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Modified Human Opinion Dynamic for Improved Tuning of Particle Filter

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ABSTRACT: Though many of the engineering problems can approximated as linear to some extent, the ground truth is that in reality there exist no perfectly linear systems. Though the assumptions of approximating systems as linear can be valid in certain cases, it may not be provide acceptable performance in many real world applications. The selection of an appropriate process and measurement noise co-variance value for a given system has a significant effect on system's performance, and needs to be tuned correctly. To tune the EKF implemented for the permanent magnet synchronous motor model for indirect measurement of pole position and rotor speed has been taken from the works of as discussed ab-initio. The proposed MGSA based methodology is shown to outperform PSO and HOD in few aspects like convergence time and ease of tuning while steady state error values of both the methodologies are found to be almost comparable.

KEYWORD: ***EKF, PSO, HOD, CODO***

I. INTRODUCTION

Kalman Filter has become one of the basic tools for most of the state estimation problems. In its most basic form as developed in 1960 by [1], it is for discrete time systems where we have a process which follows its dynamics in time domain and then we have a measurement which is used to correct the estimated obtained from the propagation of the process. A simple discrete time Kalman filter can be understood by the following flowchart. Though many of the engineering problems can approximated as linear to some extent, the ground truth is that in reality there exist no perfectly linear systems [2]. For example, even a simple resistor follows linear Ohm's law only upto a certain range. Though the assumptions of approximating systems as linear can be valid in certain cases, it may not be provide acceptable performance in many real world applications. Hence there is a high demand of non-linear estimators for many engineering applications [3].

Since the model is highly non-linear, Extended Kalman Filter (EKF) is developed to deal with the non-linearity. Another problem of EKF is that it needs to be correctly tuned for its noise covariance matrices and initial estimated error covariance matrices. In this work, a novel tuning method is proposed and implemented using Human Opinion Dynamics (HOD) based Optimization. For comparison of results, a Particle Swarm Optimization is utilized by converting the tuning problem of EKF into an optimization problem. The following algorithm is implemented and tested for synchronous motor problem. Furthermore, some modifications based on certain assumptions are also proposed for the HOD reported in literature to solve certain problems in the existing state of art and improve its performance suited for some particular applications.

II. RELATED WORK

The selection of an appropriate process and measurement noise co-variance value for a given system has a significant effect on system's performance, and needs to be tuned correctly [4]. Measurement noise co-variance matrix can though be roughly estimated from the error statistics of the sensors with a non-linear error factor, process noise is mostly unknown due to the non-observability of system states. Noise co-variance matrix tuning can either be made off-line or on-line. Recent growth of various evolutionary algorithms has opened up a new area of research for optimization of tuning parameters. In [5] the tuning of EKF has been carried out using Genetic Algorithm (GA). This methodology is an iterative process of mimicking the natural selection and natural genetics, and consists of three stages comprising of selection, crossover and mutation. However, it suffers from some inherent limitation as described in [6]. Furthermore, Particle Swarm Optimization (PSO) technique has been utilized for the tuning of EKF in [7]. PSO is an evolutionary algorithm based on social metaphor that aims to find an optimal solution, and is inspired by the food search methodology of a flock of bird [8]. Particle Swarm Optimization (PSO) is population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling in searching for food [9,10].

III. PROPOSED METHODOLOGY

To tune the EKF implemented for the permanent magnet synchronous motor model for indirect measurement of pole position and rotor speed has been taken from the works of as discussed ab-initio. The process model dynamics for the system is described by the following equations:

$$\dot{i_a} = \frac{-R}{L} i_a + \frac{\omega\lambda}{L} sin\theta + \frac{v_a + w_1}{L}$$
$$\dot{i_b} = \frac{-R}{L} i_b + \frac{\omega\lambda}{L} cos\theta + \frac{v_b + w_2}{L}$$
$$\dot{\omega} = \frac{-3\lambda}{2J} i_a sin\theta + \frac{3\lambda}{2J} i_b cos\theta - \frac{B\omega}{J} + w_3$$
$$\dot{\theta} = \omega$$

A Modified Gravitational Search Algorithm is to be formed and an optimization algorithm is to be formed using the model. The EKF is to be tuned for optimal values of Q and R using this model. Also, the same EKF is to be tuned with Particle Swarm Optimization (PSO) and the results are to be compared on the basis of convergence rate, accuracy, and robustness.

A. *Human Opinion Dynamics Model:*

Modelling human behavior has been an interesting area of research for quite a time now and a lot of theories have been put forward to emulate the real life dynamics into a mathematical model. HOD is one such recent area which has been recently claimed to solve complex optimization problem. Opinions are influenced by the opinions of its neighbors depending on their social influence which is defined here as the ratio of social rank of any individual to the distance between them and is given by:

$$w_{ij} = \frac{SR_j(t)}{d_{ij}(t)}.$$

Here, SR is determined by the inverse of the fitness value of an individual, where fitness value is the error which needs to be minimized. Each individual's opinion is updated by the following rule given as:

$$\Delta o_i = \frac{\sum_{j=1}^{N} (o_j(t) - o_i(t)) w_{ij}(t)}{\sum_{j=1}^{N} w_{ij}(t)} + \eta_i(t),\ j \neq i,$$

Where $o_j(t)$ is the opinion of neighbours of individual i, $w_{ij}$is the social influence factor, and η is adaptive noise introduced to justify individualization in society after a certain consensus limit is reached.

Algorithm: MHOD based EKF Tuning

Begin
Initialize opinions for measurement and control noise
Allocate measurement and control noise to opinion1 and opinion2
n: number of solutions
lp: number of loops
np: number of opinons *d: the domain space*
f(x):objective function as a function of estimation error
Define the objective function of f(x), where $x=(x_1,\dots\dots,x_d)$
Generate the initial population of opinions or x_i $(i=1,2,\dots,n)$
While *(i<lp)*
For *j=1 to np (all opinions)*
Allocate measurement and control noise
Apply EKF
Calculate Estimation error
Formulate cost function
Calculate Social Score based on cost function using MLE
End for
Store best individual to bfn
For *j=1 to np (all opinions)*
For *k=1 to np (for all opinions)*
If *k not equal to j*
Calculate social influence w_{jk}
End if
End for
Calculate adaptive noise standard deviation
If *j not equal to bfn*
Update opinions using discussed equation
Convert opinions
End if

If *error<threshold*
Break out of loop
End if
End while
End procedure

A new hybrid population-based algorithm (MGSA) is proposed with the combination of Modified Gravitational Search Algorithm (GSA). The main idea is to combine the exploitation ability of MHOD with the exploration capability in GSA to synthesize both algorithms' strength. The optimal DG placement and sizing problem is used to compare the hybrid algorithm with both the standard MHOD and GSA algorithms in evolving best solution.

The hybridization of two algorithms can be done in high-level or low-level having a relay or co- evolutionary method approach. They can be either homogeneous or heterogeneous. In this thesis, we hybridize MHOD with GSA using low-level co-evolutionary approach which is also heterogeneous. The reason for the hybrid to be low-level can be attributed to the fact that the functionality of both algorithms has been combined. But the co-evolutionary approach is used since both algorithms are used one after another. i.e. they both run in parallel. It is heterogeneous because there are two different algorithms that are involved to produce final results. The basic idea of MGSA is to combine the ability of social thinking in MHOD with the local search capability of GSA.

In MGSA, at first, all opinions are randomly initialized. Each opinion is considered as a candidate solution. After initialization, Gravitational force, gravitational constant, and resultant forces among opinions are calculated respectively. After that, the accelerations of particles are defined. The social ranks of agents are considered which is calculated on the basis of mass of each agent. This rank is utilized for weighting the updation of each agent according to the formula given by gravitational search algorithm. Thus the local search capability of GSA and social influence of MHOD are utilized and the results are compared.

Algorithm: MGSA based EKF Tuning

Begin
Initialize opinions for size and bus numbers
Allocate size and bus number to opinion1 and opinion2
n: number of objects
l: number of solutions
lp: number of loops
np: number of particles *d: the domain space*
f(x):objective function as a function of voltage and losses
Define the objective function of f(x), where $x=(x_1,........,x_d)$
Generate the initial population of particles or x_i $(i=1,2 ,..., n)$
While *(i<lp)*
For *j=1 to np (all opinions)*
Allocate control and measurement noise
Apply EKF
Calculate fitness function as estimation error
Formulate cost function
Calculate the fitness corresponding to each object and use objects distance asfitness
Convert Social Rank into Social Score based on cost function using MLE
End for
Store best individual to bfn
For *j=1 to np (all iterations)*
For *k=1 to np (for all objects)*
If *k not equal to j*
Calculate attraction
End if
End for
Use Social influence as force between the particles and calculate force between each pair
Calculate acceleration using Force/mass
Calculate velocity and position
Calculate adaptive noise standard deviation
If *j not equal to bfn*
Update position of each particles using discussed equation
Convert objects of control and measurement noise to tuning parameters
End if
If *error<threshold*
Break out of loop
End if
End while
End procedure

IV. Simulation Results and Discussion

All simulations were done in MATLAB R 2015b. The results of our modified algorithm are shown below.

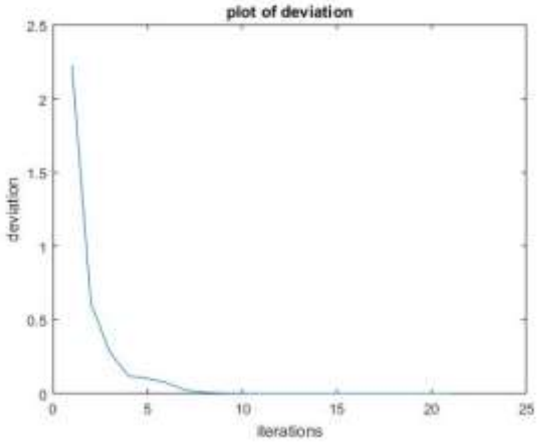

Figure 1: Standard deviation of particle 1

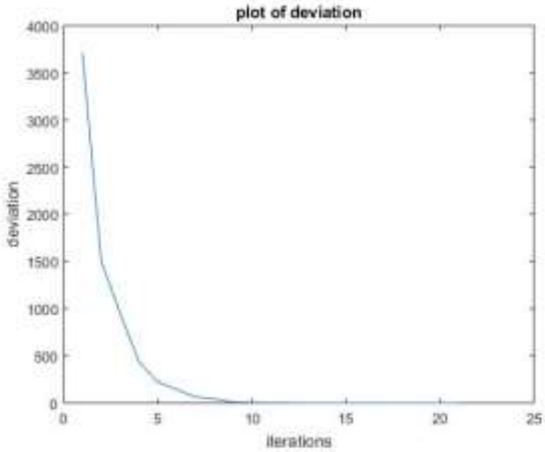

Figure 2: Standard Deviation of particle 2

Figure 1 and 2 represents plot of standard deviation of the particles 1 and 2. As shown the particles converges after some time.

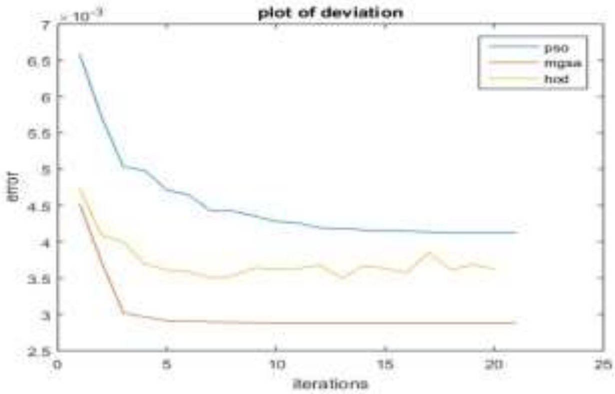

Figure 3: Error comparison

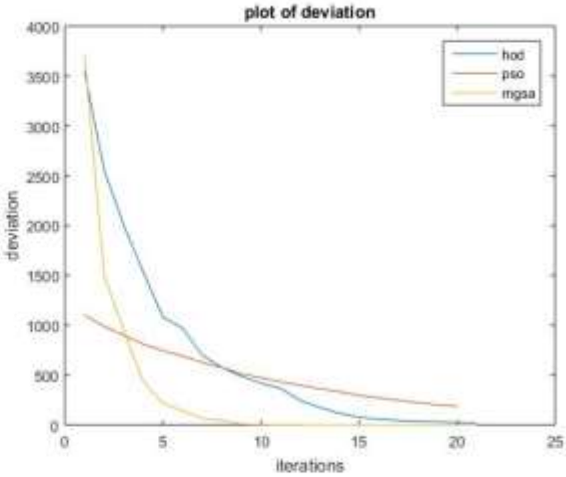

Figure 4: Comparison of deviation of particle 1

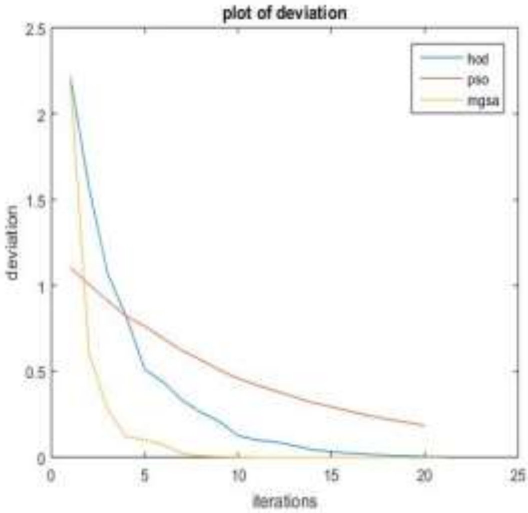

Figure 5: Comparison of deviation of particle 2

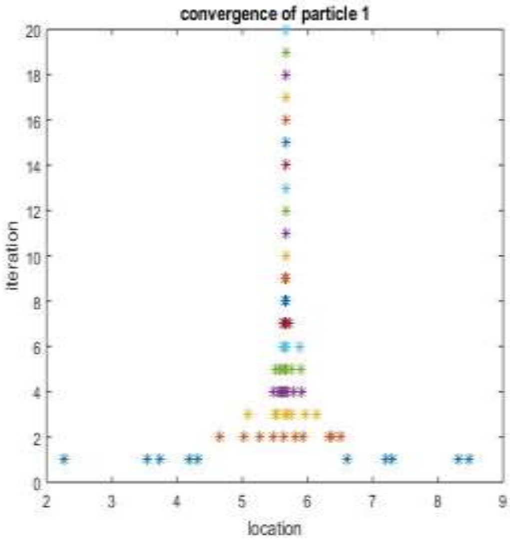

Figure 6: Convergence of particle 1

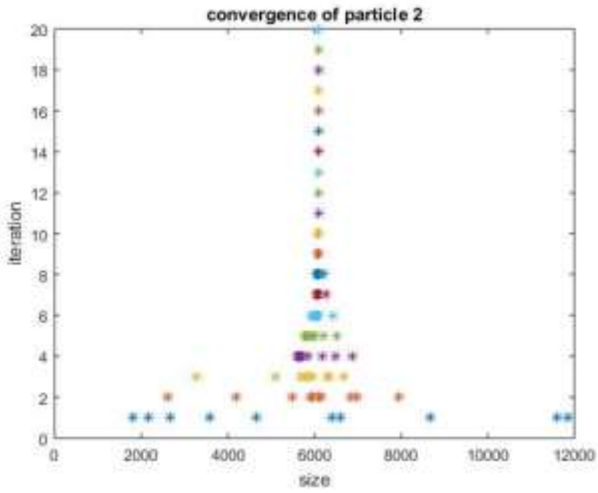

Figure 7: Comparison of particle 2

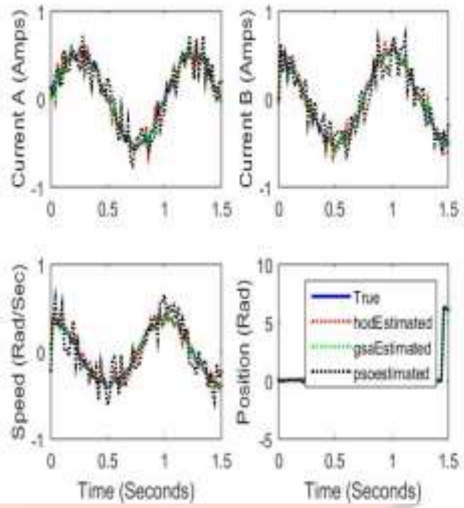

Figure 8: Results comparison of all methods

V. CONCLUSION

The proposed MGSA based methodology is shown to outperform PSO and HOD in few aspects like convergence time and ease of tuning while steady state error values of both the methodologies are found to be almost comparable. Few minor adjustments were done in the existing models of opinion dynamics which were justified and shown to yield better results.

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