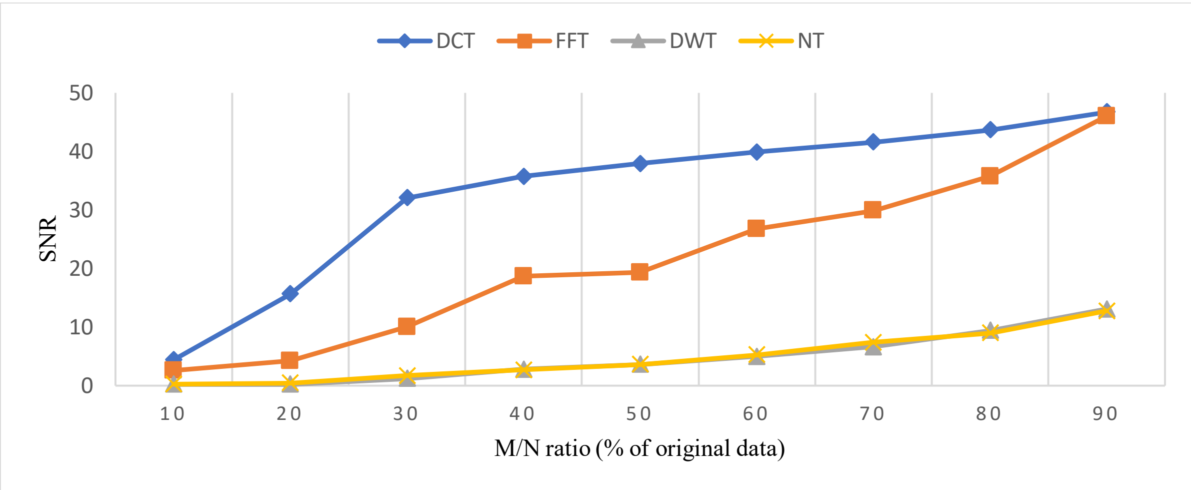


Fig. 3 *Comparison of SNR vs M/N sampling ratio for different types of transform domain*

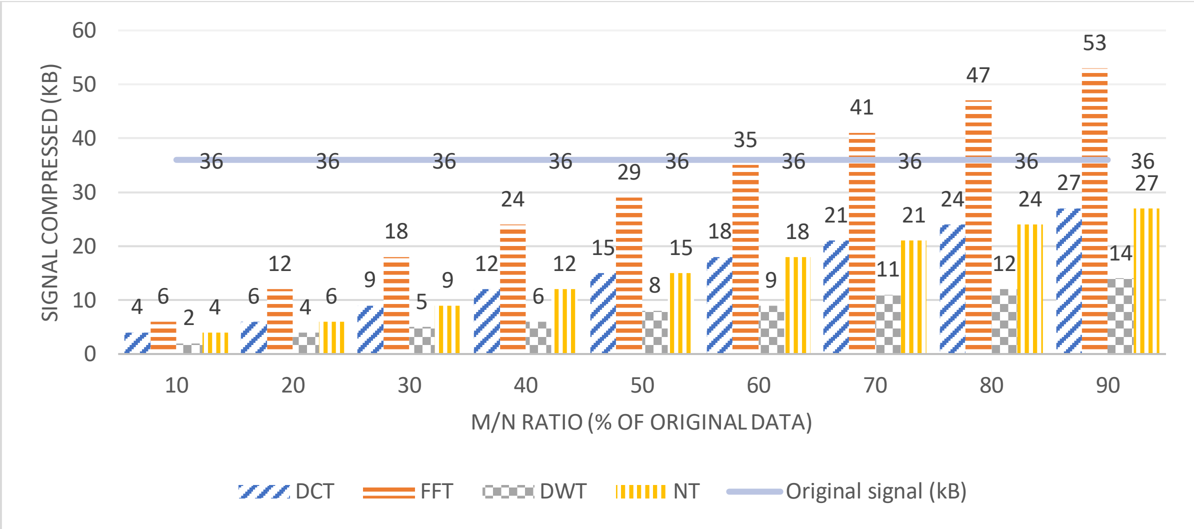


Fig. 4 *Comparison of compressed signal (kB) vs M/N sampling ratio for different types of transform domain*

4.1 Trade-off Between Quality and Compressed Signal

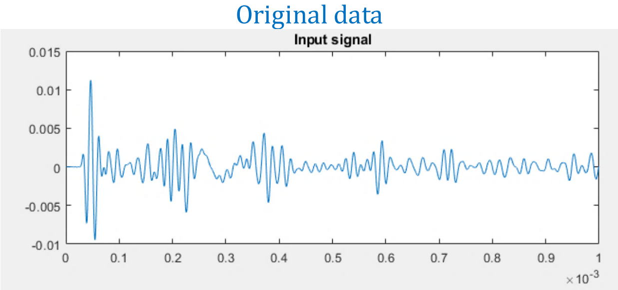
Based on the results obtained, evaluation of the performance of CS between the transform domains is essential by evaluating the trade-off between quality and data reduction. In terms of computation, DCT is more straightforward and faster than FFT. DCT is favoured over FFT in certain compression algorithms because DCT is a real transform which results in a single real number per data point. In contrast, an FFT results in a complex number (real and imaginary parts) which requires double the storage memory. This issue is shown in Fig. 3, as the FFT transform domain has a more compressed value than other domains and creates more data than the original signal when the M/N sampling ratio increases from 70 to 90%.

DWT generally gives a better compression ratio or compressed signal without losing more information but needs more processing power. While DCT needs low processing power, but it loses some information [25]. However, CS is a lossy compression that makes the DWT basis in CS unable to recover the original signal and makes the SNR value less than the DCT.

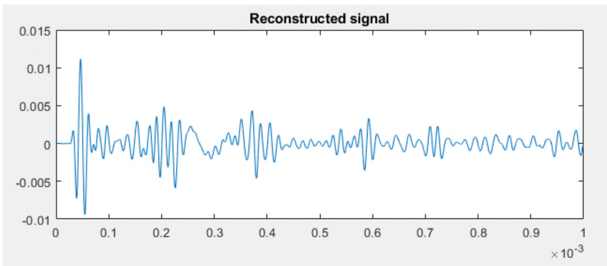
DWT has the highest data reduction but is poor in reconstruction quality. On the other hand, DCT is the best in terms of reconstruction quality with good data reduction. Taken together, the results indicate that the DCT basis is the best transform domain of CS for the guided wave ultrasonic signal tested.

Fig. 5 shows the reconstruction signal obtained compared to the original signal from CS reconstruction using DCT, FFT and DWT. In this experiment, the reconstructions were performed after removing 50% of the original samples. The reconstruction signal images are reliable with the previous finding since it clearly shows that the highest error is associated with DWT reconstruction, followed by FFT and DCT reconstruction corresponds to the slightest error with a smooth signal reconstructed, as shown in Fig. 5. DCT reconstruction signal recovered almost similar to the original signal with an SNR value of 37.9325 dB.

Original data



DCT



FFT

DWT

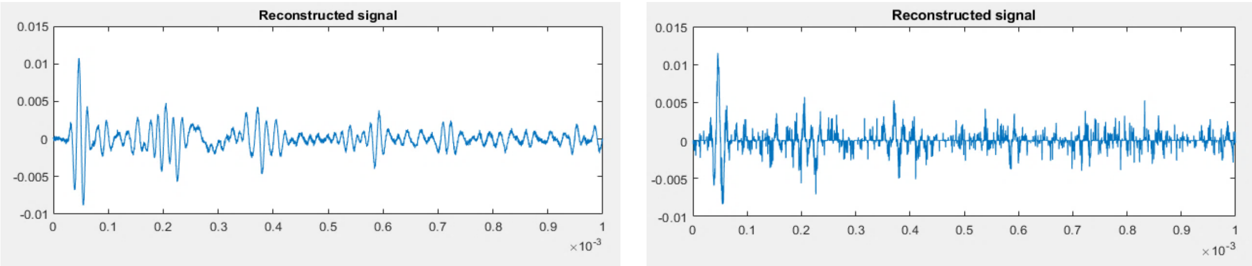


Fig. 5 *Reconstructed of DCT, FFT and DWT signal computed from 50kHz input signal with 50% M/N sampling ratio*

5. Conclusion

This paper applies the simulation of CS for GWUT signal to evaluate the performance using different signal transform domains like DCT, FFT and DWT. The results assessed in terms of reconstruction quality using MSE and SNR equations show DCT transform domain as the best signal basis with the consistency of low MSE and high SNR value for the best percentage of M/N sampling ratio from 50 to 80 percent. In data reduction, DCT also moderately reduced between DWT and FFT. In conclusion, considering the trade-off between the quality of reconstruction and data reduction of CS compression, DCT was selected as the best basis or best performance for CS-based GWUT.

In future improvements in terms of the compression part of CS, emphasis can be given to the aspect of matrix multiplication between measurement matrix and input signal, as in Equation (1), where this process involves large matrix multiplication that requires a lot of computer computation resources. Types of measurement matrix can also be compared and analysed to improve the CS performance. Instead of software, improvement using hardware acceleration with parallelism must be explored to reduce the computation time.

Acknowledgement

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM) through GPPS (Vot H534).

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Muhammad Muzakkir Mohd Nadzri;* ***data collection:*** *Muhammad Muzakkir Mohd Nadzri;* ***analysis and interpretation of results:*** *Muhammad Muzakkir Mohd Nadzri, Afandi Ahmad;* ***draft manuscript preparation:*** *Muhammad Muzakkir Mohd Nadzri, Afandi Ahmad. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Lyutak, I. (2005). Wavelet analysis of ultrasonic guided waves in pipeline inspection. In Proceedings of the Third Workshop - 2005 IEEE Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, IDAACS 2005 (pp. 517–523). https://doi.org/10.1109/IDAACS.2005.283037

[2] Yajing, S., & Bo, D. (2013). Research on ultrasonic guided wave testing pipeline corrosion based on wavelet transform. In 2013 25th Chinese Control and Decision Conference, CCDC 2013 (pp. 2802–2805). IEEE. https://doi.org/10.1109/CCDC.2013.6561421

[3] Sun, L. Y., Yang, X. D., & Li, Y. B. (2009). Research on transducer and frequency of ultrasonic guided waves in urban pipe inspection. In 2009 4th IEEE Conference on Industrial Electronics and Applications, ICIEA 2009 (pp. 2708–2711). https://doi.org/10.1109/ICIEA.2009.5138656

[4] Reber, K., Beller, M., Willems, H., & Barbian, O. A. (2002). A new generation of ultrasonic in-line inspection tools for detecting, sizing and locating metal loss and cracks in transmission pipelines. In Proceedings of the IEEE Ultrasonics Symposium (pp. 665–671). IEEE. https://doi.org/10.1109/ULTSYM.2002.1193490

[5] Liu, T., Pei, C., Wang, L., Xie, C., & Chen, Z. (2023). An Enhanced Long-Range Guided-Wave Pipe Inspection Method Based on Local Axial 2-D Signal Acquisition and Processing. IEEE Transactions on Instrumentation and Measurement, 72, 1–7. https://doi.org/10.1109/TIM.2023.3267346

[6] Yun, H., Pant, S., Genest, M., Li, L., & Liu, Z. (2023). Impact damage characterization in composite plate using ultrasonic guided waves. IEEE International Ultrasonics Symposium, IUS, 1–4. https://doi.org/10.1109/IUS51837.2023.10307194

[7] Rose, J. L. (2009). Successes and Challenges in Ultrasonic Guided Waves for NDT and SHM. In Proceedings of the National Seminar & Exhibition on Non-Destructive Evaluation (pp. 1–11).
[8] Pedram, S. K., Mudge, P., & Gan, T. H. (2018). Enhancement of ultrasonic guided wave signals using a split-spectrum processing method. Applied Sciences (Switzerland), 8(10). https://doi.org/10.3390/app8101815
[9] Fardad, M., Sayedi, S. M., & Yazdian, E. (2018). A low-complexity hardware for deterministic compressive sensing reconstruction. IEEE Transactions on Circuits and Systems I: Regular Papers, 65(10), 3349–3361. https://doi.org/10.1109/TCSI.2018.2803627
[10] Candes, E. J., Romberg, J., & Tao, T. (2006). Robust uncertainty principles: exact signal reconstruction from highly incomplete frequency information. IEEE Transactions on Information Theory, 52(2), 489–509. https://doi.org/10.1109/TIT.2005.862083
[11] Donoho, D. L. (2006). Compressed sensing. IEEE Transactions on Information Theory, 52(4), 1289–1306. https://doi.org/10.1109/TIT.2006.871582
[12] Candes, E. J., & Tao, T. (2006). Near-optimal signal recovery from random projections: Universal encoding strategies? IEEE Transactions on Information Theory, 52(12), 5406–5425. https://doi.org/10.1109/TIT.2006.885507
[13] Huang, G., & Wang, L. (2015). High-speed Signal Reconstruction for Compressive Sensing Applications. Journal of Signal Processing Systems, 81(3), 333–344. https://doi.org/10.1007/s11265-014-0954-4
[14] Zhang, W., Amin, M. G., Ahmad, F., Hoorfar, A., & Smith, G. E. (2012). Ultrawideband impulse radar through-the-wall imaging with compressive sensing. International Journal of Antennas and Propagation, 2012. https://doi.org/10.1155/2012/251497
[15] Zhang, L., Qiao, Z. J., Xing, M. D., Sheng, J. L., Guo, R., & Bao, Z. (2012). High-resolution ISAR imaging by exploiting sparse apertures. IEEE Transactions on Antennas and Propagation, 60(2 PART 2), 997–1008. https://doi.org/10.1109/TAP.2011.2173130
[16] Kang, L. W., Lin, C. Y., Chen, H. W., Yu, C. M., Lu, C. S., Hsu, C. Y., & Pei, S. C. (2011). Secure transcoding for compressive multimedia sensing. Proceedings - International Conference on Image Processing, ICIP, 917–920. https://doi.org/10.1109/ICIP.2011.6116709
[17] Colonnese, S., Biagi, M., Cattai, T., Cusani, R., De Vico Fallani, F., & Scarano, G. (2018). Green compressive sampling reconstruction in IoT networks. Sensors (Switzerland), 18(8), 1–15. https://doi.org/10.3390/s18082735
[18] Pareschi, F., Mangia, M., Bortolotti, D., Bartolini, A., Benini, L., Rovatti, R., & Setti, G. (2017). Energy Analysis of Decoders for Rakeness-Based Compressed Sensing of ECG Signals. IEEE Transactions on Biomedical Circuits and Systems, 11(6), 1278–1289. https://doi.org/10.1109/TBCAS.2017.2740059
[19] Huang, X. L., Wang, G., & Hu, F. (2013). Multitask spectrum sensing in cognitive radio networks via spatiotemporal data mining. IEEE Transactions on Vehicular Technology, 62(2), 809–823. https://doi.org/10.1109/TVT.2012.2223767
[20] Jayarani, A. E. A., Bhatt, M. R., & Geetha, D. D. (2021). An Introduction to Sparse Sampling on Audio Signal by Exploring Different Basis Matrices. Advances in Artificial Intelligence and Data Engineering, Advances in Intelligent Systems and Computing, Springer Nature Singapore (pp. 1121–1130). https://doi.org/10.1007/978-981-15-3514-7_83
[21] Thierry, V., Cantero-Chinchilla, S., Wu, W., Lhémery, A., & Chronopoulos, D. (2021). Ultrasonic guided-wave experiment data for manuscript entitled "A homogenisation scheme for Lamb ultrasound wave dispersion in textile composites through multiscale wave and finite element modelling." Zenodo. Retrieved September 20, 2022. https://doi.org/10.5281/ZENODO.4487288
[22] Thierry, V., Cantero-Chinchilla, S., Wu, W., Lhemery, A., & Chronopoulos, D. (2021). A homogenisation scheme for ultrasonic Lamb wave dispersion in textile composites through multiscale wave and finite element modelling. Structural Control and Health Monitoring, 28(6), 1–26. https://doi.org/10.1002/stc.2728
[23] Pearlsy, P. V., & Sankar, D. (2018). Implementation of Compressive Sensing for Speech Signals. In Proceedings of the 2018 8th International Symposium on Embedded Computing and System Design, ISED 2018 (pp. 162–166). IEEE. https://doi.org/10.1109/ISED.2018.8704026
[24] Bhadoria, B. S., Shukla, U., & Joshi, A. M. (2015). Comparative analysis of basis & measurement matrices for non-speech audio signal using compressive sensing. 2014 IEEE International Conference on Computational Intelligence and Computing Research, IEEE ICCIC 2014, 489–509. https://doi.org/10.1109/ICCIC.2014.7238453
[25] Katharotiya, A., Patel, S., & Goyani, M. (2011). Comparative Analysis between DCT & DWT Techniques of Image Compression. Journal of Information Engineering and Applications, 1(2), 9–18.