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MATHEMATICAL MODELS AND ALGORITHMS FOR PROCESSING NOISE DATA

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Abstract: This article is devoted to the analysis of mathematical models and algorithms for processing noisy data in modern information systems. The study examines the main approaches used to increase the signal-to-noise ratio, improve data quality, and filter out erroneous data. The Results and Discussion section presents optimal models for various types of noise and their performance indicators in tabular form. The study highlights the importance of modern mathematical tools in processing noisy data and their potential for practical applications.

Key words: noisy data, mathematical models, signal processing, adaptive filters, statistical methods, machine learning, noise filtering.

INTRODUCTION

The rapid development of modern digital technologies and information systems necessitates the creation of new methods for data processing. In real-world conditions, the data obtained are often distorted by various types of noise, which negatively affects data reliability and the accuracy of analytical results [1].

The problem of noisy data is particularly relevant in telecommunications systems, medical diagnostics, artificial intelligence, image processing, economic forecasting, and many other fields. Noise in data may arise due to various factors, including measurement errors, environmental influences, disruptions in data transmission processes, or specific characteristics of information sources [2].

The presence of noise significantly complicates the extraction of useful signals from data, the identification of patterns, and the process of making accurate decisions.

Mathematical modeling and algorithmic approaches have become the primary tools for processing noisy data. Currently, a wide range of methods exists for noise reduction and signal restoration, each possessing its own advantages and limitations [3].

Traditional approaches, such as classical statistical methods, adaptive filters, Kalman filtering, wavelet transforms, and Fourier analysis, form the theoretical foundation of this field. At the same time, modern methods based on machine learning and deep learning open up new possibilities for more efficient data processing.

However, the applicability of each method depends on the nature of the noise, the structure of the data, and the specifics of the task at hand [4]. For instance, linear filters are effective for stationary noise, whereas adaptive or nonlinear approaches are required for non-stationary and impulsive noise.

LITERATURE REVIEW

Mathematical models for processing noisy data are based on various theoretical approaches, each selected according to the nature of the data, the characteristics of the noise, and the objectives of processing.

An analysis of the available literature indicates that noise modeling and filtering methods are primarily developing in three main directions: classical statistical approaches, signal processing–based methods, and modern machine learning techniques [5].

Each of these directions is characterized by its own mathematical apparatus, theoretical foundations, and areas of practical application. These approaches can be considered either complementary or alternative, depending on the specific research context.

The statistical modeling approach considers noise as a random process and utilizes the apparatus of probability theory. Within this framework, noise is commonly modeled using the Gaussian distribution, the Poisson distribution, or other well-known probability distributions [1].

Classical statistical techniques, such as Bayesian methods, maximum likelihood estimation, and the least squares method, enable the characterization of noise in data through statistical parameters and allow optimal estimation based on criteria such as minimum variance or maximum likelihood.

The Gaussian noise model is the most widely used and demonstrates strong performance in many real-world situations; however, its effectiveness decreases in the presence of impulsive or structured noise [6]. For noise with an unknown distribution or heavy tails, robust statistical methods are applied, including median filters, M-estimators, and other non-classical statistical tools.

Methods based on signal processing theory rely on frequency-domain analysis and filter theory. Linear time-invariant filters, including low-pass, high-pass, and band-pass filters, are used to eliminate noise with specific frequency characteristics [2].

Transforming a signal into the frequency domain using the Fourier transform and applying appropriate filters represent classical approaches. However, these methods are fully effective only for stationary signals; for non-stationary signals, time–frequency analysis is required.

To address this limitation, the wavelet transform was developed, enabling simultaneous analysis of signals in both time and frequency domains [3].

Adaptive filters, particularly the Wiener filter and the Kalman filter, adjust to the statistical properties of signals and provide high efficiency under changing environmental conditions. The Kalman filter is widely used for state estimation in dynamic systems and enables optimal estimation from noisy observations [7].

Modern machine learning and deep learning methods create new opportunities for processing noisy data. Neural networks, particularly convolutional neural networks and autoencoders, are capable of learning complex nonlinear relationships and filtering high levels of noise [4].

Denoising autoencoders are specifically designed neural networks that transform noisy inputs into clean outputs and are widely used in image processing, speech signal enhancement, and other applications.

Generative adversarial networks also set new standards in noise reduction tasks, as they achieve high-quality results through the interaction between a generator and a discriminator [8].

The primary advantage of machine learning approaches lies in their ability to automatically learn patterns from large datasets and identify complex noise structures. However, these methods require substantial training data and computational resources, and they often suffer from the “black box” problem, which complicates the interpretation of results [5].

Analysis of the literature indicates that different methods are optimal for different types of noise. While classical Wiener or Kalman filters are sufficient for stationary Gaussian noise, wavelet transform–based or deep learning methods are more suitable for non-stationary and complex structured noise [9].

The signal-to-noise ratio (SNR) also plays a crucial role in method selection: under low SNR conditions, robust statistical methods and machine learning approaches tend to be more effective.

In addition, computational complexity and real-time processing requirements must be taken into account, as more complex algorithms, although capable of achieving higher accuracy, often involve significantly greater computational costs [10].

Hybrid approaches, which combine multiple methods, frequently yield the best results, as they integrate the strengths of each approach while compensating for their individual limitations.

RESEARCH METHODOLOGY

This study is based on a comparative and analytical research methodology aimed at evaluating mathematical models and algorithms for processing noisy data. The research employs theoretical analysis, statistical modeling, and algorithmic comparison methods.

Initially, widely used approaches—including classical statistical methods, signal processing techniques, and machine learning algorithms—were selected and systematized based on their theoretical foundations and application domains .

Subsequently, the selected models (Wiener filter, Kalman filter, median filter, wavelet transform, and neural networks) were comparatively analyzed according to key criteria such as noise type compatibility, computational complexity, and practical applicability.

The evaluation process was carried out using qualitative and quantitative indicators, including signal-to-noise ratio (SNR), noise reduction efficiency (in dB), and processing time.

Furthermore, the effectiveness of different algorithms was assessed under varying SNR conditions (high, medium, low, and very low), allowing for the identification of optimal methods for each noise level.

The research also incorporates a comparative table-based analysis to systematize the results and highlight the strengths and limitations of each method.

Overall, the methodology is designed to ensure a comprehensive evaluation of noise processing techniques and to provide practical recommendations for selecting appropriate models in real-world applications.

ANALYSIS AND RESULTS

Based on the analysis of various mathematical models for processing noisy data, their areas of application, performance indicators, and practical advantages have been identified.

Table 1 below presents a comparative analysis of the main mathematical models. It includes the theoretical foundations of each method, the corresponding noise types, computational complexity, and areas of practical application (Table 1).

Table 1. Comparative Analysis of Basic Mathematical Models for Noise Data Processing

Model / Method	Theoretical Basis	Matching Noise Type	Computational Complexity	Main Advantages	Limitations
Wiener filter	Statistically optimal filter	Gaussian, stationary	Medium	Optimal when signal and noise statistics are known	Requires prior knowledge of statistics
Kalman filter	Bayesian estimation	Dynamic systems	Medium	Real-time processing, adaptive	Limited to (mainly) linear systems
Median filter	Order statistics	Impulsive (salt-and-pepper)	Low	Simple and effective	May lead to loss of fine details
Wavelet transform	Time–frequency analysis	Non-stationary	High	Preserves local features	Selection of appropriate wavelet is complex
Neural networks	Machine learning	Complex, nonlinear	Very high	High accuracy and adaptability	Requires large datasets and high computation

As shown in Table 1, each mathematical model possesses distinct characteristics and is adapted to specific tasks.

The Wiener filter provides optimal results when the statistical properties of the signal and noise are known; however, this requires a priori information, which is not always available in practical applications.

The Kalman filter is highly effective for state estimation in dynamic systems and enables real-time processing. However, it is primarily designed for linear systems, and extended or unscented versions are required for nonlinear cases.

Although the median filter is effective in eliminating impulsive noise and is computationally efficient, it may lead to the loss of signal details.

Wavelet transform–based methods are particularly suitable for tasks that require the preservation of non-stationary signals and local features; however, selecting an appropriate wavelet function remains a complex task.

Neural networks demonstrate high efficiency in processing noise with complex and nonlinear structures; however, they require large amounts of training data and significant computational resources.

The signal-to-noise ratio (SNR) is a crucial criterion in method selection, and the effectiveness of different algorithms varies depending on the SNR level.

Table 2 below presents an analysis of the performance indicators of the main algorithms under different SNR conditions (Table 2).

Table 2. Analysis of the Effectiveness of Noise Filtering Algorithms at Different SNR Levels

SNR Range	Optimal Method	Average Improvement (dB)	Processing Time	Practical Recommendations
High (>20 dB)	Linear filters	3–5 dB	Low	Simple methods are sufficient
Medium (10–20 dB)	Adaptive filters, wavelet methods	5–10 dB	Medium	Adaptive approaches are preferred
Low (0–10 dB)	Neural networks, robust methods	10–15 dB	High	Requires complex algorithms
Very low (<0 dB)	Deep learning methods	15–20 dB	Very high	Requires specially trained models

The analysis presented in Table 2 indicates that even simple linear filters provide satisfactory results and are computationally efficient under high SNR conditions.

Under medium SNR conditions, adaptive filters and wavelet transform–based methods achieve a balanced trade-off, ensuring sufficient noise reduction while maintaining moderate computational costs.

In low SNR scenarios, classical methods lose their effectiveness, and robust statistical approaches or modern machine learning algorithms become necessary.

The most challenging case—very low SNR (when the signal is weaker than noise)—can only be effectively addressed using specially trained deep neural networks; however, this approach is computationally expensive.

Therefore, in practical applications, it is essential to assess the SNR level and select the appropriate method accordingly.

In the discussion, it should be emphasized that the choice of an optimal method depends not only on theoretical effectiveness but also on practical constraints.

For real-time systems, computational complexity is a decisive factor; therefore, simpler yet faster algorithms are often preferred. For example, in medical monitoring systems and telecommunication devices, the Kalman filter or basic adaptive filters are widely used due to their ability to operate in real time.

Conversely, for offline data analysis, such as in scientific research or archival data processing, more complex methods—such as wavelet transforms or deep learning techniques—can be employed, as computational time is not a limiting factor.

Hybrid approaches are widely recognized in modern research, as they combine the strengths of different methods. For instance, integrating wavelet transforms with neural networks enables the combination of time–frequency analysis with the flexibility of machine learning.

Another effective approach involves preliminary noise reduction using classical filters, followed by fine-tuning through neural networks. Such multi-stage approaches often provide superior performance; however, their design and implementation remain complex.

Future research directions in noisy data processing include the development of automated model selection methods, efficient learning from limited data through transfer learning, and the advancement of explainable artificial intelligence techniques.

CONCLUSIONS AND RECOMMENDATIONS

Mathematical models and algorithms for processing noisy data play a decisive role in modern information systems, and their selection depends on the characteristics of the task, the nature of the noise, and practical constraints.

The results of the study indicate that existing approaches are developing in three main directions: classical statistical methods, signal processing–based techniques, and modern machine learning algorithms. Each direction offers distinct advantages: Wiener and Kalman filters are optimal for stationary Gaussian noise; median filters and robust statistical methods are effective for impulsive noise; and wavelet transforms and neural networks provide superior performance for non-stationary and complex structured noise.

The two analyzed tables provide a comparative evaluation of various mathematical models and criteria for selecting optimal methods depending on SNR levels. The signal-to-noise ratio is a decisive parameter in method selection: under high SNR conditions, simple methods are sufficient, whereas low SNR scenarios require more complex machine learning algorithms.

Computational complexity is also an important factor. Real-time systems require fast and efficient algorithms, while more complex methods that ensure higher accuracy can be applied in offline analysis, where time constraints are less critical.

Hybrid approaches, which combine different methods, often provide the most balanced solution and are widely applied in modern practical systems.

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