Adaptive Kalman Filter Based on Evolutionary Algorithm and Fuzzy Interference System

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Abstract: This is a survey paper.The performance of the Kalman filter (KF), which is Algoritstandard as an outstanding implementation for dynamic system state estimation, greatly depends on its parameter R, called the measurement noise covariance matrix. . However, it's difficult to obtain the accurate value of R before the filter starts, and the value of R is possible to change with the measurement environment once the filter is working. To solve this difficulty, a new parameter adaptive Kalman filter is proposed in this paper. In this new Kalman filter, the initial value of R is offline determined by Evolutionary hm (EA), and the value of R determined by EA is online updated by Fuzzy Inference System (FIS). The new adaptive Kalman filter proposed in this paper (HYdGeFuzKF) has a stronger adaptableness to time-varying measurement noises than regular Kalman filter (RegularKF).

Key word; *-MSE, EA, FIS, KF.*

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I. INTRODUCTION

The Kalman filter is a famous optimal estimation scheme, fulfilling a mean square error performance. Kalman filter has been generally used for radar tracking and navigation systems. The Kalman filter estimation based on confident assumption about the system's mathematic model. These assumptions consist of the input and noise statistics. One of the key troubles related with Kalman filters are the statistical properties to both the dynamic and observation models.[1]

The Kalman filter works well in the situation that the a priori statistics of the stochastic error in both dynamic procedure and measurement models are assumed to be existing, which is very difficult in useful applications, gBenerally the measurement noise covariance R. First, it is not simple to obtain exact noise statistics data before the filter starts to work. And second, the noise statistics can alter with time when the filter is working. To resolve this problem, many adaptive mechanisms are used into Kalman filter, which is called Adaptive Kalman Filter (AKF). According to the filter outcome, adaptive Kalman filter be capable to optimize or estimate its noise statistics parameters a For tracking problems, rapid acceleration or deceleration and sudden change of directions are not easy to predict. Therefore, it is difficult to design a system with stable noise variance that will satisfy every situations. One of the general problems with tracking using Kalman filter is the so called overshooting problem. That is cause that the dynamic model keeps position estimation along with earlier trend while a vehicle in fact turns to another direction [3].
In current years, Evolutionary Algorithms (EA) and Fuzzy Inference System (FIS) have been effectively used in adaptive Kalman filter. In some of the earlier work on using evolutionary algorithms to optimize the primary values of the parameters of Kalman filter, but they did not consider that the initial values they obtained can alter when filter is working. In Some previous fuzzy inference system is used to change the parameters of Kalman filter in real time to meet the change of process and measurement noise, but they did not give any attention on how to choose the initial values of these parameters. However, the initial values of the parameters and their online adjustment are equally extremely important to the Kalman filter, especially the measurement noise covariance matrix R.[2]
So in this paper, we proposed a newest adaptive Kalman filter by combining evolutionary algorithm and fuzzy inference system. In this latest adaptive Kalman filter, we utilized the evolutionary algorithm to choose the initial value of parameter R. Furthermore, the fuzzy inference system is used to change the value of R with time based on the filter performance. The rest of this paper is organized as follows: Section 2 introduces the Kalman filter algorithm and its parameter adaptableness problem.Section 3 and Section 4 introduces Genetic Algorithum and Fuzzy interference system. the Section 5 introduces the new adaptive Kalman filter we proposed (HYdGeFuzKF) by combining EA and FIS.

II. KALMAN FILTER

A . Kalman Filter Algorithm

Kalman filter is one of the most well-liked algorithms in the control area. It is always been used to estimate the state of a dynamic system. The system model and measurement model for a simple linear discrete-time Kalman filter are represented as:

$$xk = \Phi xk-1 + \omega k \quad (1)$$
$$zk = Hxk + \nu k \quad (2)$$

wherever $xk \in Rn$ is the system state vector, $\omega k \in Rn$ is the system noise vector, $zk \in Rm$ is the measurement vector to system state, as well as $\nu k \in Rm$ is the measurement noise vector. Φ is the state transition matrix, which reflects the mathematical or physical relationship between system state xk and xk−1. H is the measurement matrix, which represent the relationship among the measurement zk and system state

xk. The vector ωk and vk are mutually white noise sequences with zero means and mutually independent:
wherever non-negative definite matrix Q is the system noise covariance matrix, positive definite matrix R is the measurement noise covariance matrix, E[•] represents expectation, and superscript "T" denotes matrix transpose. The idea of Kalman filter is to estimate the actual value of xk in equation (1). the key five equations of discrete-time Kalman filter is summarized as follows:

ˆ x− k = Φˆ (3)

P− k =ΦPk−1ΦT + Q; (4)

Kk = P− k HT (HP− k HT + R)−1; (5)

ˆ xk =ˆ x− k + Kk(zk − Hˆ x− k); (6)

Pk =(I − KkH)P− k . (7)

In the beyond equations, ˆ xk is the estimation value of the system state xk, Pk is the error covariance matrix defined by E[(xk − ˆ xk)(xk − ˆ xk)T], and weighting matrix Kk is the Kalman gain matrix. The Kalman filter algorithm starts with an initial condition value x0 and P0. Equations (3)-(4) are the time update equations of Kalman filter from step k-1 to k. These equations generate a prioriestimation of system state at step k. Equations (5)-(7) are the measurement update equations of the algorithm. They incorporate the measurement value zk into a priori estimation to get a better posteriori estimation, which is the output of Kalman filter at step k. The procedure of Kalman filter algorithm is showed by Algorithm 1.[2]

Algorithm 1 Kalman Filter

Set the parameters Φ, H, Q and R;
Initialize the ˆ x0, P0, k = 1;
while (need to estimate the system state) do

Time Update:
ˆ x− k = Φˆ xk−1;
P− k =ΦPk−1ΦT + Q;
Get the measurement zk;

Measurement Update:
Kk = P− k HT (HP− k HT + R)−1;
ˆ xk =ˆ x− k + Kk(zk − Hˆ x− k);
Pk =(I − KkH)P− k ;
k = k +1 ;
end while

B Problem of Kalman Filter in Parameter Estimation

Kalman filter is a exceptionally powerful technique to estimate the system state. But it only works fine in the condition that the parameters Φ, H, Q and R in the equations (3)-(7) are accurately known. incorrect value of these parameters will decrease the filtering accuracy, raise the filtering error, and even cause filter divergence. Generally, we can get the Φ and H by building accurate arrangement and measurement models, and the rate of Q is constant in a given system in the majority cases. The most difficult, and also essential is to obtain the value of R, because of its variability.

- First there is no direct way to estimate its value.
- Second, its value will vary with time.

For case in the navigation system, one very significant application of Kalman filter, once the external environment of the target which is being navigated has altered, the value of R will change instantly. So in this HYdGeFuzKF we proposed, evolutionary algorithm and fuzzy inference system is use to estimate the value of R, both before the filter starts to work and when it is working.

III. GENETIC ALGORITHUM

Genetic algorithms (GAs) are great and generally applicable stochastic search and optimization methods based on the concepts of natural choice and natural evaluation. GAs are applied to those problems which either cannot be formulated in accurate and correct mathematical forms and possibly will include noisy or asymmetrical data or it takes consequently much time to solve or it is basically impossible to solve by the conventional computational methods. Genetic algorithms were initially invented by John Holland in 1960s and be developed by Holland and his students and colleagues at the academy of Michigan in the 1960s and the 1970s . GA shows large guarantee in complex domains because it work in an iterative development manner. The search performed by it is probabilistically strenuous towards regions of the given data set that have been found to create a good arrangement performance. GAs work on a population of those represent candidate solutions to the optimization difficulty. These individuals consist of strings (called chromosomes) of genes. The genes are a helpful allele (gene might be a bit, an integer number, a real value or an alphabet character etc depending on the nature of the complexity). GAs apply the ideology of survival of the fitness, selection, reproduction, crossover (recombining), and mutation on these individuals to obtain, hopefully, a new butter individuals (new solutions). GA has been shown to be an helpful strategy in the off- line design of several fields. In this paper, GA has been used to present an adaptive decision algorithm for determining the optimum parameter of process noise covariance R of the Kalman filter. [4]

Genetic Algorithm (GA) GA searches in global search space to select the individual with greatest fitness for the given fitness function. In the process of search it first initializes a generation of individuals called as chromosomes arbitrarily and applies crossover and mutation operations by selecting individuals randomly. Then it calculates the fitness of every chromosome and the chromosomes with finest fitness are transferred to next generation and the crossover and mutation process repeats for numeral of generations .[5]

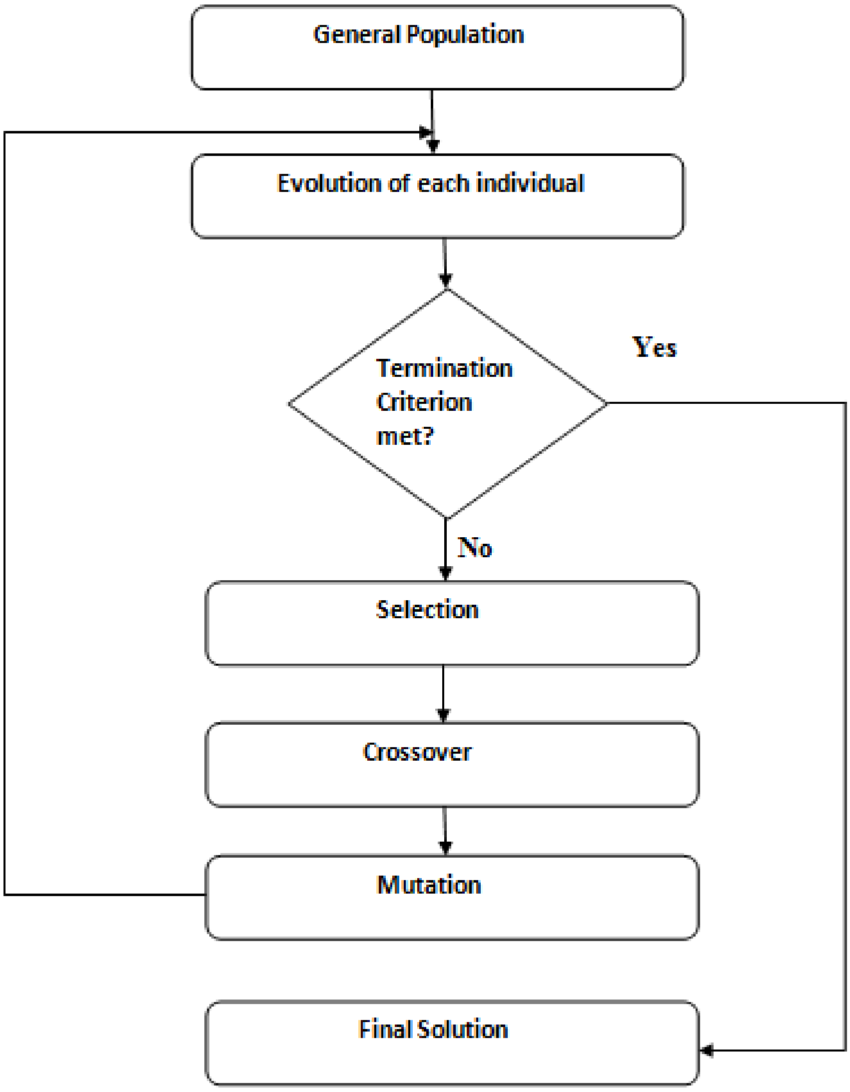

Figure 1 Flow Chart Of Genetic Algorithm

4) FUZZY INTERFERENCE SYSTEM

Fuzzy Inference Systems (FIS) can be used to approximate directly any nonlinear input– output mapping by way of a series of if–then rules . In the design of FIS, here are two major tasks, viz., the structure identification and the parameter adjustment. Structure identification determines the input–output space separation ,antecedent and consequent variables of if–then rules, number of such set of laws ,and initial positions of membership functions. The second task of parameter adjustment involves realizing the parameters for the fuzzy system arrangement determined in the previous step .[6]

Fuzzy logic was first developed by Zadeh in the mid- 1960s for representing uncertain and inaccurate information. It provides an approximate but useful means of describing the behaviour of systems that are more complex, ill-defined, or not simply analyzed mathematically. A usual fuzzy system consists of three components, that is, fuzzification, fuzzy reasoning (fuzzy inference), and fuzzy defuzzification. The fuzzification process converts a crisp input value to a fuzzy value, the fuzzy inference is answerable for drawing calculations from the information base, and the fuzzy defuzzification procedure converts the fuzzy actions into a crisp action. The application of fuzzy logic to adaptive Kalman filtering has been becoming well-liked. Introduced the Fuzzy Logic Adaptive System (FLAS) for adapting the course and measurement noise covariance matrices in navigation data fusion plan.[7]

The FKF is an extension of the discrete time Kalman filter arrangement, in which Fuzzy Subsystem calculate a scalar adaptation factor k α . This k α is used to scale the unvarying process noise covariance matrix R and gives a latest adapted process noise covariance matrix at each time step. The performance of discrete time Kalman filter improves when the adapted process noise covariance matrix is used for estimating the states as a substitute of the constant process noise covariance matrix. [8]

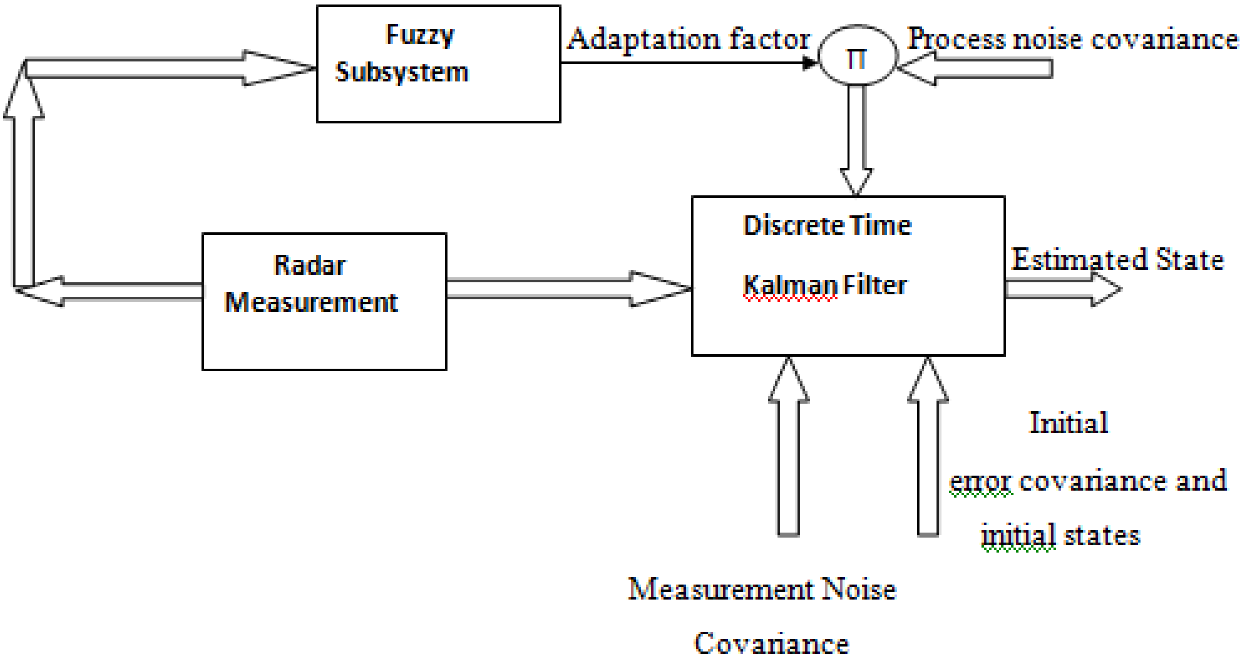

Figure 2 block diagram of fuzzy kalman filter

PROPOSED METHEDOLOGY:

THE NEW ADAPTIVE KALMAN FILTER ALGORITHM: HYdGEFUZKF

In the HYdGeFuzKF proposed in this paper, the primary value of the measurement noise covariance matrix R is optimized offline by genetic algorithm, and the optimal value obtained by genetic algorithm is adjusted online by fuzzy inference system. A. Offline Optimization of R by Genetic Algorithm (GA), a very popular branch of evolutionary algorithm.

There are basically two steps:

1) Offline Optimization of R by Genetic Algorithm.
2) Online Adjustment of R by Fuzzy interference system.

We comparing the performance of the kalman filter and proposed Adaptive kalman filter using genetic algorithm and fuzzy interference system , error will reduced when we use proposed Adaptive kalman filter HYdGeFuzKF as compare to Kalman filter.By using the results of both the filters we calulating the improvement factor and see that the new adaptive Kalman filter proposed in this paper (HYdGeFuzKF) has a stronger adaptableness to time-varying measurement noises than regular Kalman filter (RegularKF**).**

The initial rate of parameter R was unknown, and its value changed no of times in the tracking process. To solve this problem, HYdGeFuzKF got the primary optimal value by genetic algorithm at first, and then reserved adjusting this best value in real-time using fuzzy inference system. The mixture of GA and FIS is the motive why HYdGeFuzKF get the superior results than another Kalman filter algorithms.

EXPECTED OUTCOME:

In the simulation based on target tracking, the primary value of parameter R was unknown, and its rate changed four times in the tracking procedure. To solve this difficulty, HydGeFuzKF got the initial best value by genetic algorithm at first, and then kept adjust this optimal value in real-time using fuzzy inference system. The combination of GA and FIS is the reason why HydGeFuzKF got the better results than a further Kalman filter algorithms.

CONCLUSION:

In this survey paper, a latest adaptive Kalman filter by combining genetic algorithm and fuzzy inference system, specifically HYdGeFuzKF is discussed. In this new algorithm, the initial value of the measurement noise covariance matrix R is determined offline by genetic algorithm, and the finest initial value of R is adjusted online by fuzzy inference system to meet the unpredictable measurement noise. expected results indicate that the new filter algorithm we designed has additional capabilities to reduce the filtering error. It has numerous potentials in practical applications.

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