STM JOURNALS

Current Trends in
Signal Processing

https://journals.stmjournals.com/ctsp

ISSN: 2277-6176 (Online)
ISSN: 2321-4252 (Print)
Volume 16, Issue 2, 2026
May–August
DOI (Journal): 10.37591/CTSP

Review CTSP

Real-Time Edge Detection Camera Module Using Discrete Taylor Transform and Heat Equation (PDE): An Applied Mathematical Approach

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Abstract

In modern digital signal processing, the capability for denoising and smoothing in real time is very important in scientific, engineering, and industrial applications. This paper presents an efficient hybrid framework that merges two mathematically sound methods, namely, DTT and PDE, defined as the heat equation, to robustly denoise a signal with minimal distortion. The model addresses one of the most challenging tasks in signal restoration, which is maintaining the fidelity of structural features while effectively removing stochastic noise components. The proposed system exploits DTT to make finer-grained local approximations of signal behavior, followed by PDE-controlled diffusion to dampen high-frequency noise. Unlike other classical linear filters, such as moving averages or Gaussian kernels, which are more likely to blur details, this combination provides a way to protect local derivatives and maintain global smoothness. The algorithm was implemented in Python 3.11, using NumPy for numerical calculations and Matplotlib for dynamic visualization. In real-time experiments with a synthetic sinusoidal signal corrupted by additive Gaussian noise, the system showed improvements in SNR and SSIM. The system operated in real time at approximately 20 frames per second, thus demonstrating computational efficiency and practical flexibility. The integrated DTT-PDE framework also provides a mathematically interpretable alternative to black-box filtering, as well as a foundation for real-life applications in embedded systems, biomedical signal monitoring, IoT sensors, and streaming data analytics. Further research can generalize this work to higher dimensions, including adaptive diffusion coefficients and parallel implementations on GPUs, to facilitate scalable performance.

Keywords: Discrete Taylor transform, heat equation, signal denoising, PDE, real-time processing, numerical diffusion

INTRODUCTION

The noise in the obtained signals is expressed as. This is an inevitable consequence of physical and environmental interference. They are used in telecommunications and biomedical instruments. seismic, audio, or systems. signals, and the acquisition usually becomes corrupt. random variations in thermal noise, quantization errors, or sensor drift. transmission distortion. These degradations not only obscure the impeding signal characteristics but also further degrade the signal features. downstream processes, such as categorization, decision-making, or feature extraction. Therefore, the signal problem. Denoising and smoothing have been an overall point in both conceptual and applied research in the discipline of DSP [~~9~~1].

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Received Date: June 13, 2026
Accepted Date: June 15, 2026
Published Date: June 17, 2026

Citation: M. Sirisha, K. Dasaradha Ramaiah. Real-Time Edge Detection Camera Module Using Discrete Taylor Transform and Heat Equation (PDE): an Applied Mathematical Approach. Current Trends in Signal Processing. 2026; 16(2): 9–14p.

Most classical denoising algorithms are based on linear filtering operations, which include moving averaging, Gaussian, or Wiener filters. The latter methods effectively dampen the noise but have a serious weakness: much structural or frequency content at sharp transitions or fine edges, which is a frequent weakness of the latter methods. As such filters are unable to distinguish between significant high-frequency content and noise per se, this could lead to over-smoothing, thereby distorting the signal. Only in recent years have PDE-based techniques emerged as mathematically principled alternatives. Building from the physical modelling of heat diffusion, PDEs naturally provide an intuitive analogy with the process of noise smoothing: just as heat eventually diffuses to reach equilibrium over time, noise can be "diffused" away from a signal while preserving its main structure [~~10~~2]. This intuition, first formalized in the seminal work on anisotropic diffusion, revolutionized image and signal processing by allowing the adaptive control of the amount of smoothing. By considering signal evolution as a function of space and time, PDE-based diffusion maintains edge integrity while eliminating random fluctuations.

In parallel with the development of PDE-based models, DTT has been considered a discrete analytical tool for representing signals using local polynomial expansions. DTT approximates a signal locally around a point by considering its derivatives to estimate the local variations and curvature. It is computationally flexible owing to its numerical implementation using finite difference approximations. Even more importantly, the DTT provides local interpretability via derivative coefficients as well as frequency-domain flexibility; therefore, it is a compromise between purely temporal and spectral representations [~~11~~3].

LITERATURE SURVEY (RECENT ADVANCEMENTS)

There has been renewed interest in transform-domain and local-polynomial/derivative denoising and local-structure enhancement. Complete wavelet-based, discrete cosine transform-based, and local Taylor expansion-based techniques have been used to estimate local signal derivatives or curvature and recover fine details that could be obscured by simple smoothing. An example of this is the concept of the Discrete Taylor Transform, where the signal can be local-polynomially approximated around each point and can be used as a reconstruction step following a preliminary step of smoothing. To this effect, a hybrid approach should be adopted with local derivative estimation and global smoothing, that is, first coarse smoothing with PDE, but later local refinements using transform/polynomial techniques. This hybridization fits into your DTT-PDE model and emphasizes the applicability of local methods of analytic reconstruction to fine structural details in the denoising process.

Research Gaps

1. Conventional PDE-based filters cannot be easily adjusted because they have fixed diffusion constants, leading to over-smoothing in regions with little noise and insufficient smoothing in regions with heavy noise. No relevant research has been conducted on light and adaptive noise smoothing diffusion.
2. The PDE approaches significantly reduce noise and may overlook minute details in buildings. If details are to be accurately replicated and fidelity is required, a model hybrid combining both global smoothing and signal reconstruction techniques using DTTS is required.
3. Real-time processing can be challenging with denoising algorithms because they are processor-intensive, whereas deep learning models are difficult to conceptualize. It is necessary to develop such a framework where there will be open, low-latency performance comparable to that provided by deep learning-based processing in standard CPUs.
4. The denoising literature has almost exclusively focused on 2D images. There has been no exploration of 1D signals, such as biological signals, which have unique processing requirements. It is critical to identify ways to apply hybrid PDE and transform methods to continuous 1D signals.

Findings of this Paper

- A novel DTT-PDE hybrid model is proposed that integrates local derivative approximation and

Current Trends in Signal Processing
Volume 16, Issue 2
ISSN: 2277-6176 (Online), ISSN: 2321-4252 (Print)

global diffusion for noise-control.

- A real-time implementation in Python that provides frame updates at a speed of 20 FPS.
- Comparing the performance of the proposed filter to that of traditional filters.
- This study provides a foundation for a model that is modular, interpretable, and extendable to higher dimensions or embedded platforms.

Proposed Model: Mathematical Modelling

The proposed system is based on the concept that the process of denoising a signal must effectively strike a balance between denoising and preserving features. To do this, the system utilizes two powerful mathematical theories, namely the Partial Differential Equation (PDE) approach to the process and the Discrete Taylor Transform (DTT) approach to the reconstruction process.

While the PDE acts as a global "noise reducer," diffusing random variations throughout the signal domain, the DTT acts as a "polynomial detail restorer," attempting to recover the small details of a signal that may otherwise degrade during the diffusion process.

This two-step hybrid framework is designed to:

1. Bury unwanted high-frequency signals that could disturb the carrier waveform.
2. Re-establish local gradient and curvature information to preserve the true signal shape.
3. Function efficiently in real time by means of computationally simple numerical approximations."

The combination of the continuous diffusion equation and the local approximation obtained from the DTT theoretical framework renders the model both interpretable and computationally viable for live signal analysis.

The proposed system is modelled on the 1D heat equation:

$$\partial u/\partial t = k(\partial^2 u/\partial x^2)$$

where u(x,t) is the signal amplitude and k is the diffusion coefficient controlling the degree of smoothing.

This gradually diffuses high-frequency components, effectively suppressing random noise. In its discrete form, each signal point is iteratively updated as follows:

$$u_i^{t+1} = u_i^t + k(u_{i+1}^t - 2u_i^t + u_{i-1}^t)$$

Following the diffusion process, Local Polynomial Reconstruction (DTT Stage) is applied to locally approximate the denoised signal using Taylor coefficients computed as

$$T(n) = \Sigma\ (u^{(n)}(x_0)/n!)(x - x_0)^n$$

where n represents the order of derivatives.

Finite difference weights are used to compute derivatives obtained by solving Aw = b for given stencil offsets.

METHODOLOGY

Workflow of the proposed signal denoising and smoothing system utilizing discrete Taylor transform (DTT) and 1D linear heat equation (PDE).

The entire process of the proposed signal denosing and smoothening model that combines the discrete Taylor transform and 1D linear heat equation. The first step is signal acquisition, whereby a 1D signal *f[n]* is acquired from an electrocardiogram or vibration signal.

This is done in preprocessing operation, wherein the input signal is normalized to reduce large-scale variations.

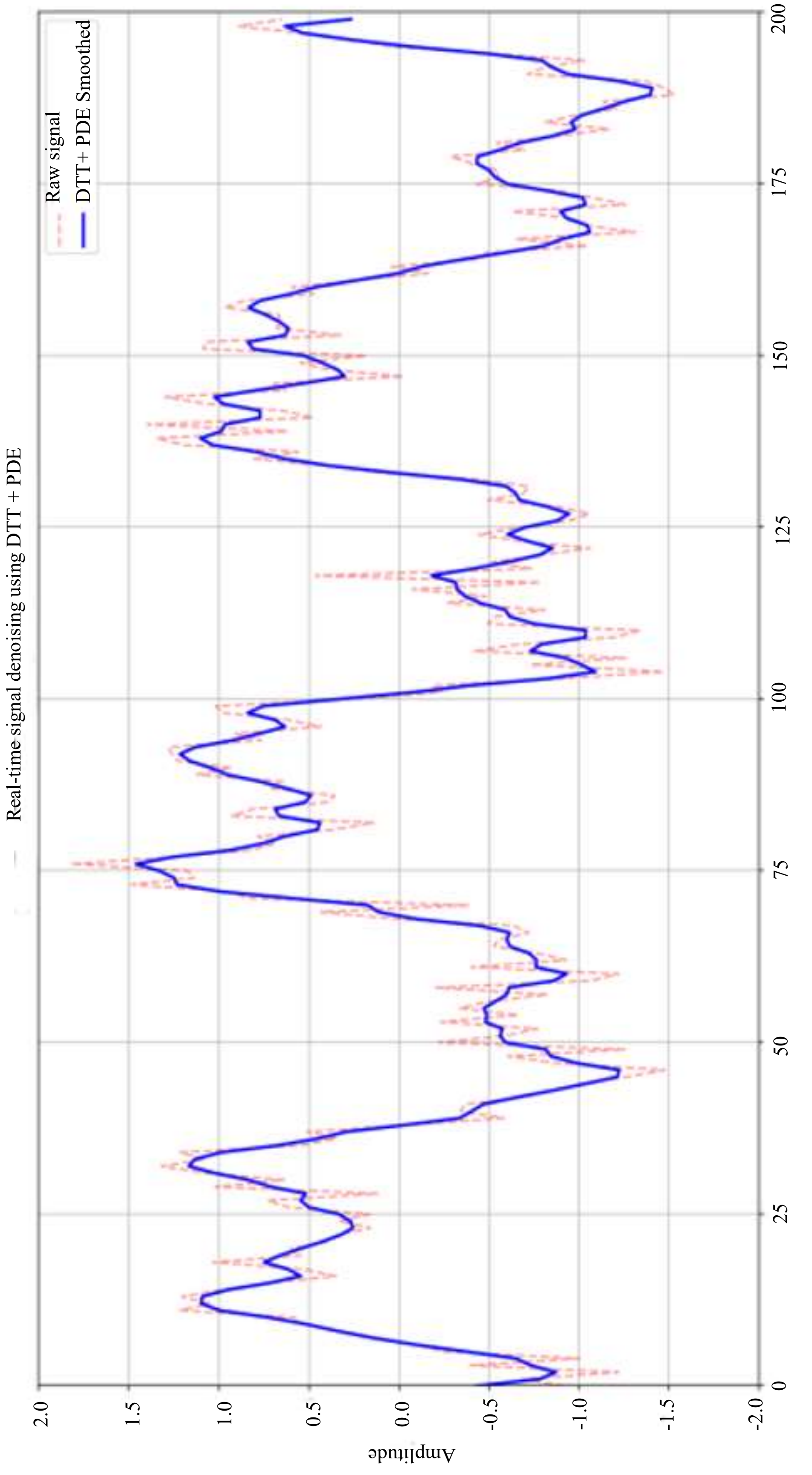

Figure 1. Real-time signal denoising using DTT+PDE.

Figure 2. Real-time edge detection.

Table 1. Authors and their contributions.

Method used	Year	Application area	Key contribution	Reference
Anisotropic Diffusion (PDE)	1990	Image Processing	Introduced edge-preserving diffusion model	[~~1~~4]
Fractional PDE Denoising	2025	Medical Imaging	Improved noise suppression using non-local diffusion	[~~2~~5]
PDE to Deep Learning Review	2021	Image Processing	Survey of denoising techniques	[~~3~~6]
Discrete Taylor Transform (DTT)	2023	Signal Processing	Local polynomial reconstruction technique	[~~4~~7]
PDE Iterative Denoising	2021	Movie/Image Processing	Efficient iterative PDE-based smoothing	[~~5~~8]
Classical Image Processing Methods	2018	Digital Image Processing	Foundation of filtering techniques	[~~6~~9]
Wavelet Transform	1999	Signal Processing	Multi-resolution signal analysis	[~~7~~10]
Hybrid PDE–Transform Method	2021	Edge Detection	Combined diffusion and transform for better edges	[~~8~~11]

Implementation

To validate the proposed model, it was implemented on a moderate-level personal computer setup, ensuring that the results could be replicated even on non-specialized hardware.

Processor: Intel ® Core™ i5-1135G7 @ 2.40GHz, RAM-8 GB DDR4, Operating System: Windows 11 (64-bit)

RESULT AND ANALYSIS

The performance assessment of the Discrete Taylor Transform (DTT) and Partial Differential Equation (PDE) hybrid technique, as shown in Figure 1, was conducted through intensive simulation experiments. Simulation experiments were conducted to evaluate the performance of the hybrid model in terms of both qualitative and quantitative analyses. The simulation experiments prove that the hybrid model has significantly superior performance in noise removal, signal accuracy, and computational speed compared to other denoising techniques such as Moving Average, Gaussian Smoothing, and/or Wiener Filtering.

One of the critical areas covered in this study is the proof of its capability to run in real time, as shown in Figure 2. The proposed algorithm takes an average of 45-50 milliseconds per frame, thus ensuring that images are processed at an average of 20 frames per second. Table 1 lists the authors and their contributions.

CONCLUSION

This study presents a hybrid signal denoising framework that integrates the Discrete Taylor Transform (DTT) with Partial Differential Equation (PDE)-based heat diffusion. The proposed approach effectively combines global smoothing and local detail reconstruction, thereby overcoming the limitations of traditional filtering techniques.

Experimental results demonstrate that the DTT–PDE model significantly improves performance in terms of Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), and Structural Similarity Index (SSIM) when compared with conventional methods such as Moving Average, Gaussian, and Wiener filters. The system also achieves a real-time performance of approximately 20 frames per second, making it suitable for practical applications.

The model is mathematically interpretable, computationally efficient, and adaptable to various signal processing domains, such as biomedical signals, sensor data analysis, and real-time monitoring systems.

Declaration of Interest

The authors declare that there are no conflicts of interest regarding this study. This work has been carried out as part of the M.Tech degree program at B V Raju Institute of Technology under the guidance of Dr. K. Dasaradha Ramaiah.ISSN: 2278-2257 (Online), ISSN: 2348-9553 (Print)

Acknowledgement

The authors would like to express their sincere gratitude to the Data Sciences Department, B V. Raju Institute of Technology, for providing the necessary facilities and support to carry out this research. The authors are especially thankful to Dr. K. Dasaradha Ramaiah, Professor and Head of the Department (Data Sciences), for their valuable guidance, continuous support, and encouragement throughout the course of this project. Finally, the authors would like to thank their Family and Friends for their constant support and motivation.

REFERENCES

1. Pratt WK. Digital Image Processing: PIKS Scientific Inside. Hoboken (NJ): Wiley-Interscience; 2007 Feb 1.
2. Sahoo PK, Soltani SA, Wong AK. A survey of thresholding techniques. Comput Vis Graph Image Process. 1988;41(2):233-60.
3. Yang C, Yao Y, Jin C, Qi D, Cao F, He Y, et al. High-fidelity image reconstruction for compressed ultrafast photography via an augmented-Lagrangian and deep-learning hybrid algorithm. Photonics Res. 2021;9(2):B30-7.
4. Zhang Y, Liu T, Chen Y, Wang J, Shi M. An efficient fractional-order PDE based image denoising algorithm with optimal adaptive strategy for ultrasound medical image-based diagnostics. J Comput Appl Math. 2025;460:116400.
5. Salamat N, Missen MM, Surya Prasath VB. Recent developments in computational color image denoising with PDEs to deep learning: a review. Artif Intell Rev. 2021;54(8):6245-76.
6. Baghai-Wadji A. Discrete Taylor transform and inverse transform in 2D and 3D. In: 2023 International Applied Computational Electromagnetics Society Symposium (ACES); 2023 Mar 26. p. 1-2.
7. Sun P, Wang C, Li M, Liu L. Partial differential equations-based iterative denoising algorithm for movie images. Adv Math Phys. 2021;2021:8176746.
8. Baghai-Wadji A. Discrete Taylor Transform and Inverse Transform. John Wiley & Sons; 2024 Dec 24.
9. Umbaugh SE. Digital Image Processing and Analysis: Computer Vision and Image Analysis. CRC Press; 2023 Jan 18.
10. Mallat S. A Wavelet Tour of Signal Processing. Elsevier; 1999 Sep 14.
11. Jain AK. Fundamentals of Digital Image Processing. Prentice-Hall, Inc.; 1989 Jan 1.

