Research on the Method of Light Intensity Detection based on Kalman Filtering

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Abstract. A light intensity detection algorithm using Kalman filtering is proposed for the usage of data fusion in multi-sensor scenarios, like industrial control, machine vision, and navigation systems. In traditional measurements, the result is often faced with noise interference, causing accuracy problems. This algorithm Kalman filtering can be a good solution to noise signal reduction and provide optimal estimation in various domains that need prediction. As Kalman filtering is suitable for light intensity measurements, This work experimented with the steps shown below. First, the light intensity data is reported by sensors, and the mean and standard deviation of the measurement data are calculated; Second, by introducing a Kalman filtering model into the detecting model, the precision of estimating is improved, and the reliability of the system is enhanced; Finally, the data and diagram are exported by Matlab, and the Kalman filtering algorithm is compared with classical algorithms like moving average, median filtering. The experimental data shows Kalman filtering can be better applied to state estimation and signal processing domains, and the average light intensity data is 949.744. This result supports that Kalman filtering provides a robust and efficient method and it bed-covers the future research in improving the precision in light intensity measurements.

Keywords: Kalman filter; light intensity detection; noise reduction; sensor fusion.

1. Introduction

Light intensity measurement plays an important role in many fields, including optical communications, laser technology, material science, and environmental monitoring. Having an accurate value of light intensity is crucial for ensuring precision and functionalities in many fields. Traditional measuring tools, however, often encounter interference such as noise performance, fluctuations, and environmental factors, which can lead to inaccuracies results of measurement. This state of affairs drives people to explore advanced techniques to enhance the precision of measurements.

The Kalman filtering is an algorithm used in signal processing for estimating the state of a dynamic system observed through a noise measurement [1]. It was developed by Rudolf E. Kálmán as a solution to linear filtering and prediction problems and has since found application in many modern areas such as self-driving, aerospace, signal processing, and more, owning to its better performance of adaptability and effectiveness in dealing with noisy background and uncertain measurements. In many domains of real-world detection, detectors are subject to various disturbances that lead to error measurement, making it difficult to reach the true state of the measurement.

The success of the Kalman filter is shown for its extension far beyond its original application in control theory. The Kalman filtering has proven itself particularly useful in scenarios containing noisy sensor data, dynamic measurement state changes, and uncertain environments. Since Kalman filtering has had many success in other fields, this work aim to find its potential in fields of light intensity measurements. This research aims to solve the limitations traditional measuring methods have and proposes a new application of Kalman filtering in light-intensity measurements to achieve more accurate and reliable results.

In this introduction, after providing the relevant background surrounding the Kalman filter, our experiment steps are shown below for a better understanding. Firstly, an Arduino-based system is developed with every component that is needed to measure light intensity, then measure the light intensity under different light intensity conditions. After three groups of light intensity data are

collected, the mean and standard deviation data are calculated. Finally, this work introduced the Kalman filter to optimize the output and minimize the effects of sunlight interference.

In a detection scenario with multiple sensors, after the sensors acquire data from sensors, it needs several steps to acquire the estimated data. To get a more accurate estimation from multiple sensors and enhance the accuracy of detection and estimation, it's important to import the Kalman filter into the sensor fusion field to get more accurate data. The filter's effectiveness lies in its ability to recursively update and refine state estimates based on a dynamic model of the system and incoming measurements. Unlike simpler methods that rely solely on the most recent observation, the Kalman filter considers both the system's predicted state and the new measurement, weighing them based on their respective uncertainties. This blending of prediction and measurement provides a more robust and optimal estimate of the true system state.

This study aims to address the application of the Kalman filter in the field of light intensity measurement. This research also seeks to make contributions to the advancement of measurement technologies, making more data reliable and generalizing the application in the field of tracking the position, telecommunications, and environment monitoring, stabilizing control systems, and estimating the driving routines of an unmanned car.

2. Literature Review

At present, many scholars from home and abroad have conducted a lot of research on Kalman filtering and have achieved remarkable results and progress. Kalman R.E. proposed the original algorithm of Kalman filtering [1]. It mainly introduced the Kalman filtering algorithm, which is innovative in linear filtering and prediction problems, and it found the formulation and methods of solution of the problem apply without modification to stationary and non-stationary statistics and growing-memory and infinite-memory filters. The main goal of Kalman filtering is to estimate the state of a system by combining a system model and actual measurements and to be able to handle noise and uncertainty effectively.

Kalman et al. proposed new results in linear filtering and prediction theory, which is an extension of the Kalman filter algorithm [2]. The key problem it discussed is how to optimally estimate the state of the system when the system’s dynamic and measurement equations are known. It has made contributions mainly to recursive filtering infinite time maintenance performance and the optimality for linear systems.

Gelb, A. describes the process and mathematics underlying random process theory. It also describes the state-space characterization of linear dynamic systems [3].

Peter S. Maybeck. Implemented stochastic processes and models for dynamic systems. It introduced Gaussian and non-Gaussian random processes [4-7], and Bayesian estimation to the model [4], then detailed coverage of the Kalman filter and its variants. It also introduced the application of the Kalman filter to state estimation in dynamic systems and accommodated it in both discrete-time and continuous-time filters.

Simon. Tells the basic concept and applications of Kalman filtering in multiple scenarios [8]. The author used the Kalman filter to solve a vehicle navigation problem and then used it to position the track. Kim Y et al. provide a tutorial-like script of the Kalman filter and extended Kalman filter [9]. It discussed about how to choose parameters and modify the algorithm in the real world. Anderson et al. mainly focused on discrete-time filtering [10]. The material covered in this book has given new perspectives on earlier materials.

3. Kalman Filter Model

Kalman filter algorithm is used for estimating a linear dynamic system under the effect of noise and uncertainties. It contains 3 parts: calculate, predict, and update. Firstly, the system is initialized and can calculate the mean and standard deviation from the data. Secondly, the state prediction and

covariance prediction formula, and the current state are used to predict the next state of the system. Finally, the state is updated by Kalman gain calculation. Through the iterative process, the prediction part and estimate measurement are updated with time steps.

For the initialization part, the system initializes the state estimate, state covariance, state measurements, state covariance, and process covariance. The state estimates are some initial data gained from the system, and the values are based on the detector's characteristic, it shows the initial guess about the internal state of the system. Initialization for the state covariance matrix indicates the uncertainty of the initial state, and it's usually a larger figure to show the uncertainty of an unmeasured system. The measurement noise and process noise covariance matrix can be gained by experience or manually set due to the measurement request. The crucial part in the process of Kalman filter is Kalman gain, it adjusts the weights of predictions and measurements in each iteration. In the initial part, a suitable Kalman gain needs to be set to ensure proper integration of a priori estimation and measurement information.

For the prediction part, the system's dynamics and previous state estimation are factors that determined the output of the current state and state estimation, which is calculated as follows:

$$\boldsymbol{x_K = A_K\ x_{K-1} + B_K u_K + W_K} \tag{1}$$

$$\boldsymbol{P_K = A_K P_{K-1} A_K^T + Q} \tag{2}$$

For the update part, the Kalman gain is computed for correction. Then the state estimate is updated based on the actual measurement and predicted measurement. Finally, the state covariance is updated through those steps.

$$\boldsymbol{X_k = \frac{P_k H_k^T}{H_K P_K H_K^T + R}} \tag{3}$$

After processing all the steps above, the prediction and measurement update parts are repeated for each new set of measurements. Through these steps, the Kalman filter is gaining more precision than its previous conditions.

4. Light Intensity Detection based on the Kalman Filter

The total experiment used an Arduino UNO board, light-dependent resistor (LDR), photon-sensitive diode, and integrated light sensor.

Three different types of light intensity detectors are used for the experiment according to their features. They are LM393, a 4-pin module; GL5516, a photo-resistor; BPV10NF, a photon diode. LM393 4-pin module includes an LM393 voltage comparator and can change its resistance linearly when it is exposed to light. For the distance measurement, this work used a ruler and measured several times to get its average value to reduce error.

When GL5516 is exposed to light, its resistance will decrease and allow more current to flow through. The data sheet of every component only gives the range of the parameters they will use. According to the lack of instruments, every experiment conducted is for theoretical research.

After the light intensity signal is received by the sensors, the voltage signal is output via the sensors. Then the voltage signal is transformed into a light intensity unit, lux, through a formula shown below that describes the transmission.

$$\mathbf{Lux = 7.2162 \times \log(3.5018 \times R) - 2.2105} \tag{4}$$

The data gained from the sensor is then imported and processed in Matlab. From the first set of experiments, it can be observed that the diagram turned out to be more stable than the origin state.

5. Discussion

5.1. Performance Evaluation

If the study choose the traditional measurement method such as moving averages, the result turns out to be not accurate enough due to the simple algorithm. Common limitations such as limited adaptability. When traditional measurements rely on fixed algorithms and lack assumptions for system dynamics, they will not perform Ill when facing a task that contains a dynamic system and multiple variables.

The performance of Kalman filter in light intensity measurements performed better than the traditional method and separate measurements. It can handle multivariate systems where they have multiple variables, which makes it useful in applications of complex measuring scenarios and sensor setups.

5.2. Kalman Filter's Parameter Selection

There are 6 parameters in a Kalman filter process. Initial State Estimate, Initial State Estimate Covariance, State Transition Matrix (A), Observation Matrix (H), Process Noise Covariance Matrix, Measurement Noise Covariance Matrix.

The Initial State Estimate shows the best guess of the system's state at the start of Kalman filtering. And it's the initial estimate of the system's state.

The Initial State Estimate Covariance represents the degree of uncertainty for the system.

The State Transition Matrix and Observation Matrix are determined by the dynamic equations and observation equations. It describes the relationship between the state and measurements.

The Process Noise Covariance Matrix's value is determined by the stability of the system. It represents the error of the system's prediction. It's usually set up with a bigger number to show the system's original instability. And it's processed and adjusted through trials and errors.

The Measurement Noise Covariance Matrix is determined by the inaccuracy of measuring tools. It should base on the characteristics of measurement tools. In usual backgrounds, the accuracy indicators for sensors are given.

Optimizing Kalman filter parameters typically involves an iterative process of testing, simulation, and adjustment. The goal is to achieve a balance between incorporating accurate information from measurements and accounting for uncertainties in the system and measurements. This study need to have a good understanding of the system being modeled to make informed decisions about parameter selection.

6. Conclusion

A light intensity system using a Kalman filter to process is proposed for the problem that the accuracy using traditional algorithms is not high enough. In this experiment, the scenario that light intensity measurement used is under room light. The Arduino UNO board and 3 types of light-intensity sensors are used. After gaining the voltage, study used a certain formula to transit it into a light intensity unit, lux. Finally, the values are processed using Matlab with a sensor fusion algorithm. From the result, this work can find the model is becoming smoother with time.

Kalman filter plays an important role in improving the accuracy of measurement in the presence of noise. Compared to the traditional measuring methods, it shows stability and accuracy on multi-scenario tasks which include processing and updating.

The successful application of Kalman filtering in light intensity measurement has significant implications for automatic driving, trace prediction, posture estimation, etc. Notwithstanding this limitation, future research can further optimize the Kalman filtering system to improve its adaptability to better meet the needs of different application requirements in different scenarios. Future research could also explore its usage in different dimensions and use different types of Kalman filters such as Extended Kalman Filter, Unscented Kalman filter, etc.

In summary, the Kalman filter is a sophisticated and ill-designed solution to a problem of state estimation under a noise-presenced scenario, making it a fundamental tool to use in measurement, signal processing, and control theory fields.

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