Information, Computing and Intelligent Systems, 2025, No. 7, 110 – 126
UDC: 004.9, 004.75 https://doi.org/10.20535/2786-8729.7.2025.341409

METHODOLOGY OF ADAPTIVE DATA PROCESSING IN IoT MONITORING SYSTEMS WITH MULTILEVEL SENSOR DATA FILTERING AND SELF-TUNING

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The study focuses on the processes of collecting and preprocessing heterogeneous sensor data. The aim of the research is to develop a method of adaptive filtering and automatic trigger adjustment that ensures stable operation of IoT monitoring systems in the presence of noise, impulse outliers, and seasonal fluctuations.

A methodology for adaptive data processing is proposed, combining multi-level data filtering with automatic self-adjustment of control thresholds in monitoring systems. This approach not only improves the accuracy of real-time sensor measurements but also dynamically adapts the monitoring system parameters to changing operating conditions, thereby minimizing the number of false incidents.

Within the study, a model of multi-level filtering was formalized, based on a median filter, a moving-average filter, and an exponential smoothing method. The use of a multi-level filter provides comprehensive data cleansing, stabilization of time series, and extraction of key trends. A mechanism for automatic adjustment of control thresholds in the `Zabbix` monitoring system was developed, where threshold values are determined based on statistical parameters and trends identified at the multi-level filtering stage. This mechanism integrates into the subsequent data-processing pipeline, ensuring that the system automatically accounts for daily, seasonal, and other fluctuations of the dynamic data-collection environment.

Experimental studies involving various types of sensors confirmed improved measurement accuracy and a significant reduction in false alerts in the monitoring system. In particular, humidity-measurement accuracy improved by an average of 6.52%, while impulse temperature spikes were reduced by 53.06%. Compared to traditional approaches, the proposed methodology provides higher noise resilience and adaptability to changing environmental conditions, making it an effective solution for industrial, environmental, and other real-time IoT systems.

Keywords: IoT, sensor measurements, adaptive control thresholds, self-adjustment, monitoring, Zabbix, seasonal adaptation.

1. Introduction

Modern Internet of Things (IoT) systems are characterized not only by high data flow intensity but also by the heterogeneity of data sources coming from a large number of different types of sensors. The primary data collected from various sensors are referred to as raw data, which often contain noise, duplication, incompleteness, and reading errors, making them unsuitable for effective processing and analysis. In IoT systems, raw data arise due to sensor signal noise (for example, temperature fluctuations or electrical interference), duplicated measurements, transmission failures or packet loss, incorrect values, and inconsistencies between sources when different sensors provide incompatible data.

On the one hand, the presence of excessive and erroneous data complicates analysis, reduces the accuracy of decision-making, and leads to an increased rate of false alerts in monitoring and control subsystems. On the other hand, transmitting data without any preprocessing creates excessive load on the network infrastructure and cloud computing nodes. This decreases the scalability and performance of IoT systems as a whole and reduces prediction quality, particularly in artificial intelligence (AI) systems.

To minimize the impact of such factors, multilevel filtering methods applied directly at the edge level of IoT infrastructure are becoming increasingly important. These methods allow different filtering techniques to be combined for signal smoothing. Such an approach enables preliminary processing and filtering of data before it is transmitted to cloud or server nodes, significantly reducing traffic volume and network resource load.

A key aspect of multilevel filtering in IoT systems is the implementation of adaptive data filtering, in which smoothing coefficients are automatically applied in real time according to the dynamics of signals arriving from numerous heterogeneous sensors. Implementing such mechanisms at the hardware-software level aims to create high-performance modules for real-time data stream processing, particularly at the edge of IoT infrastructure.

This article focuses on improving the quality of sensor data in distributed monitoring systems and ensuring their reliable processing at the IoT edge, which involves the use of noise-suppression mechanisms (data filtering), anomaly detection and removal, as well as adaptive filtering and time-series forecasting methods. Developing integrated approaches to comprehensive data cleansing is an important and relevant direction in the evolution of distributed IoT systems, as it reduces the load on global network and cloud resources and improves the efficiency of parameter processing and forecasting in monitoring systems.

2. Literature review and problem statement

In the modern digital world, the data generated by IoT devices represent a key informational and strategic resource for decision-making across various domains – from industry to smart city infrastructure. Data quality is a critical factor determining the effectiveness of IoT systems. However, the process of collecting and transmitting data is often accompanied by noise and distortions, which reduce the reliability of the obtained measurements.

Contemporary scientific research offers a number of approaches aimed at improving data quality, particularly by eliminating interference and smoothing signals using comprehensive multilevel filtering. Multilevel filtering methods combine different algorithmic techniques to achieve data stability, accuracy, and reliability. In particular, the median filter effectively removes impulse noise, the moving average reduces random fluctuations, and exponential smoothing provides adaptability to the rate of incoming data and dynamic changes in their characteristics. The combined use of these methods forms the basis for improving analytical accuracy at both the Edge and Cloud levels, reducing network load and energy consumption, and increasing the overall reliability of IoT systems. In this context, modern researchers explore various approaches to addressing temporal adaptability, noise resistance, and computational resource optimization, aimed directly at reducing false alerts in monitoring scenarios.

Article [1] examines the use of a median filter for processing temperature data from DHT11 and DHT22 sensors in monitoring systems. The author shows that applying this method reduces fluctuations and spikes in raw data caused by sensor noise, thereby increasing the stability of readings. The results confirm the effectiveness of the median filter in minimizing impulse noise without distorting the key characteristics of the signal. For the DHT11 sensor, this filter is particularly important due to its higher measurement deviation and lower accuracy. The study is practically significant for IoT systems where precise and reliable sensor data are critical.

Article [2] addresses the problem of improving data transmission efficiency in a wireless sensor network for forest fire detection based on `LoRaWAN`. The authors propose a multilevel preprocessing scheme at the data acquisition stage, using smoothing methods such as moving average and exponential smoothing to reduce noise and lower the volume of transmitted data. The results show that this approach reduces energy consumption in sensor nodes by decreasing the number of transmissions, reduces channel load, and simultaneously preserves the informativeness of measurements. The practical significance of the work lies in its applicability to real IoT environmental monitoring systems, where both data accuracy and resource optimization are important.

Article [3] focuses on improving the accuracy and reliability of position determination in systems using Ultra-Wideband (UWB) technology, which is actively applied in modern IoT navigation and monitoring solutions. The authors note that UWB signals are prone to errors due to multipath propagation, reflections, and systematic distance measurement deviations, which lead to inaccuracies in coordinate determination. To address this issue, a two-level approach is proposed: first, the ranging offset calibration is used to eliminate systematic errors, and then the moving average is applied to smooth remaining random noise. Experimental results show that integrating these two methods significantly reduces trajectory jumps and ensures more stable positioning. Although the moving average has little effect on absolute coordinate accuracy, it noticeably improves data stability and trajectory visualization. The method's practicality lies in its suitability for resource-constrained IoT systems used in personnel monitoring, logistics, smart buildings, and other scenarios where stable positioning is required without complex computational algorithms.

Article [4] investigates the impact of moving average parameters on the quality of ultrasonic sensor data. The authors analyze how changing the averaging window size affects measurement stability and accuracy. The results show that increasing the window size enhances noise suppression and improves signal stability; however, an excessively large window reduces sensitivity to real environmental changes. The optimal window size provides a balance between accuracy and system responsiveness. The practical significance of this work lies in its applicability to preprocessing algorithms in IoT applications, particularly in distance monitoring and navigation systems, where both accuracy and timely response matter.

Article [5] proposes a new real-time signal smoothing method that combines properties of the median filter and the moving average. The Smart-Median algorithm replaces the current value with the average of neighboring points if it significantly deviates from the median of surrounding values; otherwise, the median is used. Experimental results demonstrate that the method effectively reduces noise and outliers while preserving signal naturalness and smoothness. The authors highlight that the approach can be applied not only to musical signal processing but also within broader IoT and sensor system scenarios where noise resistance and low latency are essential. Thus, the method is noted for its high practical value and universality – it can be used for real-time filtering of various sensor data while maintaining a balance between accuracy, stability, and speed.

Article [6] emphasizes the adaptive nature of a method that accounts for seasonal fluctuations in water parameters in hydroponic systems. The authors highlight that water quality parameters (pH, temperature, nutrient concentration) vary significantly depending on the season, complicating prediction when classical models are used. To solve this issue, a `SARIMA` (Seasonal `ARIMA`) model is proposed, which automatically incorporates seasonal components of the time series. The results show that considering seasonal factors yields significantly more accurate forecasts compared to standard `ARIMA` models that ignore seasonality. This is especially important for IoT systems in agriculture, where seasonal trends directly influence crop growth and require dynamic environmental adjustments. The practical significance lies in demonstrating that incorporating seasonality into mathematical models is key to improving monitoring and prediction accuracy in IoT applications. The authors note that the approach can be extended to other domains with seasonal patterns, such as environmental monitoring or energy systems.

Overall, the analysis of contemporary research shows that classical data filtering methods are widely used to reduce noise and improve sensor data quality in various IoT scenarios. Median filtering effectively handles impulsive noise in low-current, noise-sensitive sensors [1]; the moving average smooths random fluctuations and stabilizes signals under high variability [2–4]; and integrating these with exponential smoothing reduces communication load and improves energy efficiency [2]. Additionally, modern multilevel filtering approaches, such as Smart-Median [5], demonstrate that combining classical methods provides a better balance between accuracy, noise resilience, speed, and system reliability.

Thus, the key challenge in multilevel filtering for IoT technologies is selecting the optimal combination of filters and correctly tuning their parameters, including implementing adaptive adjustment mechanisms. This includes adaptive regulation of filtering parameters (window size, smoothing coefficients, thresholds) according to dynamic environmental changes to ensure a balance between accuracy and low real-time latency, as well as integrating mechanisms that automatically respond to fluctuations in rapidly changing environments. Such mechanisms initiate filter corrections or other actions to maintain data relevance for subsequent analytics. In particular, article [6] presents adaptive filtering approaches in which multilevel filters account for seasonal variations in sensor data.

The literature review indicates that despite the availability of numerous digital filtering methods, the issues of their comprehensive integration, adaptive parameter tuning, and system self-adjustment to changing data acquisition conditions remain insufficiently resolved. The key challenge, therefore, is ensuring reliability, stability, and real-time processing of large volumes of heterogeneous sensor data characterized by noise, interference, missing measurements, anomalies, and seasonal fluctuations caused by dynamic changes in the sensing environment.

3. The aim and objectives of the study

The aim of the study is to improve the efficiency of data collection, preprocessing, and filtering of sensor measurements in distributed IoT monitoring systems, which are characterized by heterogeneous sensor data sources, high measurement frequency, as well as the presence of noise, distortions, and dynamic – particularly seasonal – variations of the data acquisition environment. These features define the main goal of the research: enhancing the quality, timeliness, and reliability of sensor data processing.

To achieve this goal, the following tasks were set:

– to develop a methodology for adaptive sensor data processing based on multilevel filtering and automatic self-tuning of control thresholds in the monitoring system, ensuring a balanced combination of raw data cleaning mechanisms while preserving informative characteristics and maintaining minimal delay in real-time operation;

– to develop an algorithm for adaptive adjustment of control thresholds as part of the proposed methodology, enabling automatic response to seasonal and other dynamic changes in the data acquisition environment;

– to design a hardware–software module with a multilevel filter for stabilizing sensor signals, reducing false alerts in the monitoring system, and improving measurement accuracy, intended for experimental validation of the adaptive data processing methodology.

4. Materials and methods for researching adaptive processing of measurement data in IoT monitoring systems

4.1. Object and main hypothesis of the study

The object of the study is the process of collecting, preprocessing, and filtering sensor data in distributed IoT systems, which are characterized by heterogeneous sensor data sources, high measurement frequency, and the presence of noise, distortions, anomalies, and seasonal variations of parameters. The subject of the study is the methodology of adaptive data processing in IoT monitoring systems, aimed at improving the reliability, stability, and timeliness of sensor data processing. The proposed methodology involves a set of measures for processing sensor data using multiple levels of data filtering and adjusting the monitoring system's control thresholds. The expected scientific novelty of the methodology lies in the self-adjustment of processing parameters and threshold values according to the current conditions of a dynamically changing data acquisition environment.

The main hypothesis is based on the assertion that the sensing environment is dynamic, as it contains both short-term disturbances and slow-changing processes and trends that affect the stability and reliability of sensor readings. In this context, it is assumed that integrating multilevel filtering – which responds to short-term non-stationary signal changes – with adaptive triggers that automatically adjust control thresholds according to seasonal, daily, or other long-term trends in the data acquisition environment will improve the quality of measured data and reduce false alerts in the monitoring system. Overall, this will help reduce the load on the IoT network infrastructure and on edge and cloud data processing nodes.

Multilevel filtering is performed in an intermediate module before data is sent to the monitoring system and involves combining the median filter, moving average methods, and exponential smoothing. The primary function of multilevel filtering is to eliminate dynamic environment issues such as high-frequency noise, impulse spikes, electromagnetic interference, short-term disruptions, and signal fluctuations, which collectively contribute to stabilizing the time series of measured data and reducing false notifications in monitoring systems.

At the next stage, adaptive triggers are configured to implement self-adjustment mechanisms under changing data acquisition conditions. Their role is to provide adaptive responses to such dynamic environmental changes as long-term trends, drift, seasonality, and daily cycles. The main goal of adaptive triggers is to reduce the number of false alerts in monitoring systems and improve measurement accuracy while preserving the informativeness of signals under dynamic conditions. This contributes to enhancing the effectiveness of data monitoring and real-time decision-making.

4.2. Sensor analysis and description of the experimental part

The effectiveness of data filtering methods directly depends on the characteristics of the sensors that serve as information sources in monitoring systems. Sensor networks within IoT infrastructure play a critical role in forming the primary data stream, and it is at this level that most issues related to *noise*, inaccuracies, and unstable measurements arise. Sensor nodes operate in challenging conditions – variable temperature and humidity, electromagnetic interference, unstable power supply, differing cable lengths, and more. All of this leads to the formation of "raw" data containing random fluctuations, signal *distortions*, and systematic deviations that require further filtering and smoothing.

To organize centralized collection, storage, and control of sensor node states, the `Zabbix` monitoring system was used. In this study, `Zabbix` is employed for real-time telemetry acquisition from sensors; data logging; detection of anomalous or unstable readings; verification of filtering results after applying *multilevel filtering*; and generation of *adaptive trigger*s for alerts and further analytics. Thus, the monitoring system serves as an infrastructural platform for evaluating the effectiveness of *multilevel data filtering* and threshold self-regulation mechanisms.

For the experimental part of the study, several types of sensors were used – differing in operating principles, stability, and sensitivity – typical for IoT sensor networks. This enables the assessment of filtering effectiveness under both stable and dynamic measurement conditions.

HR31 resistive humidity sensor. Highly sensitive to humidity changes but prone to instability due to temperature effects and material aging. Sharp humidity fluctuations or condensation lead to short-term "spikes" in measurements, making smoothing filters necessary.

KTY81-210 analog temperature sensor. Provides a linear relationship between resistance and temperature, but is sensitive to electrical noise and power supply fluctuations. Long wires between the sensor and controller introduce noise, especially in high electromagnetic interference environments. Analog data filtering is required before transmission to the monitoring system.

DS18B20 digital temperature sensor. Offers relatively high accuracy ($\pm 0.5°C$) and stability but reacts slowly to temperature changes. During sudden environmental transitions (e.g., opening a window or starting ventilation), measurable delays occur. Filtering helps smooth short-term deviations without losing long-term trends.

DHT11 module. The simplest and cheapest combined temperature/humidity sensor. Characterized by low accuracy ($\pm 2°C$; $\pm 5\% RH$) and high susceptibility to reading spikes caused by electrical interference or periodic readout errors. These fluctuations cause false alerts in monitoring systems; therefore, DHT11 requires node-level (edge-processing) filtering before data is sent to `Zabbix`.

DHT22 module. An improved version of DHT11 with higher accuracy ($\pm 0.5°C$; ± 2–$3\% RH$ and stability, but still features slow response time and potential errors at high humidity. Adaptive smoothing coefficients are advisable to compensate for inertia and reduce reaction delay.

Fig. 1 presents a diagram of data flows illustrating the operation logic of the experimental system: sensor nodes generate primary measurements, the controller collects and transmits them, `Zabbix` performs baseline monitoring and logs raw values, after which the data undergo multilevel digital filtering, and the results are sent back to `Zabbix` for stability analysis and comparison.

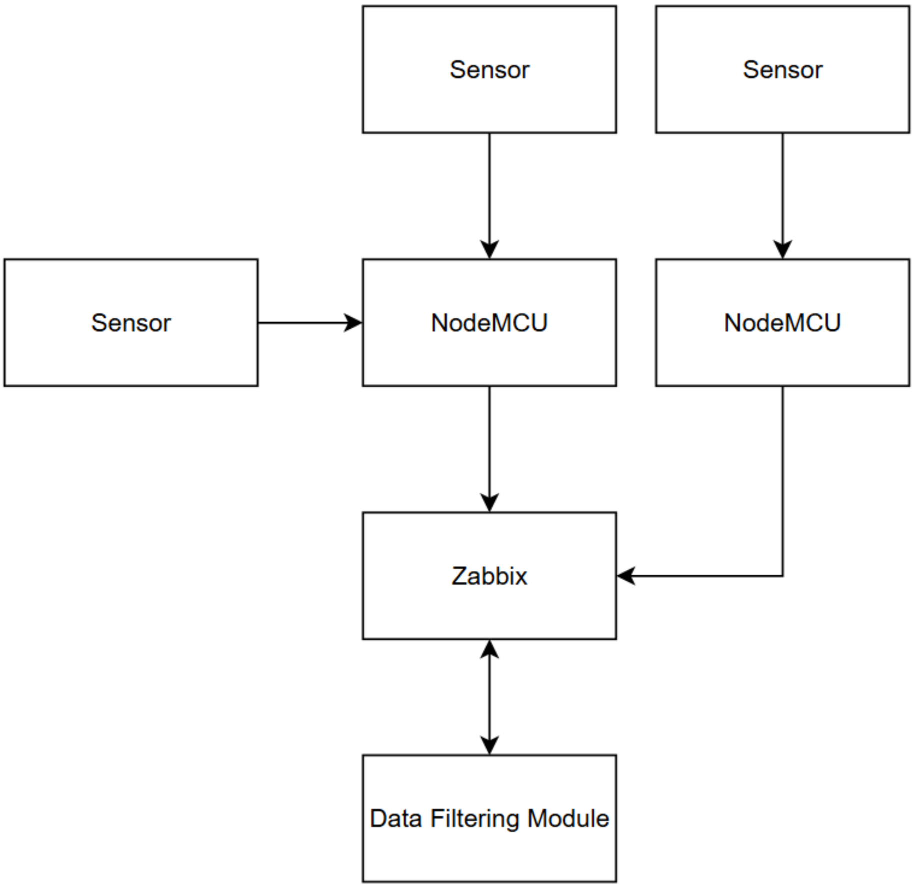


Fig. 1. Data flow diagram of the experimental system

The presented architecture provides a full cycle of sensor data quality assessment - from their physical acquisition to verification of processing efficiency. The use of different types of sensors and a real monitoring platform makes the experimental environment representative and suitable for objective testing of methods for cleaning, smoothing, and adaptive data processing in IoT systems.

4.3. Definition and mathematical formalization of data filtering methods

Multilevel filtering is based on the advantages of three different approaches to signal smoothing and noise reduction:

– the median filter [7, 8];
– the moving average filter [9];
– the exponential smoothing method [10].

Combining these methods makes it possible to simultaneously remove impulse noise, smooth random fluctuations, and account for dynamic changes in time series, which are typical for sensor data.

4.3.1. Median Filter

The median filter belongs to the class of nonlinear filters and is used to remove impulse noise ("salt-and-pepper noise"), which is characteristic of sensors exhibiting random anomalous spikes.

Purpose: removal of isolated outliers, spikes, and anomalous values, such as short temperature or humidity jumps caused by electromagnetic interference.

Input data: the input sequence of measurements $x(t)$.

For the measurement sequence $x(t)$, a median filter with a window of size $N = 2k + 1$ is defined as:

$$W(t) = \{x(t-k), x(t-k+1), \ldots, x(t), \ldots, x(t+k)\}, \tag{1}$$

where $W(t)$ is the input window, $x(t)$ is the current measurement, and $x(t-1)$ is the previous measurement.

The output sequence formed by computing the median of the local window is:

$$y(t) = median(W(t)), \tag{2}$$

where $W(t)$ is the input window, $y(t)$ is the smoothed value.

It is established that:

– a small window (3 points) provides high sensitivity to local changes and removes isolated outliers well but may allow noisy fluctuations to pass;

– a medium window (4–6 points) offers a compromise between noise removal and preservation of local trends;

– an overly large window oversmooths the data and may hide real short-term signal changes.

4.3.2. Moving Average Filter

The moving average filter belongs to the class of linear filters and transforms the input sequence $x(t)$ into the output $y(t)$ by averaging over a local window. While this reduces random fluctuations, it may partially blur abrupt changes in sensor data.

Purpose: reduction of short-term noise and stabilization of measurements prior to further analysis.

Input data: the sequence $x(t)$ after applying the median filter.

The mathematical formulation of the output sequence is:

$$y(t) = \frac{1}{N}\sum_{i=0}^{N-1} x(t-i), \tag{3}$$

where N is the window size and $x(t)$ is the input sequence.

4.3.3. Exponential Smoothing Method

This method belongs to the class of adaptive statistical smoothing techniques. It uses a recursive formula in which recent observations have greater weight than older ones, allowing the method to track trends and adapt to environmental changes. Unlike the moving average, which assigns equal weights to the last NNN points, exponential smoothing emphasizes recent values.

Purpose: extraction of long-term trends, adaptation to gradual environmental changes, and reduction of the influence of short-term fluctuations.

From the perspective of signal processing, exponential smoothing is implemented as a recursive filter:

$$y(t) = \alpha x(t) + (1-\alpha) y(t-1), \ 0 < \alpha < 1, \tag{4}$$

where $x(t)$ – input sequence, $y(t)$ – smoothed value, $y(t-1)$ – previous smoothed value, α – smoothing coefficient (larger values give more weight to recent observations).

4.4. Mathematical model and implementation of multi-level data filtering

Based on the considered filtering methods, a mathematical model of multilevel filtering was constructed to describe the process of sequential data filtering. The model is designed so that the output of each filtering stage serves as the input signal for the next stage. This approach enables comprehensive cleansing of data from different types of noise. The mathematical formalization of the multilevel filtering stages is as follows:

$$y_1(t) = median(W(t)), \tag{5}$$

$$y_2(t) = \frac{1}{N}\sum_{i=0}^{N-1} y_1(t-i), \tag{6}$$

$$y_3(t) = \alpha y_2(t) + (1-\alpha) y_3(t-1), \tag{7}$$

where $y3(t)$ is the final output of the filter.

Interpretation of the multilevel filtering model for sensor data:

– first level (median filter) removes impulse outliers;

– second level (moving average filter) smooths remaining random fluctuations;

– third level (exponential smoothing) forms a smooth and stable trend that reflects the actual state of the monitored object.

To implement the multilevel filtering model, dedicated software has been developed as a separate module intended for integration at the edge server level of the monitoring system.

4.5. Methodology of adaptive data processing in monitoring systems based on multi-level data filtering and automatic adaptation of control thresholds

4.5.1. Structure of the methodology of adaptive data processing

The research hypothesis is based on the assumption that integrating multilevel data filtering with an automatic control-threshold adaptation mechanism can significantly reduce the number of false alerts in monitoring systems while preserving the informativeness of signals under dynamic environmental conditions.

The structure of the proposed methodology represents a set of components and approaches for adaptive data processing, described as follows:

– a mathematical model of multilevel data filtering, which formalizes the processes of stabilizing the time series of measured data and preserving key trends and long-term patterns of the signal;

– a hardware-software implementation of the multilevel filtering module, enabling practical application of the mathematical model;

– an algorithm for configuring adaptive control thresholds, where the automatic adjustment of adaptive triggers – based on preserved trend dynamics – reduces the number of false alerts in monitoring systems and increases measurement accuracy while retaining signal informativeness in dynamic environments;

– the procedure for integrating and executing data processing in the `Zabbix` monitoring system, which defines the step-by-step use of the multilevel filtering module and automatic threshold adaptation for the cleaned and stabilized measurement time series, as well as sensor-state monitoring and event logging;

– an experimental setup, which includes sensor systems, the hardware-software multilevel filtering module, and software tools for verifying and evaluating the effectiveness of the methodology, all integrated into the `Zabbix` monitoring platform.

4.5.2. Algorithm for setting adaptive control thresholds

In the `Zabbix` monitoring system, a trigger is a logical condition that activates when the value of a monitored parameter exceeds a defined control threshold. Traditionally, monitoring systems use static thresholds that are set manually (for example, temperature $> 70°C$), which makes the system insensitive to changes in external conditions.

Static control-threshold settings do not account for fluctuations in measurements caused by seasonal or other uncontrolled changes in the dynamic environment. This often leads to false alerts even when the monitored system is functioning normally. To detect various anomalies and deviations from trends, the use of adaptive triggers is proposed. Their activation condition is based on adaptive control thresholds that are automatically configured using the results of prior filtered measurements.

The proposed mathematical model of multilevel filtering (Section 4.4), describing sequential signal processing (5–7), is designed to ensure comprehensive noise removal, improve measurement accuracy and stability, and preserve underlying trends. The preserved trends are then used to configure adaptive triggers. The cleaned and stabilized data obtained during filtering, together with the preserved trend information, serve as input to the automatic threshold adaptation stage.

The following steps describe the algorithm for automatic threshold adaptation in the `Zabbix` monitoring system, based on automatic configuration of adaptive triggers using the preserved trends.

STEP 1. Trend calculation for the last week.

To determine the current trend, the data processed by the filtering model from Section 4.3 is used:

– filtered data forms a daily or weekly trend;

– average values of parameters (temperature, humidity) and characteristic deviations are computed.

This allows the system to account for daily and seasonal variations and ignore minor changes caused by them.

STEP 2. Configuration of adaptive control thresholds.

An algorithm for configuring adaptive control thresholds is proposed, where trigger conditions change according to the current trends formed by multilevel filtering. In this way, the reaction threshold shifts together with the parameter's baseline, avoiding activation due to natural variations.

The baseline of a parameter is the conditional level of the signal that reflects the real state of the monitored object without noise and short-term fluctuations. It is formed by the multilevel filtering process, which removes spikes and noise while preserving the trend and long-term changes.

STEP 3. Automatic threshold adaptation (self-adjustment).

Based on the extracted trend, the system automatically adjusts the activation thresholds of adaptive triggers. For example, if the average humidity rises over the week, this increase affects the threshold through the mean value and the standard deviation, using a sensitivity coefficient. This prevents the monitoring logs from being "polluted" with false alerts and increases the informativeness of the monitoring system.

4.5.3. Procedure for integration and data processing

The new boundary value of the control threshold is calculated using the formula:

$$x_{new} = x_{7day} \pm k a_{7day}, \tag{8}$$

where: x_{new} – the new threshold value, x_{7day} – the average value of the parameter over the last 7 days, k – the sensitivity coefficient, a_{7day} – the standard deviation.

The procedure for threshold configuration accounts for both seasonal and daily trends. Fig. 2 illustrates the configuration of thresholds for weekly (seasonal) trends, and Fig. 3 shows the configuration for daily trends.

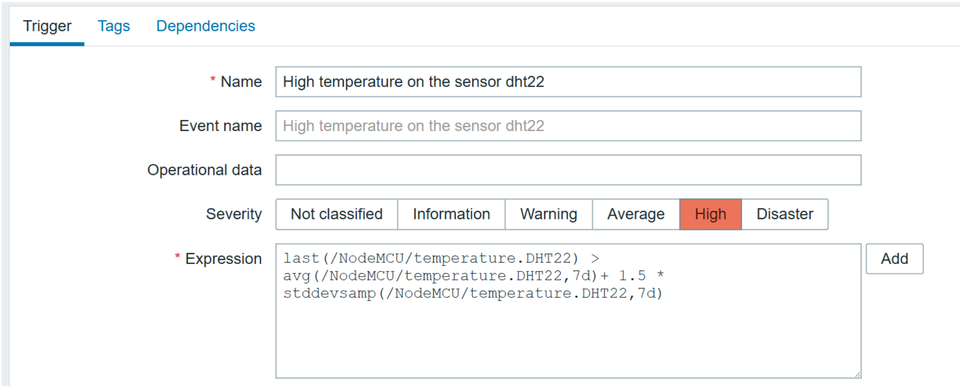


Fig. 2. Example of trigger configuration for seasonal fluctuations

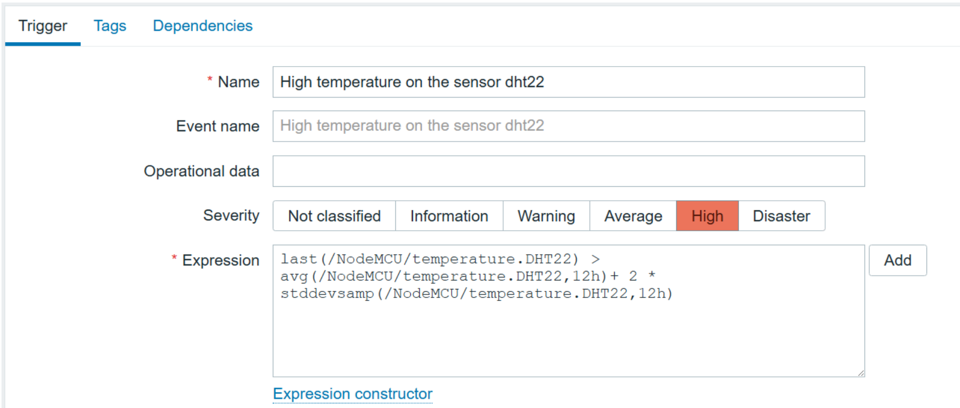


Fig. 3. Example of trigger configuration for seasonal fluctuations

Example of a basic trigger in the system:

```
last(/Node/temperature.DHT22)>49
```

Example of an adaptive trigger:

```
last(/Node/temperature.DHT22)
>avg(/Node/temperature.DHT22,7d)+1.5*stddevsamp(/Node/temperature.
DHT22,7d)
```

5. Results of the study on adaptive data processing

5.1. Experiment setup, environment and evaluation metrics

Objective: to empirically evaluate the effectiveness of multilevel filtering (see Section 4.3) combined with dynamic thresholds (see Section 4.4) in reducing noise in sensor data and decreasing the number of false alarms in `Zabbix`.

Hardware–software configuration:

– humidity sensors – DHT11, DHT22, HR31 (resistive);
– temperature sensors – DHT11, DHT22, DS18B20, KTY81-210 (analog);
– data acquisition – microcontroller (ESP/Arduino/NodeMCU) → MQTT/HTTP → Edge server;
– filtering implementation – multilevel filtering module on the edge server (see Section 4.3) with default parameters:
  – median window – 5;
  – moving average – $N = 4$;
  – exponential smoothing – $\alpha = 0.4$;

– adaptive thresholds – dynamic adaptation module (see Section 4.4), (8) with a 7-day or 12-hour window for daily trends.

5.2. General comparison of sensors

Fig. 4 illustrates humidity values from three sensors (DHT11, DHT22, HR31) collected during the experiment. Observations:

– DHT11 shows the largest variance and significant peak outliers, especially during rapid environmental changes;

– DHT22 shows smoother overall behavior but still reacts to short-term fluctuations, though with smaller spikes than DHT11;

– HR31 provides the most uniform readings, but its values gradually drift downward due to temperature influence and slow adaptation to environmental changes.

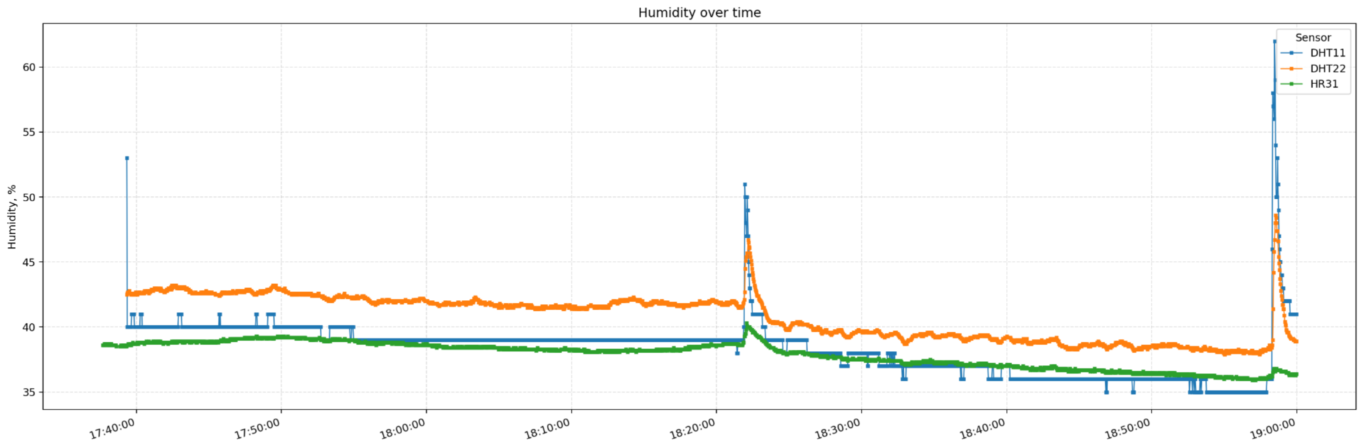


Fig. 4. Humidity measurements from three sensors

This comparative plot confirms the necessity of applying filtering methods to improve data stability.

5.3. Processing humidity sensor data

Fig. 5 shows the humidity graphs of the three sensors before and after filtering.

As shown, the filter successfully smooths single-value spikes in humidity readings. This is particularly important for the DHT11 sensor, which has low accuracy but low cost. After processing, trends become significantly more visible for all sensors.

Thus, the graphs confirm the effectiveness of multilevel filtering across all tested humidity sensors: it reduces noise, suppresses random spikes, and produces more reliable trend lines – critical for monitoring systems such as `Zabbix`.

5.4. General comparison of temperature sensors

Fig. 6 shows comparative temperature readings from four sensors: DHT11, DHT22, DS18B20, and KTY81. Observations:

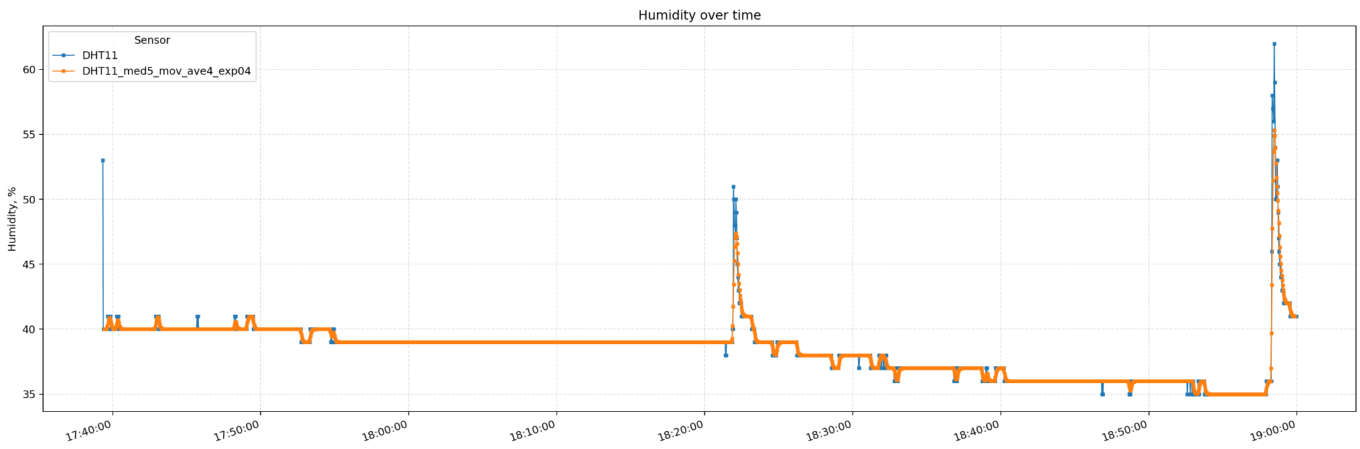
– DHT11 produces the noisiest signal, with many scattered points and sharp jumps, making unprocessed data difficult to use;

– DHT22 demonstrates smoother transitions but exhibits a "step" effect due to its internal resolution and processing algorithm;

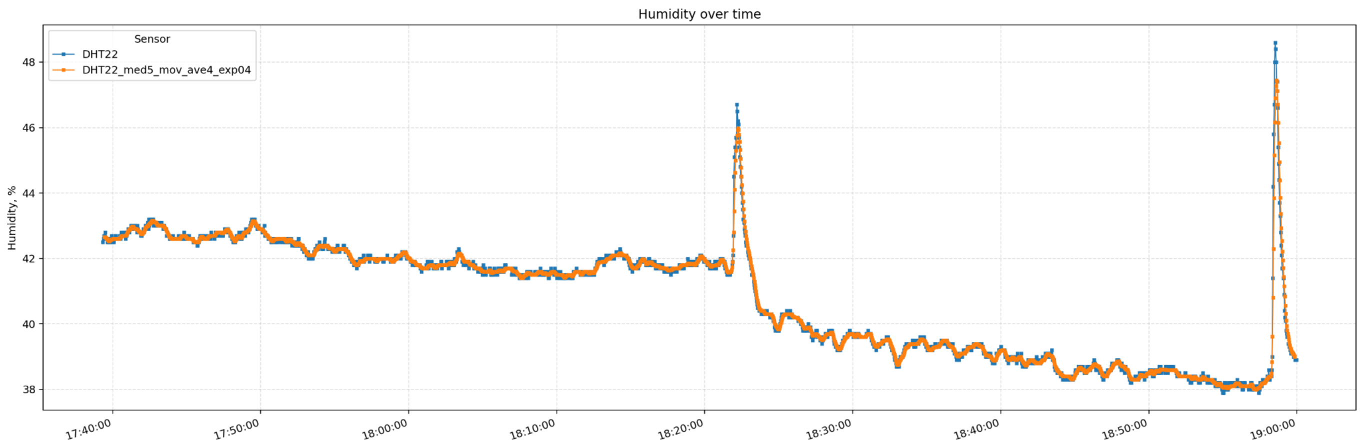
– DS18B20 shows high accuracy but still displays short-term deviations during abrupt environmental changes;

– KTY81 as an analog sensor provides a well-reproduced trend but is sensitive to electrical noise and wiring inaccuracies.

This comparative graph confirms that all sensors benefit from multilevel filtering.



a



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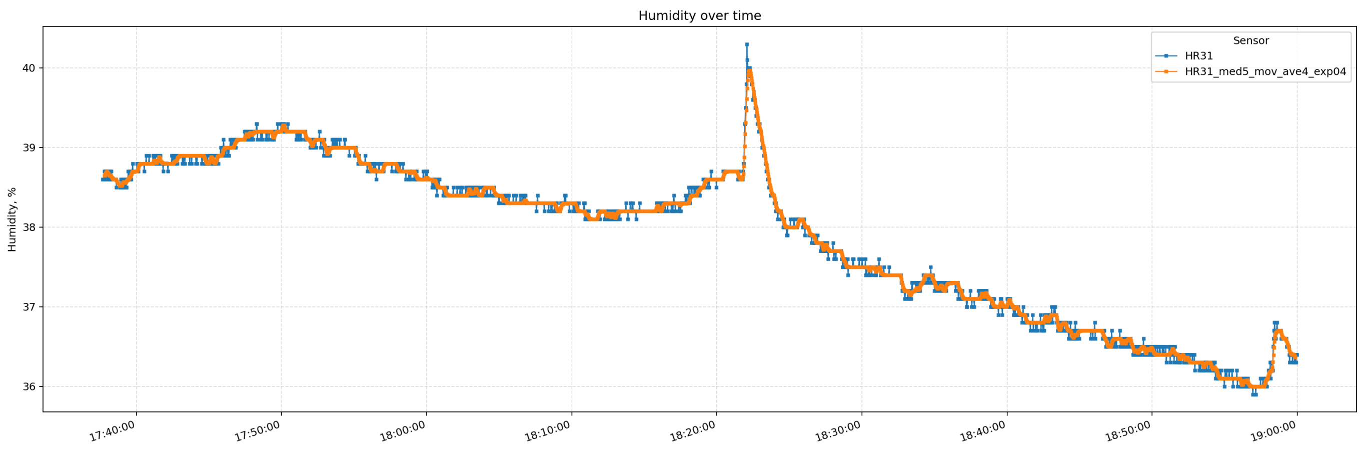

c

Fig. 5. Comparison of humidity before and after treatment: *a* – DHT11 sensor; *b* – DHT22 sensor; *c* – HR31 sensor

5.5. Processing temperature sensor data

Fig. 7 and Fig. 8 present the temperature data before and after filtering for DHT11, DHT22, DS18B20 and KTY81 sensors.

The graphs demonstrate that the filters effectively remove isolated spikes in temperature measurements. Again, the DHT11 sensor exhibits the largest deviations and therefore undergoes the strongest filtering effect.

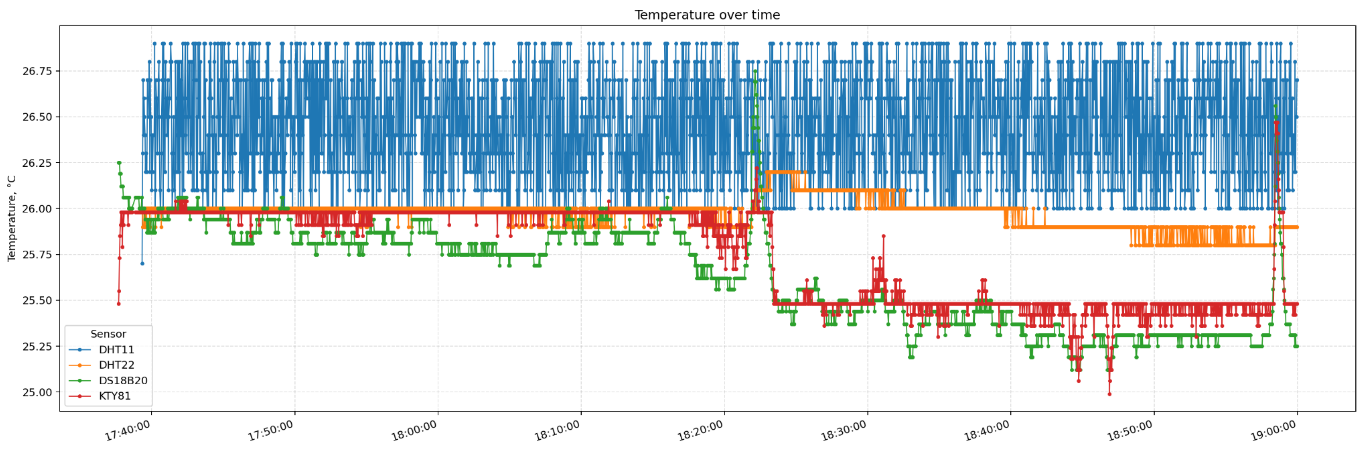

Fig. 6. Comparison of temperature data from sensors

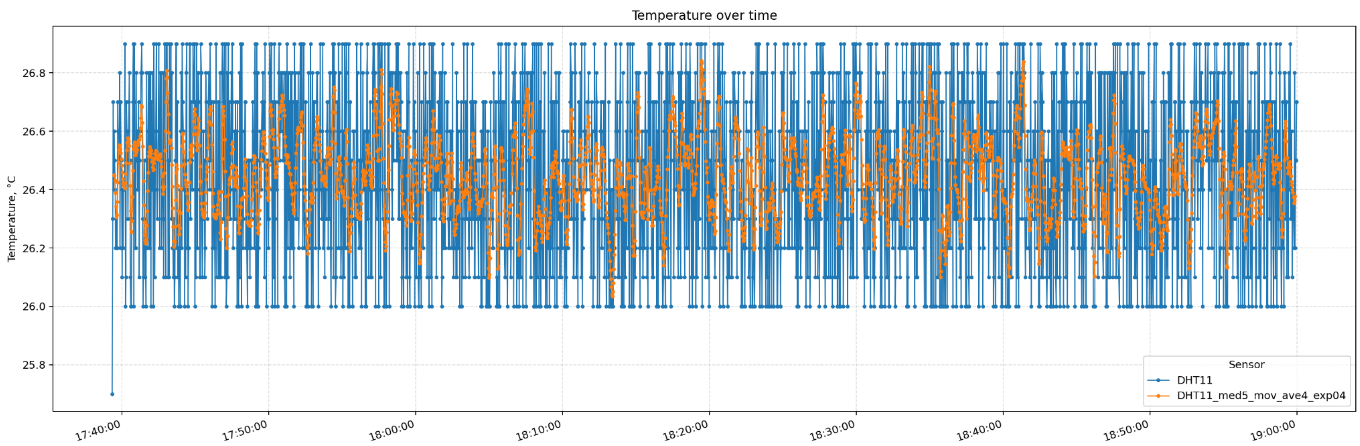

Fig. 7. Comparison of temperature before and after processing for DHT11 sensor

6. Discussion

Analysis of the experimental data obtained from digital and analog temperature and humidity sensors showed that raw measurements – even when using relatively high-quality sensors – contain significant levels of noise, spikes, and short-term deviations. These issues arise both from limitations of the hardware (low resolution, sensor inertia, electrical interference) and from external factors (ambient temperature changes, condensation, nearby objects).

To address these issues, a multilevel filtering approach was applied, consisting of:

– median filter – effectively suppresses isolated peaks and abrupt spikes (e.g., in DHT11 and HR31);

– moving average filter – smooths the overall signal trend, making it cleaner and more suitable for analysis (especially for DHT22 and KTY81);

– exponential smoothing – enables tracking of parameter dynamics in real time, preserving the ability to react to gradual environmental changes (particularly effective for DS18B20 and mixed-use scenarios).

The results demonstrate that:

– DHT11 requires the full three-stage filtering chain due to its high noise level;

– DHT22 provides more accurate data but benefits from moving-average and exponential smoothing to eliminate “step effects”;

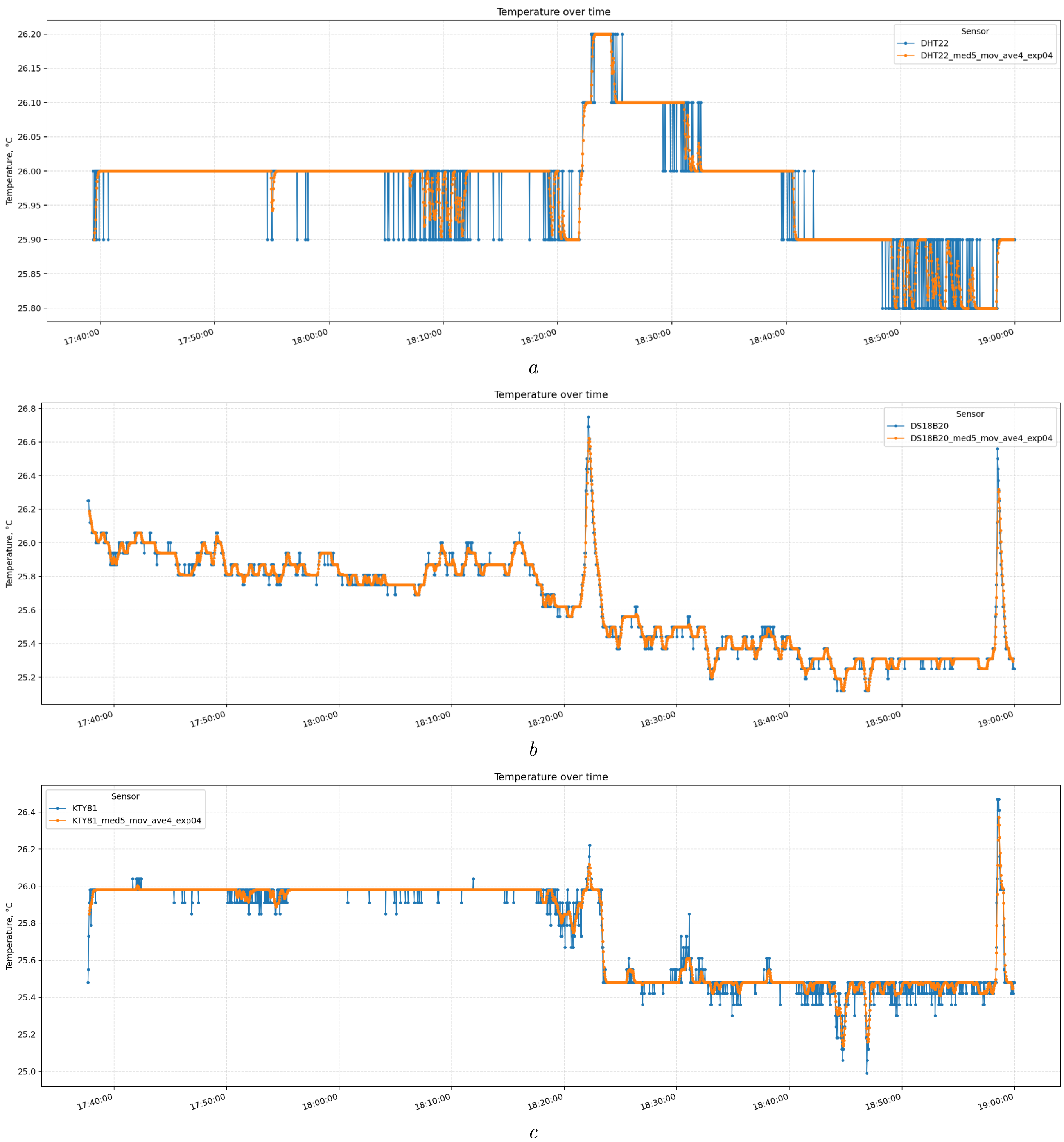

Fig. 8. Comparison of temperature from multiple sensors before and after processing: a – DHT22 sensor; b – DS18B20 sensor; c – KTY81 sensor

– DS18B20 is highly accurate but still requires filtering to suppress short-term deviations during rapid environmental changes;

– KTY81, as an analog sensor, provides a stable trend but is sensitive to interference. This is compensated through median filtering and smoothing;

– HR31 offers good humidity sensitivity but is prone to peak deviations and drift, which are effectively mitigated by combining median and moving-average filtering.

Overall, the combination of all three methods yields the best result: the processed data becomes suitable for use in monitoring systems without significant trend distortion.

In addition, the results confirm the necessity of seasonal adaptation of alert thresholds in systems such as `Zabbix`. Using dynamic thresholds based on weekly trends allows the system to:

– reduce the number of false alerts during natural seasonal changes;
– maintain sensitivity to true anomalies;
– automate system operation without manual reconfiguration of thresholds.

Thus, multilevel filtering combined with adaptive thresholds forms a comprehensive approach to IoT sensor data processing, increasing measurement reliability and improving decision-making quality in monitoring systems.

These improvements can be applied in the following scenarios:

– server / telecom nodes – sharp temperature spikes cause false alarms. The system requires fast response to real overheating without missing incidents;

– offices / classrooms / meeting rooms – humidity changes rapidly due to people and ventilation. Smoothing and adaptive thresholds can automatically control ventilation or air exchange;

– museums / archives / paper or wood storage – strict humidity / temperature control is required. Filtering prevents decisions based on false spikes;

– greenhouses / hydroponics – temperature and humidity strongly depend on operating modes. Multilevel filtering enables stable control of valves, ventilation, and irrigation;

– residential spaces / medicine / laboratories – comfort and safety require accurate detection of condensation and overheating with minimal false alerts.

Conclusion

This article addressed the challenges associated with acquiring sensor data that contain deviations caused both by hardware limitations and by environmental interference. A practical solution was proposed that removes noise from the data and improves the operation of monitoring systems by dynamically adjusting static trigger thresholds according to seasonal variations.

A methodology for adaptive sensor data processing based on three-level filtering was developed. The proposed filtering method includes median smoothing, moving-average smoothing, and exponential smoothing. The combination of these three methods enables a balanced compromise between noise suppression and the natural sensitivity of the sensor system, as confirmed experimentally. The resulting methodology provides minimal processing delay, making it suitable for real-time systems.

A second key contribution is the development of an algorithm for adaptive adjustment of threshold values, required to increase accuracy and reduce false alarms. Based on the mean value and standard deviation of a parameter, an adaptive trigger was implemented in the `Zabbix` system, where the activation threshold changes according to the long-term dynamics of the sensor signal. This approach makes it possible to:

– compensate for seasonal variations;
– automatically respond to changing operating conditions;
– minimize false alerts;
– increase sensitivity to true anomalies.

Experimental results showed that the developed module reduces measurement variability, improves accuracy, and decreases the number of false alarms. The amount of noise in the form of isolated spikes decreased from 0.32% to 2.21% for high-precision sensors. The DHT11 sensor showed the most significant improvement: humidity measurement accuracy increased by 6.52%, and temperature spikes were reduced by 53.06%. These findings confirm the effectiveness of the proposed methodology under real operating conditions.

The obtained results can be applied in industrial monitoring systems, environmental monitoring, IoT platforms, and real-time systems where reliability, noise resilience, and adaptability to environmental changes are critically important.

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УДК 004.9, 004.75

МЕТОДИКА АДАПТИВНОЇ ОБРОБКИ ДАНИХ У СИСТЕМАХ МОНІТОРИНГУ IoT З БАГАТОРІВНЕВОЮ ФІЛЬТРАЦІЄЮ СЕНСОРНИХ ВИМІРЮВАНЬ ТА САМОНАЛАШТУВАННЯМ

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Дослідження зосереджено на процесах збирання та попередньої обробки гетерогенних сенсорних даних. Метою дослідження є розробка методу адаптивної фільтрації та автоматичного налаштування тригерів, які забезпечують стабільне функціонування моніторингових IoT-систем за наявності шумів, імпульсних викидів та сезонних коливань.

Запропоновано методику адаптивної обробки даних, що поєднує багаторівневу фільтрацію даних з автоматичним самоналаштуванням порогів контролю у системах моніторингу. Такий підхід дозволяє не лише підвищити точність сенсорних вимірювань у реальному часі, а й динамічно адаптувати параметри моніторингової системи відповідно до змін умов експлуатації, мінімізуючи кількість хибних інцидентів.

У межах дослідження формалізовано модель багаторівневої фільтрації, що базується на медіанному фільтрі, фільтрі ковзного середнього та методі експоненціального згладжування. Використання багаторівневого фільтру забезпечує комплексне очищення даних, стабілізацію часових рядів та визначення ключових трендів. Розроблено механізм автоматичного налаштування порогів контролю у моніторинговій системі `Zabbix`, у межах якого порогові значення визначаються на основі статистичних параметрів та трендів, виділених на етапі багаторівневої фільтрації вимірювань. Механізм інтегрується в наступний етап обробки даних в моніторинговій системі, в результаті чого система автоматично враховує добові, сезонні та інші коливання динамічного середовища збирання даних.

Експериментальні дослідження із різними типами сенсорів підтвердили підвищення точності вимірювань і значне зменшення кількості хибних сповіщень в моніторинговій системі. Зокрема, точність вимірювань вологості в середньому покращено на 6,52%, а імпульсні стрибки температури знижено на 53,06%. Порівняно з традиційними підходами, запропонована методика забезпечує вищу стійкість до шумів та адаптивність у змінних умовах середовища, що робить її ефективним рішенням для промислових, екологічних та інших IoT-систем реального часу.

Ключові слова: IoT, сенсорні вимірювання, адаптивні пороги контролю, самоналаштування, моніторинг, Zabbix, сезонна адаптація.