

A New Optimal Fuzzy Logic Guidance Law using Time Variant Particle Swarm Optimization

Labeed Hassan

Department of Aerospace Engineering
Malek Ashtar University
Islamic Republic of Iran

Seyed Hossein Sadati

Space Research Institute
Islamic Republic of Iran

Mohamad Bagher Malaeak

Department of Aerospace Engineering
Sharif University
Islamic Republic of Iran

Mohamad Ali Ashtiani

Department of Aerospace Engineering
Malek Ashtar University
Islamic Republic of Iran

Jalal Karimi

Department of Aerospace Engineering
Malek Ashtar University
Islamic Republic of Iran

ABSTRACT

New Optimal Fuzzy Logic Guidance (NOFLG) law for the class of surface to air homing missile is proposed. The introduced approach is a modification of Optimal Fuzzy Logic Guidance (OFLG) law. Time Variant Particle Swarm Optimization (TVPSO) is used to optimize both Membership Functions (MFs) and rules' weights of the proposed design. The performance of the new guidance law is compared with that of OFLG one. Different case-studies show that the current approach provides better performance in regard to; miss distance, flight time and control effort.

Keywords

Fuzzy Logic, Time Variant Particle Swarm Optimization, Proportional Navigation Guidance.

1. INTRODUCTION

Most guidance laws used in current missiles are mainly based on classical control techniques [1, 2]. These techniques, although they are efficient in many cases, might not be effective for tracking and interception of maneuvering targets. In addition, there are a perfect knowledge of system requirement and a large computational one. Fuzzy Logic Controllers (FLCs) have number of suitable properties that diminish such difficulties, therefore, they have been used in many fields where plants exhibit uncertainties or we lack a rigorous model to describe their behavior. On the other hand, most fuzzy guidance laws are fuzzy-logic implementation of existing well-known classical guidance laws; such as, Proportional Navigation Guidance (PNG) that is because of its simplicity, effectiveness and ease of implementation [3].

In fact, tuning the parameters of FLCs is time consuming and frustrating exercise. Particle Swarm Optimization (PSO) is considered suitable technique to overcome these difficulties because of its simplicity. PSO which is first developed by Kennedy and Eberhart [4] is a population based stochastic optimization technique was inspired by social behavior patterns of organisms that live and interact within large groups as flocks of birds, schools of fish, or swarms of bees. It is one of the modern heuristic algorithms that was developed through simulation of a simplified social system, and has been found to be robust in solving complex optimization system.

In the current study, a new version of PSO that so-called Time Variant Particle Swarm Optimization TVPSP [5] will be used to investigate the NOFLG law. The investigated design will

be compared with OFLG that had been introduced in our previous study [6].

The paper is organized as follows: an overview on the pre-introduced OFLG law is briefed in Section 2. The basic PSO and TVPSO are explained in Section 3. The optimization process is discussed in Section 4. In Section 5 results and analysis are provided. Conclusions are then provided in Section 6.

2. BRIEF OVERVIEW ON OFLG LAW

The pre-introduced OFLG has been built upon the conception of PNG law. The PNG law gives commanded acceleration A_c , on its output, proportional to its two inputs; $\dot{\lambda}$ (angle rate of the instantaneous line-of-sight) and V_c (target-missile closing velocity). Mathematically it can be expressed as:

$$A_c = NV_c \dot{\lambda} \quad (1)$$

Where; N is navigation constant defined by the designer.

In our previous study, the OFLG has 49 rules with optimized triangular MFs and non-optimized weights. Each rule has weight equals 1. The rules were tabulated as plotted in Figure 1:

A_c	$\dot{\lambda}$							Numbering of the rules
	LP	MP	SP	ZE	SN	MN	LN	
LP	LP	MP	SP	ZE	SN	MN	LN	1, 2, 3, ... 7
MP	MP	MP	SP	ZE	SN	MN	MN	8, 9, 10, ... 14
SP	SP	SP	SP	ZE	SN	SN	SN	...
ZE	ZE	ZE	ZE	ZE	ZE	ZE	ZE	...
SN	SN	SN	SN	ZE	SP	SP	SP	...
MN	MN	MN	SN	ZE	SP	MP	MP	...
LN	LN	MN	SN	ZE	SP	MP	LP	43, 44, ... 49

Fig. 1: Entire Rules of OFLG

In the current work, the same rules will be used. The parameters of the MFs and the weights of the rules will be optimized using TVPSO.

3. TVPSO

In the PSO every individual i of the swarm contains parameters for position x_i and velocity v_i . The new position

of each particle is calculated by adding a velocity to the current position.
In particular, the velocity associated with each particle is calculated as [7]:

$$v_i(k+1) = wv_i(k) + c_1 \cdot r_1(k) (x_i^g - x_i(k)) + c_2 \cdot r_2(k) (x_i^p - x_i(k)) \quad (2)$$

Where;

w - Inertia weight factor.

$v_i(k)$ - Velocity of the particle i at time step k .

x_i^g - Global best performing particle up to time step k .

x_i^p - Personal best performing particle up to time step k .

$x_i(k)$ - Current location of particle i .

c_1, c_2 - Constants usually equal each to other.

r_1, r_2 - Random numbers within $[0, 1]$ those represent random fiction.

To limit the searching space $v_i(k+1)$ is limited to be within a certain range of $v_{imin} \leq v_i \leq v_{imax}$. The new location of the particle i can be calculated as:

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (3)$$

The following Figure illustrates how updating of the particle position is achieved according to the PSO's Equations.

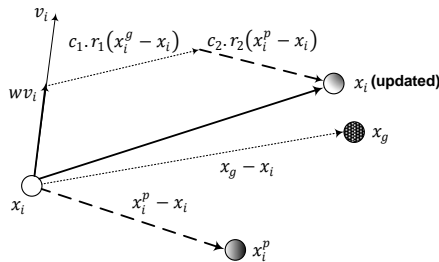


Fig. 2: Visualizing PSO.

In the TVPSO, the vital parameters; inertia weight w and acceleration coefficients c_1, c_2 , are allowed to be changed with iterations it , making it capable of effectively handling optimization problems of different characteristics. Here, the parameters; w, c_1 and c_2 are renamed as; w_{it}, c_{1it} and c_{2it} respectively.

The inertia weight w_{it} controls the influence of the current velocity on the new velocity. A large inertia weight compels large exploration through the search space; a smaller inertia weight causes reduced exploration. The value of w_{it} is allowed to decrease linearly with iteration from w_{max} to w_{min} as:

$$w_{it} = (w_{max} - w_{min}) \frac{I-it}{I} + w_{min} \quad (4)$$

Where; I - Maximum number of iterations.

The parameters c_{1it} and c_{2it} , are called cognitive acceleration coefficient and social acceleration coefficient respectively. The acceleration limits the trajectory of the particle oscillation. The smaller the acceleration, the smoother the trajectory of the particle is. However, too small acceleration may lead to slow convergence, whereas too large acceleration drives the particles towards infinity.

To incorporate better compromise between the exploration and exploitation of the search space in the swarm, c_{1it} has been allowed to decrease from its initial value of c_{1max} to c_{1min} while c_{2it} has been increased from c_{2max} to c_{2min} as follows:

$$c_{1it} = (c_{1max} - c_{1min}) \frac{it}{I} + c_{1min} \quad (5)$$

$$c_{2it} = (c_{2max} - c_{2min}) \frac{it}{I} + c_{2max} \quad (6)$$

The flowchart of the TVPSO is shown in as the following:

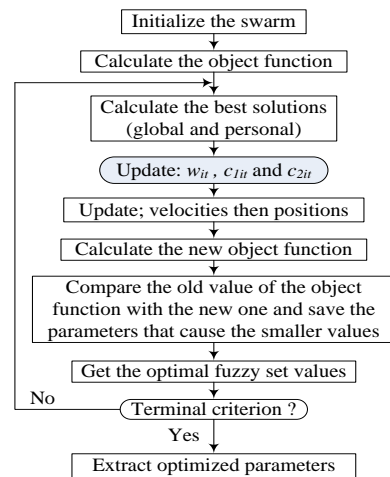


Fig. 3: Flowchart of TVPSO.

The swarm is initialized randomly and the object function is calculated. The algorithm updates the particle's velocity and adds the new velocity to the old position to calculate the new position. The updating of the velocity is influenced by both x_i^g , the best global solution associated with the lowest cost (objective function) ever found by a particle, and x_i^p , the best local solution associated with the lowest cost in the present population. The solution x_i^p is replaced with x_i^g when it causes less cost than the x_i^g does. The algorithm continues updating the velocities and adds them to the corresponding positions to evaluate the objective function until a termination criterion, such as a limit on the number of iterations or satisfactory results, is reached, thereupon the process is stopped.

4. OPTIMIZATION PROCESS

The population is set to be $P = 100$ particles and the total searching iteration is set to be $I = 500$. As suggested in [5] the following values are used throughout the optimization process:

$w_{max} = 0.7, w_{min} = 0.4, c_{1max} = c_{2max} = 2.5, c_{1min} = c_{2min} = 0.5$. The object function $F(A_{par})$ is defined as follows:

$$F(A_{par}) = k_1 \cdot \int_0^{t_f} A_c^2 dt + k_2 \cdot R_{TM}(F_t) + k_3 F_t \quad (7)$$

The first term denotes the control effort C_{Eff} while the last two ones denote the miss distance M_D and flight time F_t . Where: A_{par} is an array that includes the parameters needed

to be optimized, R_{TM} is the target-missile relative distance, whilst k_1, k_2 and k_3 are constants those referring to the terms' preference. In the current study, it supposed that all the terms have same importance, so that $k_1 = 1/C_{Eff_{max}}$, $k_2 = 1/R_{TM}(F_t)_{max}$, and $k_3 = 1/F_{t_{max}}$, where $C_{Eff_{max}}$, $R_{TM}(F_t)_{max}$ and $F_{t_{max}}$ are the maximum allowable values of the terms defined by the designer regard to the missile's ability.

The flowing figure illustrates the overall process which is built using *MatLab* environment:

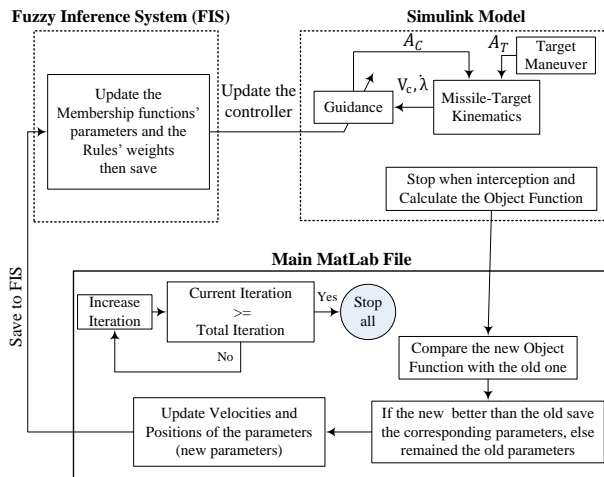


Fig. 4: The flow chart of overall process.

During the optimization process, the value's decrement of the object function can be noted as shown in Figure 5. Also it can be seen that, the searching can be terminated after about 400 iterations when there is no reduction was observed.

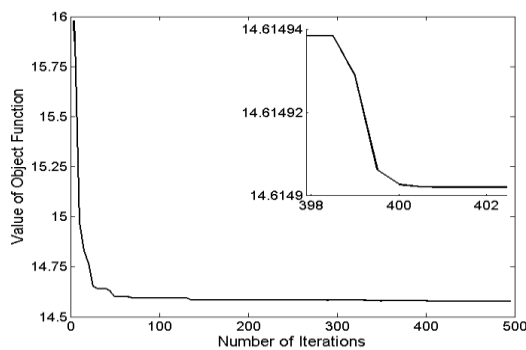


Fig. 5: The value of the object function.

As soon as the process is completed, the optimized parameters of the inputs $\dot{\lambda}, V_c$ and the output A_c can be extracted. The optimized parameters of the MFs and the rules' weights are plotted as following:

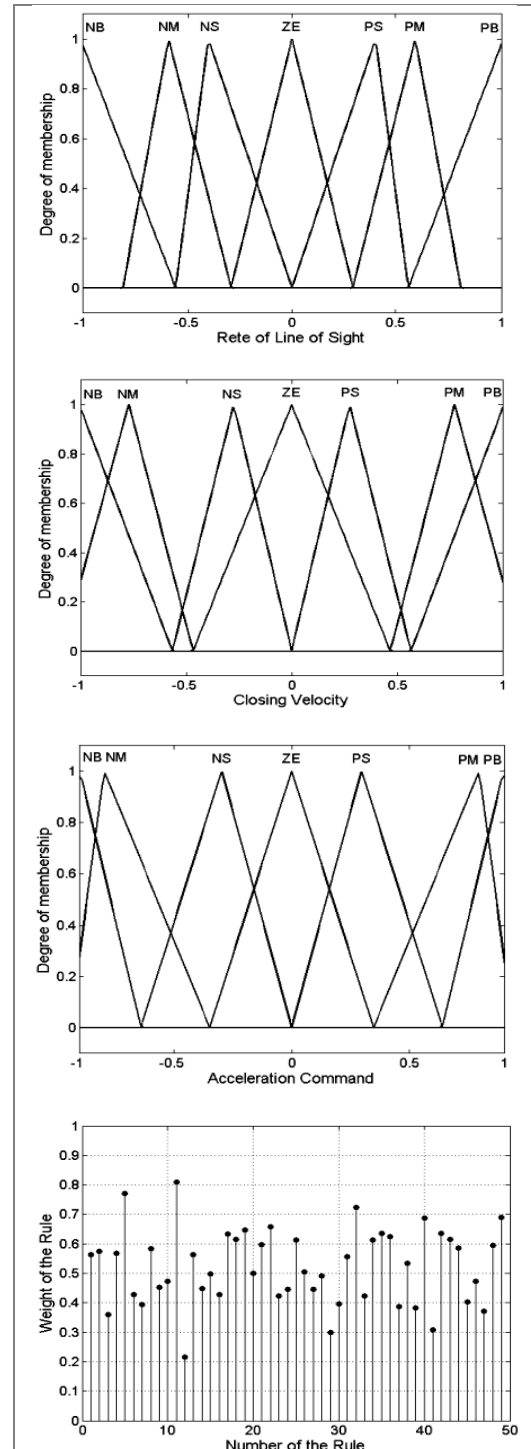


Fig. 6: The Optimized parameters of the NOFLG.

5. RESULTS AND ANALYSIS

During the simulation we suppose the missile and the target are located at $(0,0)km$ and $(10,3)km$ and moves with velocities $1000m/sec$ and $300m/sec$ respectively. Also we considered the maximum target ability to maneuver within $[-3 \text{ up to } 6]g$, where $g = 9.81$ is the gravity constant. Finally the missile has a dynamic saturation within $[-15 \text{ up to } 15]g$.

The simulation is achieved for 20 scenarios with respect to different target's maneuvers. The examined scenarios are

suggested when the values of $A_T = [-3, -2.5, \dots, 5.5, 6]g$. Root Mean Square value (RMS) of: M_D , F_t and C_{Eff} are calculated and listed in Table 1.

Table 1: calculated RMS of the values.

RMS	M_D [m]	F_t [sec]	$C_{Eff} [m^2/sec^3] \times 10^{-4}$
OFLG	5.71	8.21	4.52
NOFLG	5.24	8.11	4.06

It is clear that the NOFLG law outweighs OFLG law in all of the terms and insures 8%, 1% and 10% improvement to M_D , F_t and C_{Eff} respectively. In other words one can say that; TVPSO gives better improvement than PSO.

The following two figures show the trajectories and the accelerations for a difficult scenario that is when the target is considered to have its maximum ability with a square acceleration within $[-3, 6]g$.

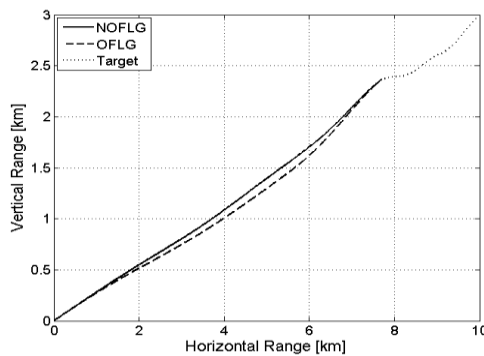


Fig. 7: Trajectories.

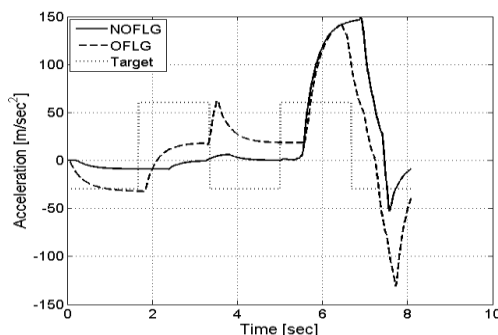


Fig. 8: Accelerations.

Figure 7 shows the trajectories achieved by the missile when using OFLG law and NOFLG law in addition to the target trajectory. While Figure 8 plots the changing of the corresponding acceleration commands.

6. CONCLUSION

In this work, a NOFLG law is investigated. Parameters of the MFs and rules' weights of the proposed design are optimized using TVPSO algorithm. The optimization is achieved under the consideration of minimizing the object function. Many cases where the target makes different maneuvering have been studied. The resulted NOFLG law is compared with an OFLG law. The results show that NOFLG behaves better in other words. The study verifies that the TVPSO performs better than the PSO.

7. REFERENCES:

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