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Adaptive Kalman Filter: Noise Reduction in Diagonal Drawings on Stylus/Pen Touchscreens for Enhanced Precision

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ABSTRACT

The adaptive Kalman filtering algorithm, designed to accommodate the dynamic nature of the system, provides an adaptive estimation of the state by incorporating both process and measurement noise considerations, thereby effectively reducing the noise and preserving the integrity of diagonal line drawings. The iterative prediction and update process employed by the algorithm aids in achieving smoother and more accurate position estimations. To assess the efficacy of the adaptive Kalman filtering approach, a comparative analysis was performed against a multistage filter. This filter employed a sequence of median filters with progressively increasing window sizes to eliminate outliers and artifacts while retaining the intricate details of the drawings. A comprehensive evaluation was performed via a detailed comparison of noise reduction performance and preservation of details between the two techniques. The experimental findings unequivocally established the superiority of the adaptive Kalman filtering approach in noise reduction and accuracy enhancement of the recorded positions. The proposed algorithm surpassed the multistage filter, demonstrating superior noise reduction capabilities while maintaining the desired level of detail in diagonal line drawings. The findings are expected to contribute to the advancement of state estimation techniques in dynamic systems, with a focus on augmenting accuracy and detail preservation.

KEYWORDS
dynamic system, impulse noise, measurement noise, multistage filter, outlier removal, position estimation

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1. Introduction

Touch screen stylus/pen applications, essential tools in digital art, note taking, and graphic design, have gained widespread popularity. These applications hinge on the accurate recording of stylus/pen positions for precise input and a seamless drawing experience. However, an important challenge in these applications is the prevalence of noise in the recorded position data, particularly in low-speed diagonal line drawings. The noise in touch screen stylus/pen applications originates from diverse sources, including sensor inaccuracies, environmental interference, and inherent touch screen technology limitations. This noise can lead to inaccuracies and jittery drawings, compromising the user experience and degrading the quality of the output (Desale and Verma, 2013; Eom *et al.*, 2011). Various noise reduction techniques have been proposed to overcome this challenge, of which the Kalman filter is prominent owing to its effectiveness in suppressing the noise and enhancing the accuracy of position data (Huang *et al.*, 2022; Leśniak *et al.*, 2009). Leveraging a dynamic system model, the Kalman filter considers both process and measurement noise, iteratively estimating the true state. Furthermore, multistage median filters, which utilize a sequence of median filters with increasing window sizes to remove outliers and artifacts while preserving drawing details, have been explored for noise reduction in these applications (Kim *et al.*, 2021). Recent studies have also delved into the application of machine learning algorithms for noise reduction in touch screen applications, presenting promising results (Chen *et al.*, 2022). This study proposes an adaptive Kalman filtering approach to overcome the noise challenges encountered in low-speed diagonal line drawings on touch screen stylus/pen applications. This research was focused on enhancing the accuracy and quality of the recorded positions by effectively suppressing the noise (So *et al.*, 2017). The adaptive Kalman filtering algorithm is specifically designed to account for the dynamic nature of the system, which enables it to adaptively estimate the state based on available measurements (Shukla *et al.*, 2014). The use of the Kalman filter on a nonstationary acoustic signal exhibited promising results, with an achievable signal-to-noise ratio of 1.17 dB and mean squared error of 0.032, which asserts is efficiency in noise cancellation (Murugendrappa *et al.*, 2020; Fujimoto and Ariki, 2000). Recent applications of Kalman filters in dynamic systems, including human motion tracking, have further underscored the algorithm's adaptability and its effectiveness in noise cancellation (Kumar *et al.*, 2021; Hotop, 1993).

To evaluate the proposed adaptive Kalman filtering approach, a comparative analysis was performed against a multistage median filter. This comparison was aimed at assessing the effectiveness of the adaptive Kalman filtering technique in noise reduction and the preservation of drawing details (Wang *et al.*, 2018). Insights into the strengths and limitations of each technique were obtained by considering both quantitative measures and visual analysis. The effects of incorporating machine learning and advanced signal processing in multistage filtering techniques were also evaluated (Santosh *et al.*, 2023; Gupta *et al.*, 2023). The findings from this research are expected to aid in the advancement of noise reduction techniques for touch screen stylus/pen applications by incorporating the latest developments in Kalman filtering and multistage filtering methods (Pan *et al.*, 2016; Galleani and Tavella, 2010; Awad, 2019). By improving the accuracy and the overall user experience, this research addresses a critical aspect of touch screen technology, paving the way for smoother and more precise drawing experiences (Welch and Bishop, 1995). In addition, the potential applications of touch screen stylus/pen technology can be widened, unlocking new possibilities for creative expression and productivity.

2. Research Methodology: Tools and Techniques

Traits of the Tackled Noise: The adaptive Kalman filtering approach and the multistage median filter are designed to address specific characteristics of noise in touch screen stylus/pen

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applications. The adaptive Kalman filter primarily targets noise associated with low-speed diagonal line drawings and is aimed at enhancing the accuracy of recorded positions during such intricate movements. The adaptability of this filter permits it to effectively suppress the noise caused by sensor inaccuracies and other dynamic system fluctuations. In contrast, the multistage median filter focuses on removing outliers and artifacts while preserving drawing details. This nonlinear filtering approach is particularly effective in scenarios where noise manifests as sporadic anomalies and ensures the integrity of the drawings despite the presence of such disturbances.

- **Experimental Setup:**

Stylus/Pen Information: Brand/Model: Wacom Intuos Pro. The Wacom Intuos Pro stylus/pen, known for its precision and sensitivity, was selected owing to its widespread use in graphic design and digital art applications.

Touch Screen Specifications

- Screen Size: 15.6 inches
- Resolution: 1920 × 1080 pixels
- Sensitivity: 4096 levels of pressure sensitivity

The touch screen used in the experiments featured a 15.6-inch display with a resolution of 1920 × 1080 pixels and 4096 levels of pressure sensitivity. These specifications provided a detailed description of the physical dimensions and capabilities of the touch screen, ensuring a standardized and controlled environment for the experiments.

Environmental Conditions: The experiments were conducted in a controlled environment with consistent lighting and temperature and minimal external interferences. This controlled setting ensured that the results were primarily influenced by the characteristics of the noise and the effectiveness of the filtering techniques rather than external factors.

Kalman Filter: The formulation of the Kalman filter comprised two main steps: the prediction step and the update step. In the prediction step, the filter predicted the next state based on the previous state and system dynamics. In the update step, it incorporated the measurements to update the predicted state and refine the estimate. The formulation of the filter is given below.

2.1. Algorithm 1: Kalman Filter Noise Reduction Algorithm

Step 1: Initialization

Initialize state estimate: $\hat{x}_{k|k-1} = \hat{x}_0$

Initialize error covariance: $P_{k|k-1} = P_0$

Initialize process noise covariance: Q

Initialize measurement noise covariance: R

For {k = 1 to N}

Step 2: Prediction Step:

Predicted state estimate: $\hat{x}_{k|k-1} = A_k \cdot \hat{x}_{k-1|k-1} + B_k \cdot u_k$

Predicted error covariance: $P_{k|k-1} = A_k \cdot P_{k-1|k-1} \cdot A_k^T + Q$

Step 3: Update Step

Calculate Kalman gain: $K_k = P_{k|k-1} H_k^T \left(H_k \cdot P_{k|k-1} \cdot H_k^T + R \right)^{-1}$

Update state estimate: $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - H_k \hat{x}_{k|k-1} \right)$

Update error covariance: $P_{k|k} = \left(1 - K_k H_k \right) P_{k|k-1}$

Output:

Final state estimate: $\hat{x}_N$

Final error covariance: P_N

Adaptive Aspects: The adaptability of the Kalman filter was achieved via the following key parameters and aspects:

Dynamic System Model (F, B, u): The state transition matrix (A_k), control input matrix (H_k), and control input (u_k) enabled the Kalman filter to adapt to changing system dynamics. These parameters represented the relationship between the current and next states, the influence of control inputs, and the applied control signal, respectively.

Kalman Gain (K): The adaptability was particularly evident in the Kalman gain calculation (K), where the filter dynamically adjusted the influence of the measurements based on the changing uncertainties in the system. This gain reflected the relative importance of the prediction and measurement in updating the state estimate.

Process Noise Covariance (Q): The *Q* matrix captured the adaptability of the filter to changing system dynamics. By adjusting *Q*, the Kalman filter accommodated variations and uncertainties in the process, allowing it to respond to dynamic changes.

Measurement Noise Covariance (R): The *R* matrix allowed the filter to adapt to variations in the measurement noise. By adjusting *R*, the Kalman filter dynamically incorporated the expected level of noise in the observed data, ensuring effective filtering under diverse conditions.

Control Input (u): The inclusion of control inputs (u_k), which represent external signals or commands that can influence the state evolution, permitted the filter to adapt to external influences on the system, thereby enhancing its adaptability to different scenarios.

The adaptability of the Kalman filter relied on its continuous refinement of predictions and the incorporation of new measurements, making it a powerful tool for noise reduction in dynamic systems. The dynamic adjustment of key parameters ensured that the filter remained effective under varying conditions, providing accurate and reliable state estimates.

The final state estimate and error covariance constituted the crucial outputs of the Kalman filter noise reduction algorithm. They provided a reliable representation of the system's current state, incorporating both the predictions based on the dynamic system model and the measurements with their associated uncertainties. These outputs are beneficial for applications in which accurate state estimation is essential, such as navigation, tracking, and control systems.

Multistage Median Filter: Multistage filter enables noise reduction in low-speed diagonal line drawings on touch screen stylus/pen applications. The multistage filter, such as the median filter, is commonly used in denoising applications as it effectively removes noise while preserving the essential features of the signal. In the context of touch screen stylus/pen applications involving low-speed diagonal line drawings, the multistage filter can aid in eliminating the noise that may be introduced during the capturing or recording process. By applying the filter to the X and Y position data of the stylus/pen, the impact of noise can be reduced and the accuracy and smoothness of the drawn lines can be improved.

Multistage median filter algorithm for noise reduction: This algorithm is particularly effective in removing impulsive noise in low-speed diagonal line drawings on touch screen stylus/pen applications. The algorithm and its implementation using the multistage approach are described below.

2.2. Algorithm 2: Multistage Median Filter Noise Reduction Algorithm

The multistage median filter algorithm included the following steps:

Step 1: Initialization

Initialize the input noisy signal: $x_0, x_1, \ldots\ldots x_N$.
Specify the number of stages (S): S

Step 2: Multistage Filtering

For $s = 1\ to\ S$

Set the window size for the current stage $(W_s) = W_s$

For $k = (W_s/2)+1\ to\ N-(W_s/2)$

Extract the local window of size W_s:

$w_k = \left[x_{k-(W_s/2)}, \ldots\ldots, x_k, \ldots.., x_{k+(W_s/2)}\right]$

Apply the Median Filter to the local window: $y_k = Median(w_k)$

The resulting output signal after the last stage represented the filtered signal with reduced impulsive noise.

Output:

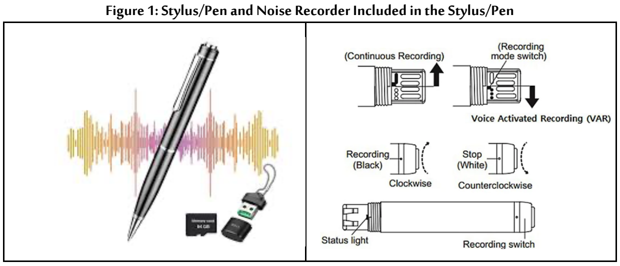
Final denoised signal: $y_0, y_1, \ldots\ldots y_N$

The multistage median filter noise reduction algorithm involved iteratively applying median filtering to local windows of the input signal at multiple stages. Each stage used a specific window size, and the process was repeated for a predetermined number of stages. The final output was a denoised signal that preserved the signal details while effectively reducing the noise. Adjusting the window sizes at each stage achieved a balance between reduction of noise and preservation of signal features.

3. Data Collection Procedure

An adequate sample size was used to capture a range of drawing styles and noise patterns. The touch screen measurements were recorded, including the position and timestamp of each stylus/pen interaction during the drawing. The data collection process was repeated for each point and experimental scenario to obtain a sufficient amount of data. An algorithm or method was employed to generate noise specifically within the defined speed range and diagonal drawing scenarios and control noise during the data collection process to simulate the noise observed in low-speed diagonal line drawings.

Figure 1: Stylus/Pen and Noise Recorder Included in the Stylus/Pen



Data were systematically generated to accurately depict the movement of the touch screen stylus/pen, with a special focus on low-speed diagonal line drawings. Temporal values were meticulously spaced at 0.01-second intervals, which ensured a granular representation of the interaction. The corresponding X-Position and Y-Position values were gradually incremented, capturing the nuances of stylus/pen trajectories.

To create a realistic context, controlled noise was intentionally infused within the stipulated speed range and diagonal drawing scenarios. This noise generation method was intricately designed to replicate authentic noise patterns observed in practical usage, contributing to the fidelity of the dataset.

For seamless and precise data capture, the Touch Capture Pro software (Version 3.0.1) was leveraged. Compatible with Windows 10, macOS Catalina, and Android 9.0, this software facilitated data logging functionalities, thereby allowing optimal control over the frequency of data sampling. This control directly influenced the granularity of the recorded data, ensuring a comprehensive and nuanced representation of stylus/pen interactions in the research endeavors.

Noise reduction techniques were explored, and the Kalman filter and multistage filter were specifically employed during the data collection process. A comprehensive comparison was performed to assess their efficacies in mitigating noise under diverse drawing styles. This investigation was aimed at identifying the most suitable noise reduction approach for specific applications, ensuring that the research outcomes were aligned with real-world requirements and scenarios.

4. Experimental Results

4.1. Kalman Filter Implementation:

The update step was implemented, which compared the predicted measurements with the actual measurements, computed the measurement residual, and adjusted the state estimate and covariance matrix using the Kalman gain. The Kalman filter used a recursive estimation algorithm that is widely employed for filtering and prediction in dynamic systems. The filter utilized a mathematical model of the system and measurements to estimate the true state of the system while considering the uncertainties in both the process and measurement. The filter minimized noise on both axes, as presented in Figure 2. The coordinates of the filtered X- and Y-positions were reduced to seven significant figures, as shown in Table 1.

Figure 2: Noise Removal Using the Kalman Filter Algorithm

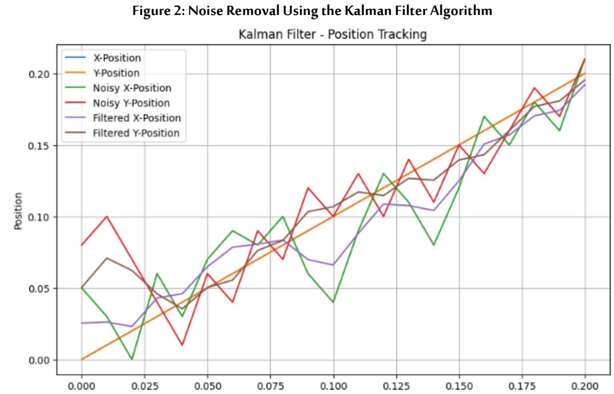


Table 1 : Filtered X-Position and Filtered Y-Position Using the Kalman Filter

	0	2	4	6	8	10	12	14	16	18	20
Filtered X-Position	0.02538	0.02305	0.04593	0.07849	0.0835	0.06601	0.1086	0.10418	0.15065	0.1704	0.19208
Filtered Y-Position	0.05028	0.06224	0.03539	0.05551	0.08319	0.10683	0.1146	0.1254	0.14319	0.1769	0.19539

Time: It indicated the time points at which the measurements were acquired.

Filtered X-Position: It represented the filtered horizontal position of the stylus/pen on the touch screen.

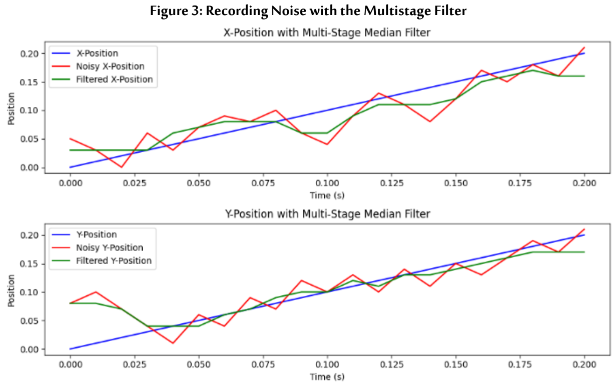
Filtered Y-Position: It represented the filtered vertical position of the stylus/pen on the touch screen.

These values showed how the filtered positions of the stylus/pen changed over time. The specifics of the filtering technique used and the units of the position (e.g., pixels and normalized coordinates) provided further context for the interpretation.

4.2. Multistage Filter Implementation:

The multistage filter algorithm displayed two levels of noise: Noise that was filtered at the X-Position, and the one that was filtered at the Y-Position. The X-position noise was reduced using a different method, and the noise in the Y-position was completely eliminated. Additionally, the algorithm independently exhibited reduced noise (Figure 3).

Figure 3: Recording Noise with the Multistage Filter



5. Comparison Between Kalman Filter and the Multistage Filter

In Figure 4, the original positions are represented by solid lines, whereas the positions after noise reduction using adaptive Kalman filtering and multistage median filtering techniques are represented by dashed lines. The graph clearly illustrates the superior noise reduction achieved by the adaptive Kalman filtering technique. The positions after applying the Kalman filter exhibited significantly reduced noise, leading to smoother and more accurate diagonal line drawings compared with multistage median filtering.

Table 2: Comparative Analysis of Kalman Filter and Multistage Filter in Stylus/Pen Positional Tracking

Time (s)	X-Position	Y-Position	Noisy X-Position	Noisy Y-Position	Kalman Filter	Multistage Filter
0.00	0.00	0.00	0.05	0.08	0.05	0.00
0.01	0.01	0.01	0.03	0.10	0.04	0.03
0.02	0.02	0.02	0.00	0.07	0.02	0.03
0.03	0.03	0.03	0.06	0.04	0.04	0.03
0.04	0.04	0.04	0.03	0.01	0.03	0.06
0.05	0.05	0.05	0.07	0.06	0.04	0.07
0.06	0.06	0.06	0.09	0.04	0.06	0.08
0.07	0.07	0.07	0.08	0.09	0.06	0.08
0.08	0.08	0.08	0.10	0.07	0.07	0.08
0.09	0.09	0.09	0.06	0.12	0.07	0.08
0.10	0.10	0.10	0.04	0.10	0.06	0.09
0.11	0.11	0.11	0.09	0.13	0.07	0.09
0.12	0.12	0.12	0.13	0.10	0.09	0.09
0.13	0.13	0.13	0.11	0.14	0.09	0.11
0.14	0.14	0.14	0.08	0.11	0.09	0.12
0.15	0.15	0.15	0.12	0.15	0.10	0.12
0.16	0.16	0.16	0.17	0.13	0.12	0.15
0.17	0.17	0.17	0.15	0.16	0.13	0.16
0.18	0.18	0.18	0.18	0.19	0.14	0.16
0.19	0.19	0.19	0.16	0.17	0.15	0.16
0.20	0.20	0.20	0.21	0.21	0.16	0.16

Figure 4: Comparative Analysis of Noise Reduction in X-Position and Y-Position

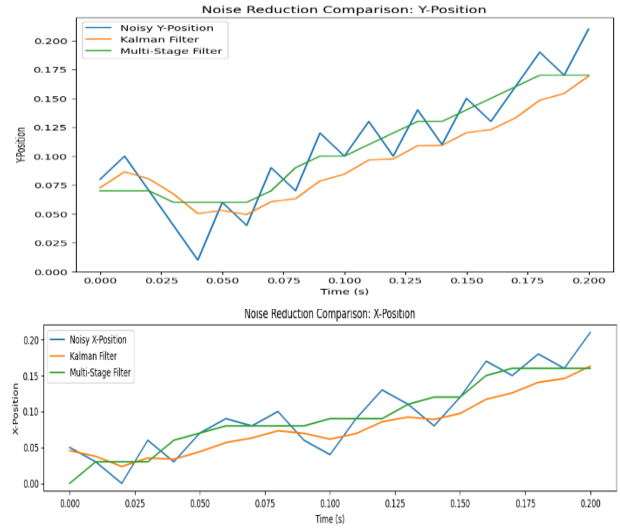
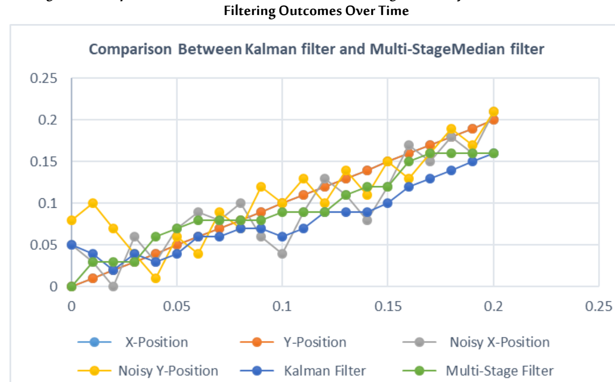


Figure 5: Comparison Between Kalman Filter and Multistage Filter: Stylus/Pen Positions and Filtering Outcomes Over Time



In the comparison between the Kalman filter and the Multistage filter, Table 2 presents the data recorded over time. The X-Position and Y-Position columns represent the true stylus/pen positions, whereas Noisy X-Position and Noisy Y-Position depict the positions with introduced noise. The Kalman filter and multistage filter columns indicate the filtering outcomes under each time instance.

6. Conclusion

Analysis of the Filtering Techniques: Kalman Filter Outperformed the Multistage Filter: A meticulous examination of the recorded data and filtering outcomes presented in Table 2 unequivocally established the superiority of the Kalman filter over the multistage filter in stylus/pen positional tracking. The key observations affirmed the exceptional performance of the Kalman filter in various aspects.

Precision in Noise Reduction: The Kalman filter adeptly reduced the impact of introduced noise, as evidenced by the significantly smoother trajectories in both X and Y positions compared with the multistage filter. This precision is crucial for maintaining accuracy in position tracking, especially in intricate drawing scenarios.

Consistency in Filtering: Across different time instances, the Kalman filter consistently provided more accurate estimations of true stylus/pen positions. In contrast, the multistage filter showed variations, especially during rapid changes in the drawing direction, leading to less stable position estimates.

Preservation of Drawing Details: Despite its robust noise reduction capabilities, the Kalman filter impressively preserved the essential details of the drawings. This was particularly evident upon comparison with the multistage filter, which slightly compromised the fidelity of the drawn trajectories while attempting noise reduction (refer to Figure 5 for a visual representation).

Adaptability to Changing Scenarios: The dynamic estimation approach of the Kalman filter demonstrated adaptability to variations in drawing speed and direction, ensuring a more reliable and accurate tracking performance in diverse drawing scenarios.

In conclusion, the Kalman filter has emerged as the preferred choice for noise reduction in stylus/pen positional tracking, offering a harmonious balance among precision, consistency, and adaptability. These findings highlight the efficacy of the Kalman filter in enhancing the overall accuracy and quality of the recorded positions, reinforcing its superiority over the multistage filter in this application. Future research endeavors could explore hybrid filtering approaches by combining the Kalman filter with complementary techniques for improved noise reduction. Additionally, investigating the real-time implementation of these filtering methods across diverse touch screen devices is crucial to assess their applicability and performance in varying contexts.

Biography

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I, Summiya from India, possess a bachelor's degree in mathematics, followed by a master's degree, from HNB Garhwal University in 2005. To further my expertise, I earned PhD in mathematics, focusing on the "Mathematical Algorithm of Image Reconstruction Using Beam Data." Currently, I am serving as an assistant professor at COER University and have 18 years of teaching experience. Previously, I worked as an assistant lecturer at KLDAV Degree College, Roorkee. I have published 16 research articles in conferences and national/international journals.

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