Design of Intelligent Early Warning Robot System for Warehouse Autonomous Patrol based on Scale Estimation Algorithm of Probability Theory

Jie Li¹, Yaoyao Tu¹* and Biao Lu²

¹Faculty of Mathematics and Statistics, Suzhou University, Suzhou, Anhui, China
²Faculty of Information and engineering, Suzhou University, Suzhou, Anhui, China
*corresponding author’s e-mail: tyy20101112@163.com

Abstract. In view of the backward monitoring status in the traditional safety management of hazardous chemicals warehouse, a patrol robot for hazardous chemicals warehouse with autonomous patrol stereo detection, intelligent early warning and remote monitoring functions is designed, and the design process of related functions of autonomous patrol navigation subsystem, environmental detection subsystem and remote monitoring subsystem is discussed from two aspects of hardware and software. Because both the camera and the target may be in motion, it is necessary to consider the scale change of target influence caused by relative distance. In order to overcome the shortcoming of invariable scale in Mean Shift algorithm, this paper adopts a scale adaptive method to estimate the size of the target, adjusts the parameters of kernel function by using ellipse feature, and takes the parameters of the current frame as the initial data of the next frame, so as to achieve the effect of adaptively adjusting the target scale. The test results show that the system can effectively traverse the map of hazardous chemicals warehouse, accurately assess the leakage of hazardous chemicals and the environmental safety of warehouse, and give early warning. The remote monitoring platform greatly facilitates the remote management of the warehouse.

1. Introduction

With the development of science and technology and the progress of society, the warehousing industry has entered a high-speed development stage, and the warehouse space area is getting larger and larger, but the warehouse supervision technology has not been developed synchronously, which leads to frequent dangerous accidents in warehouses everywhere. Chemical and chemical industry is an important part of China's economy, and hazardous chemicals account for a considerable share of chemical products[1]. Dangerous accidents in hazardous chemicals warehouses are mostly caused by changes in warehouse environment, which is coupled by variables such as air temperature and humidity, pressure, light, and concentration of leaked hazardous chemicals[2]. Detection of relevant environmental variables in the whole range of warehouses is a prerequisite for preventing dangerous accidents.

At present, there are two ways to manage hazardous chemicals warehouse: pure manual monitoring management and equipment monitoring management. However, both pure manual monitoring and equipment monitoring monitoring have great defects[3]. Under the pure manual management mode, it is very difficult to patrol without errors 24 hours a day, regardless of whether there are enough warehouse managers[4]. Moreover, because the human body is not sensitive enough to environmental information, it is not easy to detect when the warehouse environment deteriorates[5]. With the help of equipment monitoring, there are also the following problems: (1) monitoring blind areas are easy to exist in the...
fixed-point installation of monitoring devices in warehouses; The installed detection sensor is single, and the pertinence is not strong, the rate of missing alarm and false alarm is high, and the system lacks intelligence; Monitoring devices need to be installed at multiple points, and the system cost is too high[6]. In view of the above problems, this paper designs a patrol robot system with autonomous patrol, stereo detection, intelligent early warning and remote monitoring functions, which effectively makes up for the shortcomings in the safety monitoring of hazardous chemicals warehouses.

2. Overall scheme design
The patrol robot can patrol the hazardous chemicals warehouse autonomously in the whole range with the help of the patrol navigation subsystem. At the same time, it can detect and fuse various environmental parameters and leaked hazardous chemicals concentration in the warehouse through the environmental monitoring subsystem, and upload various original data and fused data to the cloud server for storage through WiFi wireless network[7]. At the same time, the robot will perform data fusion processing on all kinds of environmental data collected, and compare the data fusion result value with the alarm threshold value to judge the dangerous degree of the warehouse environment. When the robot thinks that there is a potential safety hazard in the warehouse comprehensive environment, it will send an early warning or even an alarm signal. When the manager fails to handle it in time, the robot will call the warehouse manager through GSM, and the staff can also log in to the cloud server through the remote monitoring subsystem to check the warehouse situation anytime and anywhere or send various control instructions to the robot[8]. The whole system structure is shown in Figure 1:

![Figure 1. System structure diagram of patrol robot](image_url)

3. System hardware design

3.1. Patrol navigation subsystem.
This subsystem mainly realizes the autonomous patrol function of patrol robot in indoor closed environment. In hardware, it consists of microcontroller STM32F429IG, minimum system circuit motor and drive module L298 N 6-axis motion processing module MPU 6050 infrared obstacle avoidance detection sensor E18-D80NK, etc. Firstly, L298N drive motor is used to make the robot move, and E18-D80NK sensor is used to detect obstacles. The built-in angular velocity sensor of MPU6050 is used to detect the direction angle of the robot during patrol[9]. After the robot patrols once, the patrol mode automatically switches between the right-hand rule and the left-hand rule. At the same time, PID algorithm is used to control the robot's traveling path during patrol, thus realizing the robot's autonomous patrol navigation function in the hazardous chemicals warehouse. The hardware structure diagram of patrol navigation subsystem is shown in Figure 2:

3.2. Environmental detection subsystem
This subsystem mainly realizes the functions of multi-sensor data fusion, data communication and video monitoring for detecting various environmental variables around the robot, Hardware includes microcontroller STM32F429IG (shared with patrol navigation subsystem), gas detection sensor MQ2 (which can detect liquefied gas, alkane, benzene, hydrogen, alcohol smoke, etc.), flame sensor Rb-02s022a, temperature and humidity sensor DHT11, and other environmental monitoring sensors (if necessary, the required sensors can be added to the reserved MCU interface according to different needs)[10]. Communication module includes SIM808 and WiFi module RTL8188EUS, which integrate GSM bluetooth technology. video monitoring adopts the combination of electrically controllable pan/tilt and camera, and users can view images from all angles in the warehouse by remotely controlling the pan/tilt through the camera. On the working principle, it firstly detects the surrounding environment by using the above-mentioned sensors carried by the robot itself during the patrol process, at the same time, it uses MCU to fuse the data collected by each sensor with the multi-sensor data fusion model based on BP neural network, and judges the danger degree of the current warehouse environment by itself according to the fusion results[11]. When the fusion results approach the alarm threshold, the robot will automatically send corresponding early warning or even alarm signals to the remote monitoring platform through WiFi, and when the managers fail to process them in time, the robot will also use SIM808 to call the managers. The hardware structure diagram of the whole environment detection subsystem is shown in Figure 3:
4. System software design

4.1. Autonomous patrol function

Autonomous movement in indoor environment is the premise for robots to monitor the environment. In order to realize autonomous patrol of robots in indoor environment, infrared sensors are used to detect the boundaries of walkable areas, and the left-hand rule and the right-hand rule are used as the guidelines for robots to patrol the whole map. At the same time, the azimuth and mileage accumulated during the robot's forward movement are detected by angular velocity sensors and the number of turns of motors. After each turn, the robot switches patrol between the left-hand rule and the right-hand rule at 45 degrees, and the robot moves forward in parallel along the edge of indoor map with PID control algorithm. In this paper, the left-hand rule is defined: in the process of autonomous patrol, when an obstacle is detected on the left side (that is, the boundary of the walking area), the robot uses PID algorithm to keep a certain distance from the boundary and move along the boundary until it completes one turn. In the process of the robot moving forward, the distance traveled and the converted direction angle are continuously accumulated. When the distance is equal to the preset perimeter of the indoor open space patrol path and the steering angle of the robot orientation reaches 360, it is considered that the robot has completed one turn. The right-hand rule is similar. The flow chart of autonomous patrol algorithm used in this system is shown in Figure 4:
4.2. Multisensor data fusion function

It is a very important function of patrol robot to estimate the potential danger degree of the environment by detecting various parameters of the surrounding environment. It is the most commonly used detection method to sense the temperature, humidity, toxic, flammable and explosive gas concentration in the environment by carrying multiple special sensors. However, due to the coupling effect of various environmental variables in different degrees, for example, when the relative humidity in the air is greater than 60%, there are few fires, and the safe concentration threshold of flammable and explosive gases in the air is greatly improved; When the humidity is between 40% and 60%, it can smoke and burn, but it is not easy to expand the burning area. When the air humidity is between 30% and 40%, it is easy to burn and spread, while when the humidity is lower than 25%, it is easy to have a fire, and a very small amount of flammable and explosive gases in the air may also cause disasters. For this reason, the system makes use of the complementarity of multiple heterogeneous sensors to enrich the detection of various variables in the space environment, and designs a feature-level data fusion model with BP neural network as the core algorithm to evaluate the risk of environmental parameters.

The multi-sensor data fusion system based on BP neural network is designed in this paper. Its principle is to collect warehouse environment variables through N special-shaped sensors of patrol robot system, then denoise the collected data by using Laida rule, then normalize the data, and take the processing results as the standard input data of BP neural network. Finally, the trained neural network is used for fusion processing, and the fusion results are output as the basis of robot alarm decision.

The neural network model designed in this paper includes an input layer, a hidden layer and an output layer. For the convenience of research, this paper selects three typical environmental variables (including air temperature x1, air relative humidity x2, the comprehensive value of various toxic or flammable hazardous chemicals concentration x3) as the network input, and selects the early warning
variable \( 0 \leq y \leq 1 \) as the output of the network output node.

### 4.3. Remote monitoring subsystem

On the one hand, during patrol, the robot periodically collects the surrounding environment data through the environment detection subsystem, fuses the collected data by using the BP neural network data fusion model, and then uploads the collected environment data (including the fusion results) to the cloud server through the gateway. When the fusion results are close to the alarm threshold, the robot will also send an early warning signal to the monitoring platform, and when the manager fails to handle it in time, the robot will also send an alarm signal to the administrator's mobile phone through GSM. On the other hand, managers can also access the server through the PC monitoring platform or mobile phone monitoring platform, view the current warehouse environment anytime and anywhere, and send instructions to the robot remotely through the monitoring platform if necessary.

The remote monitoring subsystem includes robot program, cloud server program, PC monitoring platform program and mobile phone App program. Among them, the robot program mainly realizes the functions of collecting environmental information, fusing data, uploading and sending alarm signals and receiving control signals. The cloud server is based on the PaaS Internet of Things open platform oneNET provided by China Mobile, and is mainly used to receive and save the data uploaded by the robot and provide data access services for PC monitoring platform and mobile App; The PC monitoring platform is implemented by using oneNET's supporting WEB service, which is mainly used to read the environmental information uploaded by the robot and the state parameters of the robot itself from the cloud server. In addition to the PC monitoring platform program function, the mobile App also adds the robot remote control function, and its workflow is shown in Figure 5:

![Figure 5. Work flow chart of remote monitoring subsystem](image)

#### 5. Mean Shift target tracking based on scale estimation

The size of the target changes with the movement. When the target object moves in the shooting range, because the search window is fixed and the size of the target itself becomes larger, some points of the
The target pixel will be excluded from the search window, resulting in inaccurate convergence of local maxima of sample points and tracking errors. When the target size becomes smaller, non-target pixels will be included in the search window, that is, non-sample particles will be locked, which will often lead to tracking failure. Therefore, this paper uses scale estimation to improve the tracking drift phenomenon caused by the constant window of traditional Mean Shift. In the tracking process, the tracking window is adaptively adjusted according to the change of target size.

5.1. Parameter adjustment of kernel function

In this paper, target color features are used as target input information. Based on the traditional Mean Shift, the ellipse which is the closest to the target description is established as the search area, which converges in the area. The template parameters are constantly updated by using the iterative idea of Mean Shift, and the target parameters of the previous frame are used as the initial parameters of the next frame, so as to achieve the purpose of adaptively adjusting the scale according to the change of the target. When using Mean Shift algorithm to track the target, firstly, the initialization setting is carried out, that is, the parameters of the system are set. The initialization methods can be divided into two types: automatic mode and semi-automatic mode. The biggest difference between the two methods lies in the different methods of obtaining the target area to be tracked. The automatic method is to automatically obtain the target area to be tracked by the method of target detection, while the semi-automatic method is to specify the interested target area in the original picture by manual method. In this study, a semi-automatic method is adopted, that is, the tracking target is selected manually[12].

Suppose \( \{x_i \}_{i=1,2,\ldots,n} \) is the target model of normalized pixels, the center point is 0, and the probability density \( q_u(x) \) of the target model can be expressed as:

\[
q_u(x) = C \sum_{i=1}^{n} k\left( \|x_i - x\|^2 \right) \delta[\delta(x_i) - u].
\]

In which \( \delta \) is dirac function, \( \delta(x_i) \) is index function, which reflects bin sequence of pixel \( x_i \), \( C \) is normalized correlation coefficient, \( k(\cdot) \) is kernel function, and the mathematical expression of kernel function in this paper is shown as follows:

\[
k(\cdot) = k\left( \frac{X_0 - x_i}{h} \right).
\]

Too small or too large kernel function bandwidth will have different degrees of errors in the state description of the system, filtering out most of the target state information. In this paper, the scale estimation algorithm uses ellipse feature to adjust the parameters of kernel function \( k(\cdot) \), so as to adjust the target scale and approach the real state of the target to the greatest extent. Because this paper aims to monitor and track the target pedestrians, the traditional Mean Shift uses circles to search the target in the region, and the appearance model of pedestrians is closer to ellipse, so the ellipse feature method is used to estimate the size of the target model. The convergence diagram is shown in Figure 6:
Figure 6. Convergence diagram

Let $\{x_i\}_{i=1,2,\ldots,n}$ be the target sample point, and define the change of target scale as the same direction, $y = (y^1, y^2)$, $x_i = (x_i^1, x_i^2)$, the location of pixels in the target area will be estimated, and the probability density of the target model is:

$$q_u(x) = C \sum_{i=1}^{n} \left( \frac{x_i^1}{a^2 + \frac{x_i^2}{b}} \right) \delta[b(x_i) - u].$$  \hspace{1cm} (3)

The values of $a$ and $b$ are set to be half of the rectangular side length of the target area, and the parameter equation of ellipse is introduced into this function to modify the parameters of the function. The selected kernel function bandwidth is $h$, that is, the scale value of the current state of the target, and $y_0$ is set as the central area of the target. The probability density $p_u(x)$ of the candidate target model is as follows:

$$p_u(y_0, h) = C_h \sum_{i=1}^{n} \left( \frac{(y_0^1 - x_i^1)^2}{a^2 h^2} + \frac{(y_0^2 - x_i^2)^2}{b^2 h^2} \right) \delta[b(x_i) - u].$$  \hspace{1cm} (4)

Since $C_h$ is a normalized function, its parameter equation is as follows:

$$C_h = \frac{1}{\sum_{i=1}^{n} \left( \frac{(y_0^1 - x_i^1)^2}{a^2 b^2} + \frac{(y_0^2 - x_i^2)^2}{a^2 b^2} \right)}.$$  \hspace{1cm} (5)

5.2. Target scale estimation

The similarity between the target template and the template to be tested is estimated, and the target position and scale of the previous frame are estimated as the starting state of the target of the next frame until the target is collected, so as to achieve the purpose of self-adaptive adjustment of the scale. Similar to the traditional Mean Shift algorithm, the similarity between them is measured by Babbitt coefficient, as shown below:

$$\rho[P_u(y, h)q] \approx \rho(y, h) = \sum_{i=1}^{n} \left( C_h \frac{h_i^2}{h^2} \sum_{i=1}^{n} k \left( \frac{(y_0^1 - x_i^1)^2}{a^2 h^2} + \frac{(y_0^2 - x_i^2)^2}{b^2 h^2} \right) \delta[b(x_i) - u]q_u \right).$$  \hspace{1cm} (6)

$w_i$ is defined as:
\[ w_i = \sum_{i=1}^{n} \sqrt{q_i/p_i} (y_i - u) \]  

(7)

The traditional Mean Shift method for solving the target position is to calculate the moving vector \( \mathbf{l} \) of the target sample from the initial position to the actual position, as follows:

\[ L(y_0, h_0) = \frac{\sum_{i=1}^{n} x_i w_i g \left( \frac{(y_0 - x_i)^2}{a^2 h^2} + \frac{(y_0 - x_i)^2}{b^2 h^2} \right)}{Y} - y_0. \]  

(8)

Among them, the parameter equation of \( y \) is:

\[ Y = \sum_{i=1}^{n} w_i g \left( \frac{(y_0 - x_i)^2}{a^2 h^2} + \frac{(y_0 - x_i)^2}{b^2 h^2} \right). \]  

(9)

It can be seen from the above that the current estimated position \( A \) and the estimated value \( B \) of the scale of the target are:

\[ y_1 = \frac{1}{a^2} L(y_0, h) + y_0 \]

\[ y_2 = \frac{1}{b^2} L(y_0, h) + y_0 \]  

(10)

\[ h_1 = \left[ \frac{\sum_{i=1}^{n} w_i k \left( \frac{(y_0 - x_i)^2}{a^2 h^2} + \frac{(y_0 - x_i)^2}{b^2 h^2} \right)}{Y} \right] \left[ \frac{\sum_{i=1}^{n} w_i g \left( \frac{(y_0 - x_i)^2}{a^2 h^2} + \frac{(y_0 - x_i)^2}{b^2 h^2} \right)}{h_0 Y} \right] \]  

(11)

5.3. Design of Mean Shift Algorithm for Scale Estimation

In order to verify the effectiveness of the multi-sensor data fusion algorithm of patrol robot, a large number of safety early warning tests were carried out in the laboratory by using patrol robot by adjusting and controlling different temperature, humidity and gas leakage in the experimental warehouse. In order to facilitate verification, the safety degree of 30 groups of data in the test process was judged manually according to safety rules, and the robot fusion output value \( y (0\leq y \leq 1) \) was taken as the robot early warning basis. It was stipulated that the closer \( y \) value was to 0, the higher safety degree was, on the contrary, the closer it was to 1, the lower safety degree was. And set no alarm when \( y \leq 0.3 \), yellow alarm when \( 0.3 < y \leq 0.7 \) and red alarm when \( y > 0.7 \), with 30 sets of test data listed in Table 1.

Table 1. 30 sets of test data sheets.

| serial number | relative humidity/% | Air temperature/°C | CO concentration/ppm | Expected value of alarm | Expected judgment result | Robot fusion result value | Robot decision node |
|---------------|---------------------|-------------------|----------------------|------------------------|------------------------|------------------------|-------------------|
| 1             | 74                  | 32                | 30                   | 0                      | safe                   | 0.004                  | safe              |
| 2             | 50                  | 25                | 23                   | 0                      | safe                   | 0.0029                 | safe              |
| 3             | 77                  | 50                | 14                   | 0                      | safe                   | 0.003                  | safe              |
It can be seen from Table 2 that although the fusion results of 30 sets of test data by the robot have certain deviation from the alarm expectation, they are all within the allowable error range. The automatic judgment results generated according to the rules are consistent with the manual judgment results, which can be fully applied to the hierarchical early warning of the robot patrol process.

5.4. Analysis of Scale Estimation Algorithm
In this experiment, according to the different moving modes of the target in the camera range, two groups of experiments are taken to verify it. When the target moves in the shooting range, there are two moving situations. The farther away the target is from the camera, the smaller the target size is. On the contrary, the target size is getting bigger and bigger. The monitoring equipment used this time is 20 m,
and the focal distance is fixed. The size of the selected sequence is 302×412 pixels, the length is 60 frames, and the frame rate is 30fps. When tracking the target, the tracking window of Mean Shift algorithm is fixed with the change of target scale. The scale change algorithm adopted in this paper improves the circular iteration of Mean Shift in searching for sample points. This paper adopts an approximate elliptical search method, which is closer to the appearance of human beings. With the change of target size, the tracking window is adjusted adaptively, which optimizes the disadvantages of traditional Mean Shift algorithm. That is to say, when the size of the target becomes larger, the local maxima affecting sample particles in some sample points will be ignored, which will lead to errors in tracking results; When the target size becomes smaller, some non-sample points are included in the search area, which increases the calculation amount, and will cause the non-sample points to have larger weights, resulting in the convergence error of sample points. Therefore, according to the distance between the target and the acquisition equipment, the size of the target changes obviously. The algorithm in this paper adjusts the adaptive window according to the change of the target size, which proves the effectiveness of this algorithm. Compared with the traditional algorithm, its stability is better.

This paper makes statistics on the error pixels at the center of the target in the above two groups of experiments, as shown in Figure 7.

![Figure 7. Target center point error pixel](image)

It can be seen from the data graph that in the process of the target from far to near, at first, because the target size is smaller than the target template size, some target points are included in the convergence area, and weights are given for the next frame iteration, so the early error is larger, but as the target size gets closer and closer to the template size, the error gradually becomes smaller and enters normal tracking. With the moving target, the distance from the camera is getting closer and larger, and some sample points are excluded from the convergence area, which affects the local maximum of sample points. With the decreasing distance, more sample points are eliminated, and the convergence error increases. At about 30 frames, the tracking error is relatively small, mainly because the target template is closest to the fixed size in this time period, so the tracking effect is relatively ideal. The scale estimation algorithm used in this paper uses ellipse feature to adaptively adjust the convergence area of the target, which minimizes the error between the actual scale of the target and the tracking scale, and the tracking effect has been relatively stable, approaching the actual scale of the target to the greatest extent. In view of the above two moving modes of targets, this paper makes statistics on the target scale value in the moving process, and compares the actual target scale value in the Mean Shift fixed window with the scale value of the scale estimation algorithm adopted in this paper. The experimental results are shown in Figure 8.
6. Concluding remarks

Based on the application background of the safety monitoring of hazardous chemicals warehouse, this paper designs a robot which can patrol autonomously in the hazardous chemicals warehouse, and can use the environmental detection subsystem to carry out environmental detection data fusion and intelligent early warning during the patrol process. With the remote monitoring platform and cloud server, it realizes the remote monitoring and control function of managers to the hazardous chemicals warehouse. In this paper, scale estimation is used to improve the tracking drift phenomenon caused by the constant window of traditional Mean Shift, and the parameters of kernel function are adjusted by ellipse feature, so that the target search area and target template can be adjusted adaptively. In the tracking process, according to the change of the target's own scale, the tracking window will be adjusted adaptively. The algorithm is verified by two groups of experiments, and the effectiveness and stability of the method are proved by analyzing the pixel error in the center area of the target. The experimental results show that the autonomous patrol algorithm designed in this paper can traverse all the storage points of hazardous chemicals in a single island (only one middle obstacle zone) warehouse or no island, and the leakage points of hazardous chemicals can be detected quickly through the mounted environmental detection subsystem. At the same time, the mounted multi-sensor data fusion model can integrate the detection results of various sensors for data fusion processing, which can avoid false alarm and missing alarm in various situations, improve the accuracy and reliability of early warning of patrol robot system, and make the early warning mechanism of robot have certain intelligence.

Acknowledgments

Humanities and Social Sciences Research Project in Anhui Universities (SK2020A0527); Social Science Popularization Plan in Anhui Province (LZ201948); Anhui Quality Engineering Project (2019jyxm0468); Key Research Projects of Suzhou University (2019yzd17); Suzhou University School Quality Engineering Project (2018jyxm12).

References

[1] Cyrill S. Robotic mapping and exploration [M]. Springer Tracts in Advanced Robotics, vol55, ISBN: 978-3-642-01096-5, 2019.
[2] Z. Fang, H. Liyan. A Survey of Multi-sensor Information Fusion Technology[J]. Journal of Telemetry, Tracking and Command, 2016, 3: 000.
[3] D.A. Pomerleau Neural network perception for mobile robot guidance[M]. Springer Science & Business Media, 2016.
[4] MA li, HA Park, CSG Lee. Closed-form inverse kinematic joint solution for humanoid robots[C]. Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on. IEEE, Taipei, Taiwan, 010: 704-709.
[5] Di Giampaolo E Martinelli F. A passive UHF-RFID system for the localization of an indoor autonomous vehicle [J]. IEEE Transactions on Industrial Electronics, 2017, 59(10): 3961-3970.

[6] Xiao P, Luan YQ, Guo R, et al. Research of the laser navigation system for the intelligent patrol robot [J]. Automation & Instrumentation, 2018, 27(5): 5-9.

[7] Hess W, Kohler D, Rapp H, et al. Real-time loop closure in 2D LIDAR SLAM[C]//Robotics and Automation (ICRA), 2016 IEEE International Conference on. IEEE, 2016: 1271-1278.

[8] Qin H, Cong L, Sun X. Accuracy improvement of GPS/MEMS-INS integrated navigation system during GPS signal outage for land vehicle navigation [J]. Journal of Systems Engineering and Electronics, 2015, 23(2):256-264.

[9] J.B. Gao, C.J. Harris. Some remarks on Kalman filters for the multisensory fusion [J]. Information Fusion, 2017, 3:191-201.

[10] A. Weckenmann, X. Jiang. Multi sensor data fusion in dimensional metrology [J]. CIRP Annals-Manufacturing Technology, 2019, 58:701-721.

[11] Gerasimos G. Rigatos. Extended Kalman and Particle Filtering for sensor fusion in motion control of mobile robots [J]. Mathematics and Computers in Simulation, 2015, 81:590-607.

[12] Eva Besada-Portasa, Jose A. Lopez-Orozcoa, Juan Besada. Multi sensor fusion for linear control systems with asynchronous, Out-Of-Sequence and erroneous data [J]. Automatica, 2019, 47:1399-1408.