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HATS : Hybrid adaptive transform selection for wavelet-enhanced OTFS in sparse IoT communications

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Abstract

The fast expansion of Internet of Things (IoT) networks operating in healthcare settings and low-power environments requires robust communication systems which maintain their performance in sparse and noisy communication channels. The performance of OTFS modulation becomes worse when it operates under conditions of high sparsity and elevated noise levels. The current fixed-transform methods, which use wavelet, DCT, and spline techniques, do not adapt to non-stationary signal patterns, which limits their ability to function well in dynamic IoT environments. The proposed HATS framework (Hybrid Adaptive Transform Selection) selects the most suitable transform domain dynamically to boost OTFS transmission by adapting to signal sparsity and noise characteristics. The evaluation of HATS on the MIT-BIH Arrhythmia Database for ECG signal recovery and QRS detection resulted in a minimum MSE of 0.000268, 41.57 dB PSNR, and R-peak correlation, which surpassed fixed-transform baselines. The proposed improvements become vital for biomedical IoT applications because they maintain diagnostic feature preservation of QRS complexes and reduce energy consumption. The HATS framework shows effective capabilities to boost reliability in IoT systems which handle restricted data while dealing with communication interference.

Subject Classification: *Primary 68M25, Secondary 68M14.*

Keywords: *Sparse IoT networks, Dynamic channel adaptation, Adaptive wavelet transforms, Delay-doppler domain processing.*

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1. Introduction

The Internet of Things (IoT) functions as the fundamental base for contemporary wireless communication systems which support applications from distant medical tracking to factory process control. The systems function with limited power devices that have restricted power supply while they send occasional critical data through unstable wireless communication channels [1], [2], [3]. The systems require high-speed data transfer with minimal errors because bandwidth restrictions and device movement and environmental interference create major operational difficulties. The wireless communication technology OTFS modulation shows promise as a better solution than traditional multicarrier schemes including OFDM for high-mobility and doubly dispersive channel environments. The robustness of OTFS does not protect it from performance deterioration when signals contain noise or insufficient sparsity which frequently occurs in IoT real-world deployments. Signal preprocessing techniques that use transform-domain representations have become widely used to address this limitation. The discrete wavelet transform (DWT) [4] and discrete cosine transform (DCT) along with spline-based [5] methods demonstrate effectiveness in compressive sensing and denoising, and feature extraction, particularly in biomedical signal processing applications such as electrocardiogram (ECG) analysis [6]. The majority of current methods use predetermined transform choices which restrict their ability to adapt and do not maximize signal characteristics under different noise levels and sparsity conditions [7]. This paper introduces Hybrid Adaptive Transform Selection (HATS) as a new framework which adds an adaptive preprocessing stage to the OTFS transmission system. HATS dynamically selects the most suitable transform wavelet, DCT, or spline based on the statistical properties of the input signal. This selection process enhances signal sparsity and denoising prior to modulation, thereby improving overall communication reliability. The proposed method is particularly relevant for biomedical IoT applications, where data integrity is critical. We evaluate HATS using the MIT-BIH Arrhythmia Database, focusing on ECG signal transmission and QRS complex detection accuracy. The existing OTFS systems depend on fixed-transform methods (DWT, DCT, or spline), which fail to adapt to changing signal conditions [8], [9], [10], but this work presents HATS as the first framework that selects optimal transforms dynamically according to real-time signal characteristics. The main contributions consist of:

(1) A new cost-function-based selection method which selects wavelet, DCT, or spline transforms automatically through signal sparsity evaluation and reconstruction error and feature preservation metrics assessment.

(2) A lightweight implementation suitable for resource-constrained IoT devices.

(3) Experimental validation showing 41.57 dB PSNR improvement and near-perfect R-peak correlation in ECG recovery, significantly outperforming fixed-transform methods.

The following sections comprise the rest of this paper. The system model and problem formulation are presented in Section II. The experimental setup is described in Section III, followed by results discussion in Section IV. The paper concludes in Section V with future research directions.

2. Methodology

The Hybrid Adaptive Transform Selection framework proposes an improvement for OTFS communication through OTFS signal chain integration of adaptive transform-domain preprocessing, which works well in sparse and noisy IoT environments. The OTFS system functions through symbol data mapping into delay-Doppler space, which creates built-in resistance against fading signals that change with time and weak signal power, thus making it suitable for new IoT and biomedical systems. The OTFS system produces poor results when input data lacks sparse patterns or when it contains substantial amounts of noise [11]. The system addresses its current restriction through an adaptive system which chooses the best transform basis from wavelet, discrete cosine, and spline transforms to enhance signal sparsity and noise resistance before modulation occurs. The transform selection process depends on a cost-based system, which determines the best combination between accurate reconstruction results and maintained features. The HATS system implements standard OTFS modulation and demodulation methods to improve signal recovery for limited energy signals and non-stationary signals through its existing system design, which supports real-time IoT operations [12].

The built-in resistance of OTFS modulation against doubly dispersive channels does not prevent its performance from being restricted by the characteristics of the transmitted signal, which affects its behavior in IoT and biomedical applications with their noisy and low sparse signal nature. The non-stationary characteristics of unprocessed ECG signals require transform-domain preprocessing because fixed preprocessing pipelines do not work effectively to enhance sparsity and reduce noise while maintaining essential diagnostic features before OTFS modulation [13], [14]. The performance of any single transform remains suboptimal when dealing with different signal types and various noise conditions because wavelet, spline, and DCT-based methods show different advantages and disadvantages. The Hybrid Adaptive Transform Selection framework solves this problem by continuously testing different transform candidates through reconstruction accuracy, sparsity, and structural fidelity assessments to choose the transform which achieves the lowest total cost [15]. The system employs an adaptive selection method which functions as a light-weight process to execute strong preprocessing operations when signal statistics and channel conditions become unstable. The system achieves its best performance for real-time operation in restricted resource environments of IoT and V2X communication systems. The HATS framework operates within the standard OTFS transmission system through its integration with the existing modulation and demodulation process by implementing transmitter-side adaptive preprocessing and receiver-side postprocessing. The transmitter

chooses the best transformation method based on signal properties before performing OTFS modulation, while the receiver uses the correct inverse transformation after OTFS demodulation to retrieve the original signal. Transform information is conveyed using lightweight side signaling or pilot-assisted inference. The adaptive design structure enables better noise reduction performance while preserving essential features and sparse data structures in the OTFS framework which results in minimal processing delays that enable real-time operation in limited IoT and biomedical communication systems.

3. Experimental Setup

The proposed Hybrid Adaptive Transform Selection framework is evaluated using real-world sparse biomedical communication scenarios based on ECG signals from the MIT-BIH Arrhythmia Database [16], with all experiments implemented in a Python-based pipeline using open-source scientific libraries. The ECG recordings which were recorded at 360 Hz sampling rate were chosen from records 100, 101, 103 and 105 to show typical heart rhythms and irregular heart rhythms. The researchers took 10-second segments from each record which they normalized to zero mean and unit variance. The R-peak detection method allowed researchers to determine RR intervals which function as vital clinical indicators to assess reconstruction quality [17]. The signals were processed through a modular compression and reconstruction pipeline under compressive sensing constraints, where the HATS framework adaptively selected the most suitable transform for each input. The compression system employed wavelet-based compression which used multiple candidate bases to perform multi-level decomposition and threshold-based sparsification before executing Lasso regression for sparse recovery and dimensionality reduction. The system used DCT-based compression together with spline-based interpolation through sparse recovery when wavelet-based reconstruction either did not complete its process or generated poor results. The system used its sparse recovery technique to evaluate HATS against fixed-transform methods for different signal types under different noise levels.

4. Results and Discussion

The assessment examines how the proposed HATS framework performs against standard methods for OTFS-based ECG signal compression when the compression ratio remains constant at 30 percent using records 100, 101, 103 and 105 from the MIT-BIH Arrhythmia Database. The evaluation process evaluates signal reconstruction quality and biomedical feature preservation through the results which are shown in Figure 1 through 4. The evaluation of Reconstruction fidelity depends on three performance indicators which include MSE and PSNR and NRMSE [18]. The results show HATS achieves better performance than fixed-transform methods in all records while records 103 and 105 demonstrate the most significant improvements. In record 101, HATS achieves an MSE of 0.000268, outperforming fixed wavelet and DCT approaches by an order of magnitude due to its adaptive preference for wavelet

transforms in segments with high R-peak fidelity under low SNR conditions [19], [20], [21], [22]. The cost function operates to maintain essential medical characteristics which produces better QRS duration error results than using fixed reference points. The PSNR results as shown in Figure 2, demonstrate that HATS produces optimal results because it achieves its highest value at 41 dB while outperforming spline and DCT methods in all cases especially when processing intricate ECG signals. The R-peak correlation analysis demonstrates that HATS maintains correlations above 0.999 throughout all records while achieving complete correlation in record 105 because its adaptive transform selection method protects vital biomedical data during sparse and noisy data transmission.

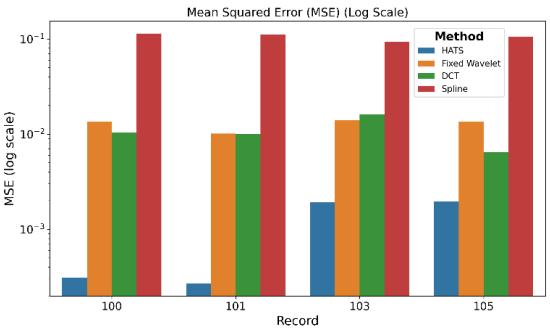

Figure 1

Mean Squared Error (MSE) across all methods for records 100–105.

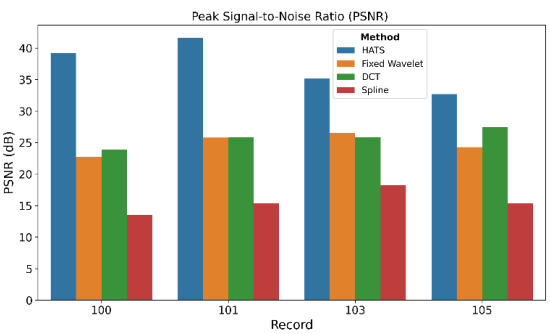

Figure 2

Peak Signal-to-Noise Ratio (PSNR) comparison across records and methods.

The QRS duration error appears in Figure 4 as a vital diagnostic tool. The QRS error measurements from HATS exceed all other methods in records 103 and 105 by showing 30 ms and 17 ms, respectively. The QRS error measurements from fixed wavelet and spline methods exceed 60 ms in these specific cases. The HATS method delivers equivalent results to the top-performing alternative method in records 100 and 101, which have simpler

characteristics. The HATS framework demonstrates superior performance to fixed-transform methods in all evaluation metrics, which assess ECG signal reconstruction and biomedical feature preservation according to Figures 1 through 4.

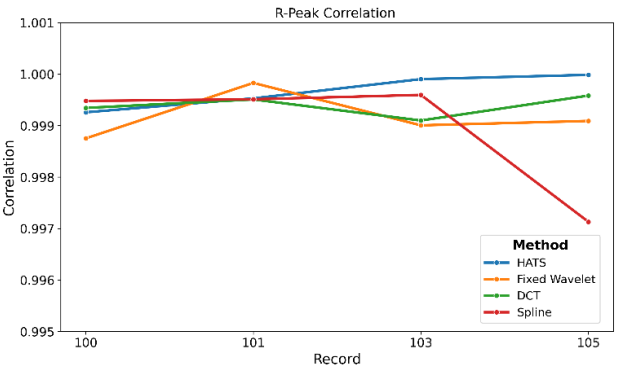

Figure 3

R-peak correlation between original and reconstructed ECG signals across methods.

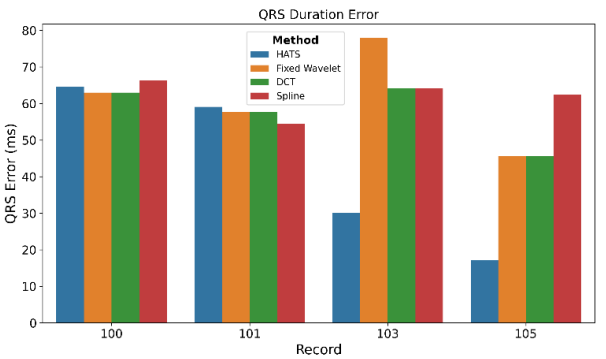

Figure 4

QRS duration error (ms) for each method across different records.

The Mean Squared Error of HATS reaches its lowest value while its Peak Signal-to-Noise Ratio reaches its highest value which shows that the method produces minimal distortion and maintains excellent noise resistance better than wavelet and DCT and spline-based methods. The R-peak correlation analysis as shown in Figure 3, demonstrates that all vital clinical indicators stay functional while QRS duration results achieve enhanced time measurement accuracy. The diagnostic information loss in fixed-transform methods results in their poor performance when dealing with complicated signal patterns. These results demonstrate that adaptive transform selection enables consistent waveform integrity and reliable biomedical feature retention for sparse IoT-based ECG transmission.

5. Conclusion

This paper presents HATS, a Hybrid Adaptive Transform Selection framework that enhances sparse IoT signal recovery in OTFS-based systems by dynamically selecting the most suitable transform basis using a data-driven cost evaluation. The MIT-BIH Arrhythmia Database ECG signals underwent experiments through doubly dispersive channels which showed HATS outperformed fixed-transform methods in all aspects of compression and reconstruction accuracy and biomedical feature maintenance especially for non-stationary and complex signals. The framework enables QRS detection with more than 50% error reduction while keeping its lightweight processing requirements suitable for IoT systems with limited resources. The system of HATS operates without issues when used with OTFS modulation because it needs only small amounts of additional data. The system faces two main difficulties when used for ultra-low-power devices because it causes small decreases in data transfer rate and it needs to perform real-time transform evaluations. The research investigates ECG signals but HATS adaptive design allows researchers to easily implement its methodology for analyzing various biomedical and industrial IoT signals which include EEG and EMG and sensor monitoring data.

References

[1] A. A. Hussain and B. A. Dawood, "A survey on IoT-cloud task in healthcare system," *J. Supercomput.*, vol. 81, no. 1, Art. no. 141 (2025), doi: 10.1007/s11227-024-06629-1.

[2] P. M. Urs, A. T. N. Reddy, S. Mallikarjunaswamy, and U. M. Lakshminarayan, "An innovative IoT framework using machine learning for predicting information loss at the data link layer in smart networks," *Eng. Technol. Appl. Sci. Res.*, vol. 15, no. 2, pp. 20904–20911 (2025), doi: 10.48084/etasr.9597.

[3] H. Soy, "An adaptive spreading factor allocation scheme for mobile LoRa networks: Blind ADR with distributed TDMA scheduling," *Simul. Model. Pract. Theory*, vol. 125, Art. no. 102755 (2023), doi: 10.1016/j.simpat.2023.102755.

[4] S. Singh, S. Kumar, S. Majhi, U. Satija, and C. Yuen, "Blind carrier frequency offset estimation techniques for next-generation multicarrier communication systems: Challenges, comparative analysis, and future prospects," *IEEE Commun. Surveys Tuts.*, vol. 27, no. 1, pp. 1–36 (2025), doi: 10.1109/COMST.2024.3472109.

[5] P. Liang, L. Yang, Z. Xiong, X. Zhang, and G. Liu, "Multilevel intrusion detection based on transformer and wavelet transform for IoT

data security," *IEEE Internet Things J.*, vol. 11, no. 15, pp. 25613–25624 (2024), doi: 10.1109/JIOT.2024.3369034.

[6] N. Subramanyan and K. Arunesh, "Entropy based model for lossy image compression scheme using wavelets, SVD, and two-channel coding techniques," *J. Comput. Anal. Appl.,* vol. 33, no. 5, pp. 436–459 (2024).

[7] A. Mishra, S. Bhusnur, S. K. Mishra, and P. Singh, "Comparative analysis of parametric B-spline and Hermite cubic spline based methods for accurate ECG signal modeling," *J. Electrocardiol.,* vol. 86, Art. no. 153783 (2024), doi: 10.1016/j.jelectrocard.2024.153783.

[8] W. Yuan, S. Li, Z. Wei, Y. Cui, J. Jiang, H. Zhang, and P. Fan, "New delay Doppler communication paradigm in 6G era: A survey of orthogonal time frequency space (OTFS)," *China Commun.*, vol. 20, no. 6, pp. 1–25 (2023), doi: 10.23919/JCC.fa.2022-0578.202306.

[9] P. Mangal and D. Lakshmi, "Advanced biomedical signal processing techniques for real-time health monitoring systems," in *Deep Learning in Medical Signal and Image Processing*, pp. 45–62 (2025), doi: 10.4018/979-8-3693-9816-6.ch003.

[10] W. Yuan, L. Zhou, S. K. Dehkordi, S. Li, P. Fan, G. Caire, and H. V. Poor, "From OTFS to DD-ISAC: Integrating sensing and communications in the delay Doppler domain," *IEEE Wireless Commun.*, vol. 31, no. 6, pp. 152–160 (2024), doi: 10.1109/MWC.018.2300607.

[11] L. Xiao, S. Li, Y. Qian, D. Chen, and T. Jiang, "An overview of OTFS for Internet of Things: Concepts, benefits, and challenges," *IEEE Internet Things J.*, vol. 9, no. 10, pp. 7596–7618 (2022), doi: 10.1109/JIOT.2021.3132606.

[12] M. H. Abid, I. A. Talin, M. A. Matin, and M. I. Kadir, "Wavelet-aided OTFS: A 2-D multicarrier modulation format for high-mobility communications," *IEEE Open J. Commun. Soc.*, vol. 6, pp. 2660–2678 (2025), doi: 10.1109/OJCOMS.2025.3533027.

[13] Q. Deng, Y. Ge, and Z. Ding, "A unifying view of OTFS and its many variants," *IEEE Commun. Surv. Tuts.,* vol. 27, no. 6, pp. 3561–3586 (2025), doi: 10.1109/COMST.2025.3542467.

[14] A. Noonia, D. Thakral, P. Mathur, F. Sheth, H. Shaikh, and A. K. Gupta, "A discrete mathematical model and cryptography for secure medical image analysis: Encrypted chest X-ray classification," *J.*

Discrete Math. Sci. Cryptogr., vol. 28, no. 5-A, pp. 1473–1486 (2025), doi: 10.47974/JDMSC-2146.

[15] E. Shtaiwi, A. Abdelhadi, H. Li, Z. Han, and H. V. Poor, "Orthogonal time frequency space for integrated sensing and communication: A survey," arXiv preprint arXiv:2402.09637 (2024).

[16] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. Ch. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation,* vol. 101, no. 23, pp. e215–e220 (2000).

[17] C. Shen, H. Lin, and J. Yuan, "Error performance of rectangular pulse-shaped OTFS with practical receivers," *IEEE Wireless Commun. Lett.,* vol. 11, no. 12, pp. 2690–2694 (Dec. 2022).

[18] A. Kumar, S. Chakravarthy, N. Gaur, and A. Nanthaamornphong, "Hybrid approaches to PAPR, BER, and PSD optimization in 6G OTFS: Implications for healthcare," *J. Commun. Netw.*, vol. 26, no. 3, pp. 308–320 (2024).

[19] Z. Lin, S. Duan, M. Liu, C. Dang, S. Qian, L. Zhang, H. Wang, W. Yan, and M. Zhu, "Insights into materials, physics, and applications in flexible and wearable acoustic sensing technology," *Adv. Mater.,* vol. 36, no. 9, Art. no. 2306880 (2024).

[20] X. An, Q. Liu, Y. Liu, G. K. Stylios, Y. Zhao, and S. Lu, "Adaptive motion artifact reduction in wearable ECG measurements using impedance pneumography signal," *Sensors,* vol. 22, no. 15, Art. no. 5493 (Jul. 2022).

[21] R. Joshi, P. Mathur, A. K. Gupta, S. Singh, V. Paliwal, and S. Nayar, "Mathematical modeling of intelligent system for predicting effectiveness of premenstrual syndrome," *J. Interdiscip. Math.,* vol. 26, no. 3, pp. 551–562 (2023).

[22] S. S. Kushwaha, S. Joshi, and A. K. Gupta, "An efficient approach to secure smart contract of Ethereum blockchain using hybrid security analysis approach," *J. Discrete Math. Sci. Cryptogr.,* vol. 26, no. 5, pp. 1499–1517 (2023).

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