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Enhancing Speed Estimation in DC Motors using the Kalman Filter Method: A Comprehensive Analysis

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ABSTRACT

The accurate estimation of speed is crucial for optimizing the performance and efficiency of DC motors, which find extensive applications in various domains. However, the presence of noise ripple, caused by interactions with magnetic or electromagnetic fields, poses challenges to speed estimation accuracy. In this article, we propose the implementation of the Kalman Filter method as a promising solution to address these challenges. The Kalman Filter is a recursive mathematical algorithm that combines measurements from multiple sources to estimate system states with improved accuracy. By employing the Kalman Filter, it becomes possible to estimate the true speed of DC motors while effectively reducing the adverse effects of noise ripple. This research focuses on determining the optimal values for the Kalman Filter parameters and conducting experiments on a DC motor to evaluate the performance of the proposed approach. The experimental results demonstrate that the Kalman Filter significantly improves the control of speed oscillations and enhances the stability of the DC motor system. Furthermore, a comprehensive analysis of the system's response and parameter tuning reveals the impact of different parameter combinations on settling time, overshoot, and rise time. By carefully selecting appropriate parameters, the proposed approach contributes to accurate speed estimation and effective control of DC motors, advancing the understanding and application of the Kalman Filter in various relevant fields. Overall, this research provides valuable insights into enhancing the performance and efficiency of DC motors through the integration of the Kalman Filter method.

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1. INTRODUCTION

Speed is a ubiquitous concept in today's society, commonly associated with various forms of transportation, such as motorcycles, cars, and boats [1], [2]. The propulsion systems of these vehicles often rely on motors, including internal combustion engines fueled by fossil fuels [3], [4] and DC motors driven by electrical energy from batteries. DC motors[5]-[7] have become indispensable in our daily lives due to their wide-ranging applications and numerous benefits. These motors find utility in diverse areas, including household appliances (blenders [8], [9] and fans [10], [11]), personal transportation (electric motorcycle [12], [13], electric cars [4], [14], [15], hoverboards [16]-[18]), public transportation (electric bus[19]-[21], electric train [22]), and even robotics (drones [23]-[26], UAVs [27]-[30]).

Despite their high-speed capabilities, DC motors suffer from a non-absolute efficiency characteristic [31], [32]. A key weakness lies in the occurrence of disturbances in the form of noise ripple when DC motors operate near objects generating magnetic or electromagnetic fields [33]-[35]. This phenomenon arises due to the reliance of DC motors on electromagnetic fields to drive the rotor [36]-[38]. Consequently, a method is required to accurately estimate the actual speed of DC motors, thus enhancing their efficiency by mitigating the impact of noise ripple.

This research proposes the implementation of the Kalman Filter method [39] as a promising solution to address the speed estimation challenges associated with DC motors. The Kalman Filter, a recursive mathematical algorithm, combines measurements from multiple sources, such as sensors and prior information, to estimate system states with improved accuracy [40] and stability [41], [42]. By employing the Kalman Filter, it becomes possible to estimate the true speed of DC motors while effectively reducing the adverse effects of noise ripple.

The application of the Kalman Filter in estimating the speed of DC motors holds significant research value. Given the inherent instability and susceptibility of DC motors to noise ripple, coupled with their extensive utilization across various domains, developing a speed estimation system using the Kalman Filter presents an intriguing challenge for researchers. By overcoming the limitations posed by noise ripple, the efficiency and performance of DC motors can be enhanced, facilitating their applications in numerous fields, ranging from transportation to robotics.

2. METHODS

This research focuses on the determination of the optimal values for parameters R and Q in the Kalman Filter algorithm, with the aim of achieving accurate speed estimation for a DC motor. The testing phase involved conducting experiments on the DC motor using the optimized parameter values. In this section, we provide a detailed overview of the research methodology, which encompasses crucial steps such as system design, wiring design, and the specific implementation of the Kalman Filter algorithm employed in this research. By outlining these essential aspects, we aim to provide a comprehensive understanding of the experimental setup and the techniques utilized to optimize the Kalman Filter parameters for reliable speed estimation in DC motors.

2.1. Kalman Filter

The Kalman Filter algorithm is a powerful tool for estimating and predicting data in a system, with the goal of minimizing the Root-Mean-Square Error (RMSE) [43]. Its versatility and reliability have made it a popular choice in various fields. The Kalman Filter can effectively handle situations where the system model is unknown, enabling accurate estimation of current and past data while also providing predictions for future data [44].

Different mathematical variants of the Kalman Filter have been developed, including the Standard Kalman Filter, Extended Kalman Filter [45]-[47], Unscented Kalman Filter, and Ensemble Kalman Filter [48]-[50]. In this research, the standard Kalman Filter is used for distance measurement estimation because it provides suitable parameters for noise reduction and stability for DC motor [41], [42]. The Kalman Filter is typically implemented through two main stages: prediction and update. During the prediction stage, the algorithm uses prior knowledge to estimate the current state of the system, while the update stage incorporates new measurements to refine the estimation. This iterative process ensures continuous improvement in the estimation accuracy.

The mathematical equations governing the Standard Kalman Filter have been derived and simplified to facilitate implementation. These equations define the relationship between the estimated variables, covariance matrices, and the gain factor. By utilizing these equations, the Standard Kalman Filter provides a robust framework for estimating and predicting data, contributing to improved performance and efficiency in various applications.

Prediction:

$$x_{t|t-1} = x_{t-1|t-1} \tag{1}$$

$$P_{t-1} = P_{t-1|t-1} + Q_t \tag{2}$$

Update:

$$x_{t|t-1} + K_t(y_t - x_{t|t-1}) \tag{3}$$

$$K_t = P_{t|t-1}(P_{t|t-1} + R) \tag{4}$$

$$P_{t|t} = (1 - K_t)P_{t|t-1} \tag{5}$$

In this context, the variable x refers to the input value being estimated, P_t represents the covariance matrix during estimation, Q is the process noise covariance matrix utilized in the estimation, and K_t denotes the Kalman Filter gain factor. Furthermore, R represents the measurement noise covariance matrix, $t|t$ signifies the value of the variable at the current measurement, $t-1|t-1$ depicts the value of the variable at the previous measurement, and $t|t-1$ represents the intermediate value between the current and previous measurements.

2.2. Design System

The system design in this research encompasses several components, including the system block diagram, wiring diagram, and flowchart. The system block diagram is presented in Fig. 1.

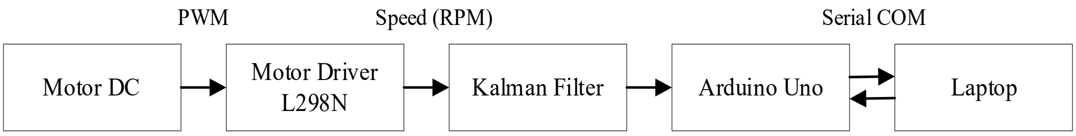


Fig. 1. System Block Diagram

Based on Fig. 1, the input data from the DC motor is controlled by a motor driver using PWM to regulate the motor speed in RPM (Rotations Per Minute). The data is then processed using the Kalman Filter algorithm on an Arduino Uno microcontroller to reduce the noise present in the DC motor. Finally, the processed data is transferred via serial communication to a laptop for further display and analysis. The block diagram is implemented in the system hardware in Fig. 2 and the flowchart is shown in Fig. 3.

Based on Fig. 3 presents the system flow utilized in this research, outlining the steps involved in estimating the speed of the DC motor through the Kalman Filter approach. The initial stage focuses on minimizing encoder sensor error and optimizing the R, Q, and P_t parameters via the Kalman Filter's reinforcement mechanism. Subsequently, the sensor block is employed to gather data on the DC motor speed, which will be subject to estimation using the Kalman Filter. Within this block, the sensor value is predicted based on equation (1). The predict error sensor block calculates the discrepancy between the predicted and actual sensor values, as determined by equation (2). The updating prediction sensor value block further refines the predicted encoder value for subsequent speed estimation measurements, employing equation (3). The calculate Kalman reinforcement value block calculates the necessary reinforcement value, as per equation (4), to rectify input errors and displays it on the laptop using the serial monitor. The updating error value block ensures continual updates to the error value for subsequent calculations. This comprehensive workflow enables the system to accurately estimate the speed of the DC motor, utilizing the motor itself, and consistently generate up-to-date and reliable data.

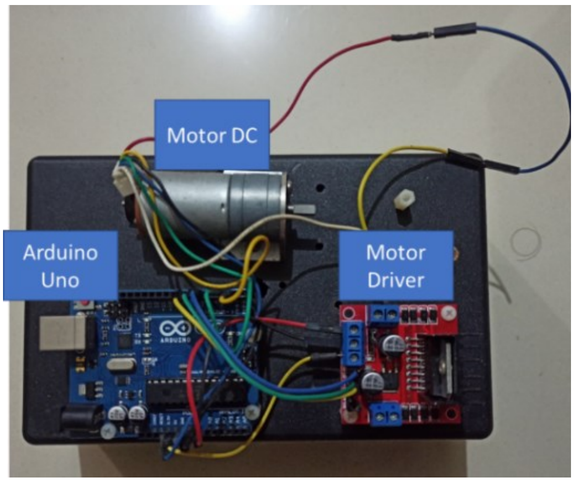


Fig. 2. System Hardware

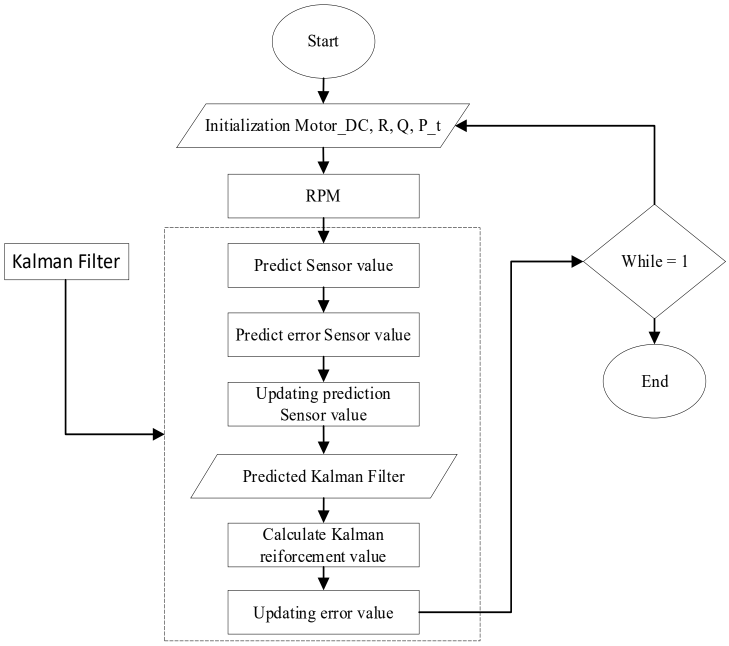


Fig. 3. System Flowchart

3. RESULTS AND DISCUSSION

This research aims to reduce speed errors in DC motors through a comprehensive evaluation that involves assessing the performance of DC motors and the utilization of the Kalman Filter method. The testing is conducted to assess the extent to which the Kalman Filter can accurately estimate speed values in DC motors. In this research, variations in the Kalman Filter parameters and the performance of the DC motors are carefully analyzed to gain a deeper understanding of the effectiveness and reliability of the Kalman Filter method in mitigating speed errors in DC motors.

3.1. DC Motor Performance

In this research, a comprehensive set of experiments was conducted to activate the DC motor by applying a range of PWM values from 50 to 250, with a step size of 25 PWM for each test. The rotational speed of the motor was measured in RPM (rotations per minute) and recorded using the serial monitor for subsequent analysis. The obtained results, presented in Fig. 4, provide a detailed insight into the performance of the DC motor throughout the experimental procedure.

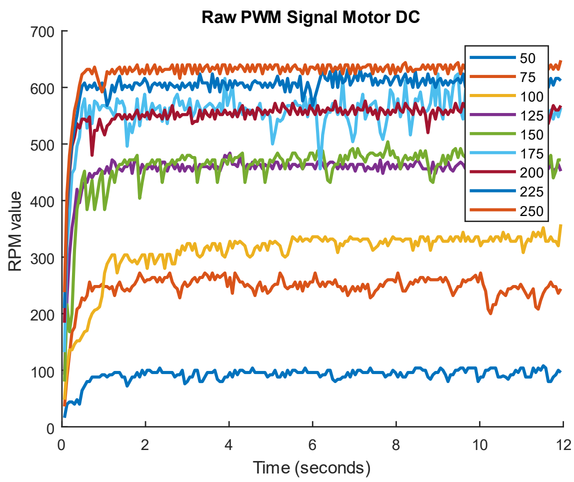


Fig. 4. PWM value testing on motor DC

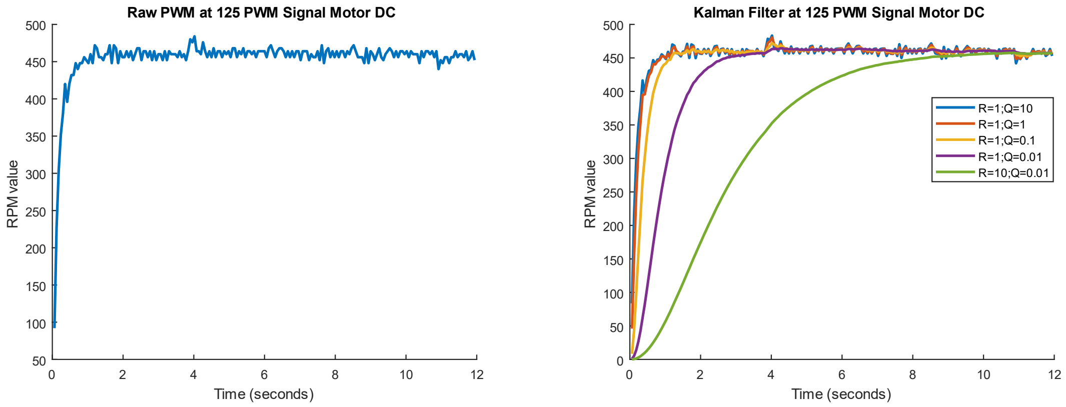
Based on the results shown in Fig. 4, it is observed that the motor speed increases with an increment in the PWM value. However, performance testing of PWM on the DC motor reveals the presence of unstable fluctuations or oscillations. To further analyze the performance of PWM on the DC motor, speed measurement data using the Pulse Width Modulation (PWM) method with various PWM parameter variations were recorded and presented in Table 1. The table includes measured parameters such as Rise Time, Settling Time, Settling Min, Settling Max, and Overshoot.

Table 1. Result testing before using Kalman Filter

PWM	Rise Time	Settling Time	Settling Min	Settling Max	Overshoot
50	0.64	NaN	72	108	12.5
75	0.4898	NaN	200	272	8.8
100	1.0933	NaN	272	358	8.4848
125	0.4198	NaN	432	484	5.2174
150	0.404	NaN	384	504	5.8824
175	0.3577	NaN	456	624	10.4425
200	0.2525	NaN	480	576	3.0411
225	0.3233	NaN	568	636	4.6053
250	0.3222	NaN	592	648	2.3697

3.2. Kalman Filter Implementation

Before the implementation of the Kalman filter, the measured output speed (RPM) of the second DC motor exhibited significant disturbances in the form of noise. The presence of this noise can hinder the feedback process involved in calculating the control signal. To address this issue, the Kalman filter method was employed, known for its ability to mitigate noise in DC motor speed measurements. The Kalman filter utilizes information from previous values, input signals, and measurements to estimate the next state value. This process entails predicting the state based on the previous prediction and subsequently updating it by incorporating the current value. Following the application of the Kalman filter's filtering process, the output voltage of the second DC motor becomes smoother, devoid of high levels of noise. The effectiveness of the Kalman filter in refining the DC motor's speed (RPM) can be observed in Fig. 5.



(a) (b)

Fig. 5. Graph of tuning parameter Kalman Filter on speed Motor DC (a) Raw Data, (b) Filtered Data

In Fig. 5(b), it is evident that the utilization of the Kalman filter on the DC motor results in a notable improvement in controlling speed oscillations (RPM) and achieving a more stable signal. The implementation of the Kalman filter effectively mitigates the previously observable noise in the output voltage, thereby facilitating more precise and efficient signal processing for control purposes. This significant finding underscores the substantial enhancement of measurement quality and control in the DC motor system through the application of the Kalman filter, as it effectively mitigates the adverse effects of noise in the output voltage. Table 2 provides a comprehensive overview of the measured parameters, including Rise Time, Settling Time, Settling Min, Settling Max, and Overshoot, obtained during the process of tuning the Kalman filter parameters.

Based on the findings presented in Table 2, the utilization of the Kalman filter in the measurements demonstrates an enhancement in settling values and a faster attainment of stability. However, it is crucial to carefully consider the selection of the R and Q values to prevent them from being excessively large, as this can lead to slower measurement responses and an increase in rise time. Although the measurements exhibit improved stability [41], [42], there are still shortcomings in the system's response that necessitate further investigation and resolution.

Table 2. Hardware testing results of tuning parameter Kalman Filter.

R	Q	Rise Time	Settling Time	Settling Min	Settling Max	Overshoot
-	-	0.4198	NaN	432	484	5.2174
1	10	0.4229	11.8540	430.8360	483.3468	5.0754
1	1	0.4334	11.2392	423.8460	480.4400	4.4435
1	0.1	0.6220	4.1146	419.5482	472.1680	2.6452
1	0.01	1.5131	2.7597	415.9643	464.3502	0.9457
10	0.01	4.6936	8.4634	415.1432	457.5832	0.1903

In this research, we conducted a parameter selection process to optimize the performance of the Kalman filter in estimating and controlling essential values. The chosen parameter combinations were $R = 1$ and $Q = 0.1$, $R = 1$ and $Q = 0.01$, and $R = 10$ and $Q = 0.01$. These selections were based on evaluating criteria such as fast settling time and low overshoot compared to other parameter values. However, it is important to note that the implementation of R=10 and Q=0.01 revealed issues related to the system's response that require appropriate measures to improve its speed. We will undertake necessary steps to address these issues and ensure the attainment of optimal system performance. By carefully selecting the appropriate parameters, our objective is to guarantee accurate estimation and effective control of the significant values considered in this research using the Kalman filter. Consequently, this research contributes to enhancing the understanding and application of Kalman filter technology in diverse relevant applications.

Moreover, Fig. 6 and Table 3 showcase the implementation of the Kalman filter across various PWM values applied to the DC motor using parameters $R = 1$ and $Q = 0.01$. This implementation enables us to observe the impact of employing the Kalman filter on the overall performance of the DC motor system under different PWM variations. The results provide valuable insights into the system's behavior and demonstrate how the Kalman filter influences and enhances system performance by mitigating the effects of noise [44].

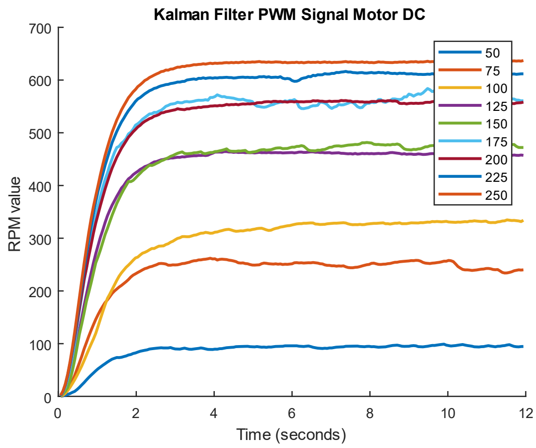


Fig. 6. PWM testing on Motor DC after Filtered with Kalman Filter (R = 1 and Q = 0.01).

Table 3. Hardware testing results after using Kalman Filter with R = 1 and Q = 0.01.

PWM	Rise Time	Settling Time	Settling Min	Settling Max	Overshoot
50	1.7282	11.8348	86.5385	99.0381	3.1646
75	1.5052	11.293	226.4012	261.9995	4.7998
100	2.5665	5.8677	297.1077	334.7951	1.4531
125	1.5131	2.7597	415.9643	464.3502	0.9457
150	1.8137	6.6343	431.1801	481.6516	1.1873
175	1.6238	9.7759	514.3652	583.9695	3.3574
200	1.6478	10.6216	506.2981	561.3389	0.4184
225	1.5541	3.0449	547.9486	616.3967	1.381
250	1.5374	2.8695	572.047	637.0828	0.645

4. CONCLUSION

Based on this research, it has been determined that DC motors possess inherent characteristics of rapid speed and high efficiency, although these attributes are not absolute. However, DC motors are subject to limitations, such as the presence of noise ripple, which can impede their efficiency. To address this issue, the Kalman Filter methodology is employed to accurately estimate the true speed and mitigate noise disturbances. The findings of this research substantiate that the integration of the Kalman Filter in DC motor systems leads to enhanced control over speed and the generation of a more stable signal. By effectively reducing noise in the output voltage of DC motors, the Kalman Filter facilitates precise and efficient signal processing for the purposes of control. The experimental measurements demonstrate notable improvements in settling time values, indicating faster attainment of stability following the implementation of the Kalman filter. Nevertheless, it is imperative to carefully consider the selection of R and Q values to ensure that the gap between them remains within optimal limits, thus preserving the system's optimal response. Consequently, these findings provide compelling evidence that the application of the Kalman Filter significantly augments the accuracy of readings and the level of control achieved in DC motor systems by mitigating the deleterious effects of noise. Future research endeavors may explore alternative techniques, such as PID or LQR, in order to propose methods that expedite rise time.

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