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PREDICTION OF SENSOR DEVICES' FAILURE IN UNMANNEDAERIAL VEHICLES USING KALMAN FILTER & PARTICLE FILTER

JALAJAKSHI V[1] , DR. MYNA A N[2]

Research Scholar, Department of CSE, Navkis College of Engineering, Hassan
Professor and Head of the Dept. of CSE, Navkis College of Enginnering, Hassan

E-mail: jalajakshi.prakash@gmail.com, mynaan@gmail.com

ABSTRACT

Unmanned aerial vehicles like drones or certain type of helicopters are having rising importance over the past few decades due to utilizing them in various applications. Since there is no human pilot to respond to any aberrant event, reliability is an important concern in UAV operation. The numerous sensing systems and aerospace navigational instruments used in large aero planes is not applicable to be installed in small UAVs because of the size and budget limitations. As a result, various measures such as analysis redundancies should indeed be used to detect and boost the dependability of positioning instruments. Based on cognitive redundancies, this work provides a sensory fault diagnosis and diagnostic system for tiny unmanned drones. The defect is detected by comparingany significant change in the aircraft's behavior to the mistake performance, which is approximated with the help of an eyewitness. With the Extended Kalman filter Identification, the observation is derived from input-output observational data. Utilizing feedback experimental observations, the Kalman methodology may recognize the systems and an observers with qualities comparable to a Kalman filter and also provide an extra care with incorporating particle filter mechanism to minimize the noise in the equipment to the least value possible. The suggested technique yields comparable findings to the Kalman filter and in addition to particle filter, and there's no need to calculate systems matrix or sensors and processing noise covariance. The technology was solely tested with actual drones aircraft performance, and the findings were matched to those obtained using alternative methods.
Keywords: *Drone · Kalman Filter · UAV · Prediction . Particle Filter*

1 INTRODUCTION

Flying vehicles that are not operated by pilots like drones are rapidly increasing beingemployed in a variety of situations where ground pounders are unable to reach targeted places owing to terrain characteristics or the presence of impediments. Drones are always the vital methods to reach a target in order to acquire data or install equipment. Drones with fixed - wing aircraft serve as a framework and aircraft carriers with variousfeatures have indeed been suggested and tested. Drones have a lot of aerodynamic efficiency and can glide. They are also ideal for rapid target detection, as well as inspections and surveillance duties that necessitate maintaining a location and obtaining detailed analyses.

Additionally, in so many situations, drones or choppers with vertical/horizontal takeoff and landing are also beneficial. Drones that are remotely controlled are naturally unsteady and extremely quick. Even with enhanced stabilization advantages of this process, management of them is a difficult task since flying requires a knowledgeable, experienced driver [1][2]. The management of an autonomous drone involves a multivariate non - linear accessible unsustainable equilibrium with sensor saturation levels.

Furthermore, in the event of a malfunction, drones lack the elegant decline featuresof repaired planes or aeroplanes. As a result, any malfunction in the unmanned drone'ssensing, motors, process control, or other components can be deadly. As an outcome, itis critical for unmanned aircraft to watch their behaviour to identify and correct flaws when they cause serious accidents. Due of the restricted computational power available on drones, this surveillance must be effective. To identify problems in sensing devices,damage detection and extraction procedure have indeed been frequently utilized in theprocess industry [3]. If a fault is discovered, the operator's architecture can be altered toget the best possible system behavior, or the computer can be shut down. Self-driving vehicles such as autos, aeroplanes, tilt angle drones, polymorphic drones, underwater automobiles, and groups of co-operative UAVs have almost all used fault detection approaches.

All data about the network, particularly information about just the kinematics, couldbe used to observe the activity of the factory in the design of Fault detection method. The prevalence of defects is identified using what are known as royalties, or variables that are oversensitive to malfunction [4]. Residual generation can be done in a variety of ways, including parity formulas, observer-based production, and parameterization approaches. In prototype Fault detection, artificial neural and fuzzy sets are also used.The most often used approaches for detecting defects are peer regarding and parametersrange.

Spectator approaches are also used in the number of modern publications on fault detection systems for autonomous cars. The observation or filtration technique works by estimating the program's output from observations using either particle observers in a predictable situation or Kalman filtering in a probabilistic environment.

Regarding fault detection in automated driving, various techniques have been employed. On an Airbus A-380 mathematical model, neural pathways were employedto determine sensing and actuation failures. On a space program high-altitude unmanned vehicles simulation model and on airbus - A-380 actual flight data, a combination of Iterative methods and artificial neural were employed for sensors fault detection [5]. A bank of Iterative methods has indeed been applied to a linear and non-linear simulation model of a raptor adjustable unmanned for defect detection in aeroplanes. In unmanned drones, linear watchers have been employed to detect actuators faults. Nevertheless, there are limited findings in the research on defect detection for driverless drones. A machine - learning fault detection system is describedin the context of a programmable flight control structure for unmanned vehicles in the sources]. ARX models derived from flight data were also employed in thedevelopment of chopper actuators and sensors. Detecting flaws.

Optimal control detection is a period system for determining a system model and related observers from empirical data input concurrently. In the face of disturbance, the recognized observers cohere to an optimum viewer using the Kalman filter. The fundamental advantage of this strategy is that it does not need any previous knowledgeof these things, system matrix, or statistical evidence including such sensors or processes noise correlations. The kalman filter can calculate the state variables and theExtended kalman gains immediately from period data input, which makes it a useful tool in practice. The Kalman filter was originally designed to identify massive flexibleworkspace formations, but it has also been used to identify aviation systems [7][8]. Kalman filters are extensively incorporated when the data is linear in form and it is easy to predict the faulty whereas if we have equipment in the flight data where the equipment provides non linear data and Kalman filter might not give the exact ratio so we use the additional facility of particle filter to cover all round issues.

The Interactions Grid is a comparable idea which has been used to isolate faults in actuators and sensors defect detection in formations. The use of a system to diagnose sensing problems in an unmanned chopper is examined in this research. The kalman filter method was used to create the prototype. Trials with a self-driving chopper have indeed been carried out. Initial findings are reported. The remainder of the paper is laidout as follows: second part discusses smart connected drones. The kalman detection technique is introduced in this part too. The problem identification and isolation strategy is presented In other parts, the outcomes of applying these concepts to an autonomous drones are discussed. Finally, the results are discussed.

When given observational parameters, a particle filter aims to determine the probability density of the system parameters. When there are both concealed and visible factors in a system, as in a hidden Markov model, the particle filter is created.

2 LITERATURE SURVEY

In this section we have performed a comprehensive literature study of how various others have influenced this work in an accurate direction leading to a fruitful results.

The survey done by Sharim . H [3] has presented a efficient analysis of quadrator which is a kind of drone which, the author has presented a view on how the sensorsare aligned in a typical drone and how effective they're with reference to multiple environmental conditions and has presented some linear and non linear methods of how a drone functions in a real time scenario.

The research paper presented by the Chen, M in [1] has emphasized on how sensors behave universally in various unmanned vehicles mainly in the scope of water safety management, offshore patrol and maritime rescue, they have articulated on how coupling system can be utilized in the studies of drone and its mechanism. They have mainly focused on creating an unmanned vehicle in a more modernized manner which will be suitable to contemporary methods in getting the functionalities in hard terrain success.

In the paper presented by Abbaspour, in [7] a generalized approach of common faults and failures detected in sensors and actuators which are mainly responsible for degradation of the functionalities of the application wither a flying vehicle or a simple stationary electronic device is discussed. They have presented a study on fault tolerant and control systems, in the whole term of sensors, there might be various types of failures in sensors based on the facts of various parameters right from materials used toenvironmental conditions to impacts while the sensors are in action.

Miao, Q. [15] has presented an approach of studies in non linear approach of the unmanned vehicle mechanism and other ventures of the present vehicle fraternity. Thisauthor has presented the findings on non linear mechanism using Proportional integrity

for fault diagnosis. They have an observer who will be monitoring all the time in non-linear methods and shown that the upper bound of fault estimation using their algorithms.

The author D'Amato in [15] has presented a detailed research paper on sensorsin Unmanned aerial vehicles using fault detection and isolation in Duplex Altitude Estimation approach. They have considered linear based mechanism on basis of kinematic approach in the calculations of sensor failure systems.

3 MAIN OBJECTIVE

In this present world, we have seen a rapid advancement in the field of aviation. Five decades ago, there were hardly any planes in our country carrying citizens, there were only very few prestigious aeroplanes where people used to find it difficult to travel.If we have a view into this contemporary world, we observe that there are more than 10 lakh citizens travelling in aeroplanes. These aeroplanes have an eclectic source of sensors used, right from GPS to working of various parts of the aeroplane parts. Over the years, we have observed a lot of aeroplane crashes which are due to technical snags or malfunctioning of certain parts in the aeroplane.

It is quite alarming that the gravitas of the situation in aviation industry, we haveto improve the current trends in fault analysis and keep a diagnosis ready to handle theaeroplane faults. In a similar fashion, even drones are being used in various industries, right from military to delivering foods, we have many types of drones, manned, unmanned and drones which are suitable for various types of terrain and environmentalconditions. This work is giving a possible approach in finding the fault analysis in Unmanned vehicles referring to three different fault analysis and its detailed results.

4 EXPERIMENTAL DESIGN

4.1 Drones Mechanism

Numerous miniature unmanned drone prototypes have indeed been created at various research institutes throughout the world in recent decades. The prototypes are usually based on a conventional aircraft that has sensors, processors, and communications systems installed to it. In many situations, the aircraft is a standard model chopper (see Figure 1), such as the winfare, VAYUSEV, or GARUDA autonomous drones. The Ferrari FX spraying aircraft is sometimes used as an aircraft. With controlling and stabilisation, aeroplane autonomously flying require accurate position and aspect data. An inertial unit of measure with three gyros, three inertial measurement units, anda three-axis gyroscope for transformation function, a millimetre motion a detector for trying to measure

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the main rotor rpm, and an ultra - sonic or atmospheric pressure heightdetector for liftoff are among the detectors carried by highly autonomous airliners.

If a problem from one of the detectors goes unnoticed, it can cause position and altitude estimate inaccuracies. Within those circumstances, reconfiguring usually entails disconnecting the malfunctioning sensor and relying on the other sensors to determinethe best location and orientation prediction. The empirical data provided in this research

was collected using an aircraft based on a standard model aircraft (see Figure 2).Three gyro sensors, three inertial measurement units, and three piezo-electric inertial measurement units, as well as an ultrasonic range facing down and a Novatel RT-2 carrier phase differential GPS receiver, are used to determine location and inclination.

Fig. 1: Unmanned Chopper

Fig. 2: Unmanned High-tech Drone

4.2 Kalman Filter Method

For years, researchers have been studying the Median filtering problem. The modellingapproach, as well as the specific processes and noise covariance covariance, must be specified in order to calculate the Kalman filter gain [10]. A mathematical model approach can be used to build a parametric representation using feedback measurement results, either theoretically or empirically. Analyzing the reaction of the sensing devices can provide an estimate of the measurement noise covariance. Nevertheless, measurement device of the system noise covariance matrices is practically impossible, thus some assumption is needed. As a result, determining the particular process and measurements noise characteristics is challenging.

Systems uncertainty and output noise are included in the layer. However, their data is found in the program's data input as a whole. The Kalman median filter can generatean observers sensors that merges to the Kalman gain from data input immediately.

International Space program created the Kalman detection algorithm to model huge flexible workspace formations. In this part, an explanation of how kalman detection is used in practice is provided. The sources section contains a more detailed discussion ofthe procedure. Given that the genuine world processes is distorted by negligible whitenoise, the linearization method minimises the error in the observers, which also will converge to the real Kalman filter for the data set employed.

The linearization technique of structural analysis constructs a discrete realisation of the system using just data and information. Many developments on the underlying idea have been reported since its creation at ISS for the identification of gently spatial.The Kalman method of identifying has a number of advantages [9]. The key benefitis that the model may be constructed using simply input and output data, with no previous knowledge of the system required. Second, the kalman technique generates aquasi state estimate, which is particularly useful in process control. Finally, the systemsnodal balance realization ensures that termination mistakes are minimal. As a natural outcome, even though there is a model order mistake, the consequences will be limited.

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Algorithm 1 Kalman Filter Pseudo Code Initialization

Input: Sensor inputs – X_{in}, Y_{in}
Output: X and U outputs from sensors
1: Initialise the H matrix as per the parameters present2: Predicted state vector and covariance matrices
$X_{prd} = Fx_{estimated}$
$Y_{est} = FP_{est}F^T + Quality\ threshold\ Parameter$
3: Estimation
$S = H \quad P_{prod} \quad H^T \quad S^{-1} \quad * \quad * \quad *$
4: Calculation of Kalman Gain
$K_{prof} = P \quad H^T \quad *$
5: Presenting Outputs
$X_{Output} = X_{prod} + K_{Pro\ f} Y_{Output} = Y_{prod} + K_{pro\ f}$ **return** X_{output}, Y_{output}

Here in the above pseudo code, we have done the modifications to suit our Kalmanfilter fault analysis based on the Kprof parameters calculation and other steps as presented above to provide a perfect analysis

The standard state-space differential formula for an system is the initial step in implementing the kalman detection methodology to the experimental results.

$$W_{u+1} = EW_u + FL_k \quad (1)$$

$$Y_u = GY_u + HY_u \quad (2)$$

wherein u is the input image, x is the position vector, L is the position to generate, and u is the index time variables. If the system is assumed to start at zero and the inputare set to unit cost for one sampling at zero time, the system's unit pulse reaction is obtained by convolution of the equations.

The reaction goes back to the systems Stochastic characteristics if the input u is a unit wave at time zero. The generalised matrix is formed by assembling these systems factors into a specified form.

$$Y_k$$

$$Y_{k+1} \dots \; Y_{k+\beta-1} Y_{k+1} \quad Y_{k+2} \; \dots \qquad H \quad =$$

$$Y_{k+\beta}$$

$$k-1$$

$$\ddots$$

(3)

$$Y_{k+a-1} \; Y_{k+a} \dots \; Y_{k+a+\beta-2}$$

Since this Eigenvalue matrix can be deconstructed into the product of the quantitative measurements matrices, a transition probability matrices, and a manoeuvrability matrix in an interference scenario, the Eigenvalue structure will haveorder n, wherein n is the systems order [12]. However, interference will distort the Eigenvalue matrix's rank shortfall in actual data, therefore the Hankel matrix is alwayssystematically in order. As a result, the Eigenvalue matrix is shortened at an orderthat adequately represents the situation using principal component analysis. The least significant bits of the Eigenvalue matrices are displayed in practice, and the eigenvalues steadily decline until a sharp drop shows the models order. This sharp drop is a feature of the game's shift between genuine and noise mode.

In a balancing realisation, this shortened Hankel matrix is then utilised to recreate the trigonal A, B, and C. This realisation method identifies the aeroplane model, and arevised version of it that includes information correlations is employed. It is therefore able to ascertain the structure of the systems and construct a balancing effective model for management using the system Stochastic characteristics [15]. Nevertheless, in real - world systems, merely troubling the network with a step input will not yield the entirepulse reaction. A pulse with sufficient energy to stimulate all mode just above noise floor might saturate the actuator or cause it to respond nonlinearly. But, from a steady flow of continuous systems source and target behaviors, the game's pulse reaction may be recreated.

An asymptotic stability observers could be used to form a sustainable finite state model of a system instead of defining the structure stochastic variables, which may degrade extremely slowly [17]. The system's poles can be assigned freely, allowing for the specification of the rate of decay of the service's Stochastic variables with the observers, as well as the set of variables required until they have declined to an insignificant level.

4.3 Sensor Defect Prediction Technique

By tracking individual the sensing devices outcomes, the drone sensor fault diagnosissystem accomplishes the functions of defect identification and detection. These reflect

regular trends under normal incidence, within such

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a range set by the amount of uncertainties imposed by random system disturbances and collected from sensors error. Sensory Predictive control tasks are usually completed by watching when a damaged sensor's data detracts from its expected response.

A network of outputs estimation methods has indeed been constructed to identify problems in the chopper instruments, as shown in Figure 3. The overall number of estimation methods is the same as the total number of simultaneous outputs [13]. As a result, each component is controlled by a single output and all of the program's sources. A failure on the i^{th} feedback sensing solely impacts the function and quality of life of the output observers or filter powered by the i^{th} outcome in this scenario.

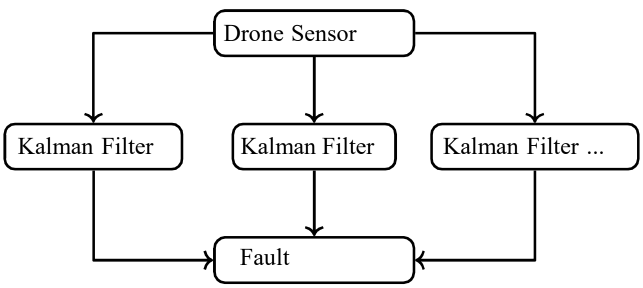

Fig. 3: Fault Detection In Drones

For each sensing, a residue is assessed by multiplying the estimate outcome to the sensing element. Because other sensors have no effect on the

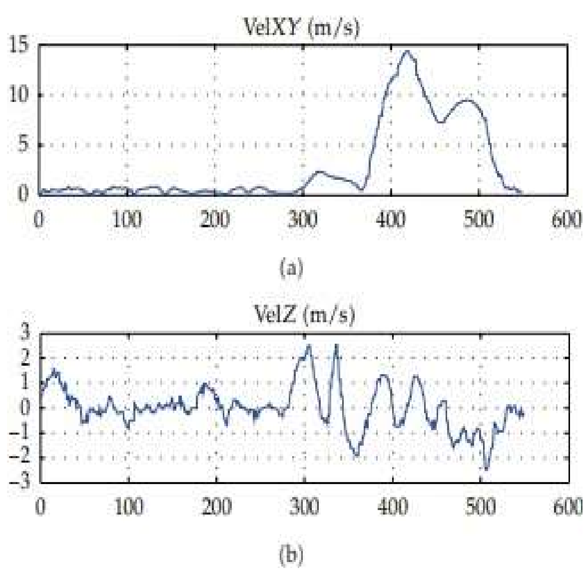

Fig. 4: Drone Velocities In The Experiment

residuals, defect detection is simple [14][15][16]; each resultant is only responsive to a single helicopter sensor. A failure in sensor k has been discovered if the residue rk exceeds the specified level. The Kalman filters developed using the kalman filter detection method were used to create this system with the above structure. The findings are reported in the section below.

4.4 Kalman Filters Technique for Drone Operation

Drones is made up of combination of mutliple outcome systems with multiple inputs and outputs that are nonlinearly linked. A modelling approach, on the other hand, can be adequate for many purposes when coping with unthreatening flight situations such as hover, updown [19], and the forward flights. Moreover, the models are used in fault detection to anticipate drone position and direction as well as sensor output in the nearterm.

In any event, for safety reasons in the studies, the identifying flight data does not cover the entire flight envelope. The planned Fault detection system must next verify that the flight circumstances were within parameters of some identifying factors.

Until one of these factors is beyond the prescribed range, the fault detection method will send a warning; however, whenever the flight parameters are within the selected limits, the fault detection method must verify the problem statement after the caution [28].

The drone velocity in the X - Y direction in global longitude and latitude Acceleration 15 m/s, the unmanned aerial vehicles acceleration in world coordinates Velocity 2 m/s, the unmanned aerial vehicles rotor position Pitch 20, and the unmanned aerial vehicles roll angle Roll ¿ 10 are the variables used to clarify the payload fairing covered by the identity information, as well as the limit values. Figure 4 depicts drone velocities in a typical identifying exercise.

In terms of practicality, an Fault detection system based on the linear observers iseasier to install on highly autonomous drones with minimal computational capacity[20]. Although the Defect detection algorithm has been validated with real droneexperimental data, linear watchers were employed in this article for fault identification. Sensory distortion and environmental disturbances are the principal sources of inaccuracy in aeroplane and drone modelling and control. The kalman formulationclearly accounts for noise power [21]. Air instability and gusty winds are the principalcauses of environmental disturbances, which are treated as process noise in the kalman approach. The kalman approach has the benefit of obtaining the parameter estimatesof these sensors and processes noises immediately in the kalman identification withouteven any interference. As a basic guideline in system identification, the only criterion is that the insight data be adequately representational of the dynamic systems.

4.5 Different Sensor failure types

Sensory devices in self-driving drones can malfunction in a variety of ways [30][31]. Some types of errors are common to all sensors, while others are unique to a single device. The below are the breakdown kinds which have been explored.

Recurrent output in all the situations In this type of failure, we can see the sensor always gives the same output for any given different input, this makes a huge problemin real time scenarios, with constant values of the output, it tends to break the system, this is mainly due to technical problem or any sync problem among various componentsin the system

Shift of a constant in the sensors This is a widespread problem which is witnessed inalmost every appliance due to environmental changes, there might be situations wheredue to a temperature change felt by the internal parts of the sensor, the output drifts with a constant added always, it tends to give wrong output which will be erroneous to consider.

Scaling error This is an error which is caused by an incorrect scaling mistake which gives wrong values due to internal computation of critical operations.

Dataset consideration for computation of the process A good diagnosis needs high flight information. The reliability of the estimated vehicle statuses and the availabilityof information of the aircraft performance, and whether the observations contain proofof the essential dynamic systems, are the significant concerns. The mechanism was identified utilising input-output data collected while piloting the drone in order to gather documentation of the pertinent motion control [29]. The only realistic way to gather these information is to use the aircraft for specific reason research. In these feedback control studies, a single pilot employed an input vector in one of the drone's inputs while keeping the other impulses practically steady. These feeds were minimally tweaked by the handling person to maintain stability if necessary. Here we consider a dataset of the same of a famous Drone flight information from the aviation control limited.

4.6 Additional Particle filter mechanism for drone system

The attitude estimate issue is solved using a particle filtering strategy that can handle non-Gaussian noise distribution and non-linear motion models. Results demonstrate how effective this strategy is. The SFDI method was tested using data from a tri-rotor flight platforms flight that included actual sensor disruptions from vibrations and changes in the magnetic field. Every inserted fault was accurately identified by the suggested method, even in difficult situations like gradual drifts and frozen failures. The suggested design doubles the amount of on-board sensors, hence increases network dependability. When compared to the industry standard triplex avionics design, this results in weight, cost, and power consumption reductions, but at the cost of decreased speed and accuracy.

5 RESULTS DISCUSSIONS

In this section, the results of MARVIN sensor FDI system using Kalman filters obtained with the OKID method are presented.

In this presented part, we provide an integrated denouements of a highly sensitive sensor which uses the application of fault detection utilizing Kalman Filters as the maintheme. Even during flight aviation control project's basic investigations, flight data wastaken from many experiments performed at the international airstrip. These tests were carried out in the summer, when the weather was around 40°C and there was little wind.The highly sensitive drone includes 8 sensors: three gyro sensors, two

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accelerometers, three Geolocation sensors. Since there are so many conceivable sensors and breakdownpairings, just a few example cases will be detailed in this subsection. For the providederror signal, the component of the gyro vertical speed sensor would be used as a stagingpoint of sensing fault diagnosis. These results have presented an outcome of a shift +3 than the results presented using particle filters and other methods.

5.1 Recurrent output in all the situations

The gyro sensor outcomes becomes locked with last actual output first before error occurs in this situation. Output sensor failure is also included in this class. A fault in the gyro-z sensors has been recreated in depicted graph of fig 5. The residue producedby that of the kalman filter estimator is illustrated in Fig 5a. Picture 5b shows howthe residue rises just above dotted straight axis shortly after the defect, indicating that the fault has been identified. The kalman fault detection method identified this typeof "severe" breakdown in all situations for all instruments, with really no wrongful convictions.

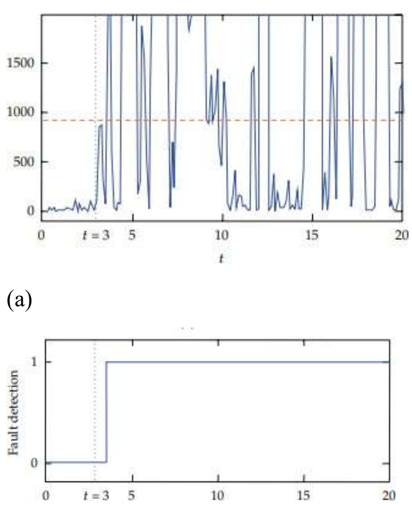

Fig. 5: Constant Bias Detection Overview

In table 1 below it shows the actual results which can be ovserved from the particle filter which adds on as a additional security cover to increase the reliance on the aircraft's life line and quality. The computing time is displayed while taking into account various particle counts. The findings are based on 100 algorithm iterations for each value

Table 1: Results Seen From Particle Filter

Number of Particles	Computation Time (s)	
	Average	Standard Deviation
1024	0.0138	0.0012
2048	0.0303	0.0022
4096	**0.0682**	**0.0030**
8192	0.1573	0.0050
16,384	0.3401	0.0071

5.2 Shift of a constant in the sensors

The outcomes of the defect detection of compound defects in rotating sensing elementare shown in Exhibits 6. A 4.5 C drift has already been introduced to Figure 6, and theremnant finds the problem quite quickly. At a 1.5 C drift was introduced to the sensingelement in Figure 5b. With the addition type sensors failures, a defect detection range investigation was conducted.

6 CONCLUSION

Due to unpreventable possible disasters, the employment of driverless drones, especially in civil purposes, necessitates the strengthening of protection and safety. In this environment, fault detection and isolation are critical. The kalman detection with additional feature of particle filter and particle filter approach was used to build a system for detecting sensor faults in helicopters. The suggested product's main advantage is that it eliminates the need to estimate all systemic matrix, as well as the measurement and process noise covariance matrices, because all of the knowledge is derived from actual data input. Experiments with an autonomous helicopter to capture input-output data in a variety of flight circumstanceshave been done. Several types of failure have been suggested. Breakdowns that are

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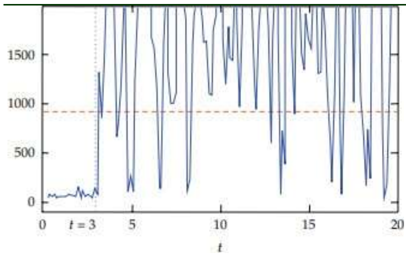
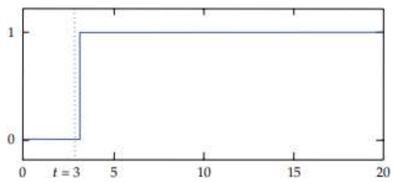


(a)



(b)

Fig. 6: Constant Shift With 3+ Degrees Celsius

”difficult” in a kalman detection fault warning system can simply identify nil or steady’s capabilities which will be further proceeded to particle filter to gain more errorless mechanis,. Sensor with additive or multiplicative error is recognized as ”gentle” failure, dependent on the error size. Errors that are too small could be differentiated from background noise. The findings of kalman detection and particle filter fault detection are compared with those obtained using the linear and non-linear observers.

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