Open-Loop and Closed-Loop Optimal Guidance Policy for Samarai Aerial Vehicle with Novel Algorithm to Consider Wind Effects

M. Tafreshi, I. Shafieenejad, A. A. Nikkhah

Abstract__In this research, novel algorithm based on the optimal control theory is proposed for *Samarai* micro aerial vehicle optimal guidance policy. Considering wind effect in the system dynamic equation increase the robustness of this optimal guidance. Open-loop optimal control is obtained regarding to novel and new proposed method. In this way, intelligent methods such as GA-PSO optimizer and neural-fuzzy are utilized in the proposed new algorithm. Results of new algorithm are compared with pseudo-spectral optimal control solver and show high accuracy. Closed-loop guidance not only damped noises but also simplify controller performance for this unstable vehicle. Next, closed-loop optimal guidance base on neural-fuzzy method is proposed to achieve autonomous guidance to increase the stability of this unstable micro vehicle versus wind effects.

Keywords Optimal Control; Wind Effect; Autonomous Guidance; GA-PSO Optimization; Neural-Fuzzy

I. INTRODUCTION

Rescue vehicles for earthquake to get information from damages or generally civil applications of unmanned air vehicles have increased in recent years. Small unmanned air vehicles (SUAV) are used in civil projects where the focus is on autonomous vehicles; however, MAVs like Samarai make use of radio controls [1]. Lockheed Martin's Intelligent Robotics Laboratories has spent the last five years to develop an unmanned micro aerial vehicle to replicate the motion. The idea was based on maple seed; the seeds that drop from maple trees, whirling softly to the ground like silent one-winged helicopters, Therefor, these air vehicles are the inspiration for a new kind of flying machine that could be useful for military and civil information-gathering missions. Lockheed Martin Advanced Technology Laboratories (ATL) developed the Samarai MAV, a 30- centimeter-radius maple seed like aircraft that can take-off/land vertically and fly laterally (like a helicopter) to the intrinsic stability of nature's maple seeds [2]. Dynamic systems solutions in the optimal control framework can be classified as the two main categories of open-loop and closed-loop. Open-loop solution is proper, if there are no un-modeled disturbances and/or process noises. Unlike open-loop optimal controls, closed-loop optimal controls are considered as functions of states.

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Hence, closed-loop optimal controls increase robustness of the vehicle against noises and/or undesirable disturbances exerted on the system. Of course, it is usually difficult to achieve closed-loop optimal controls. Therefore, finding a method with robust characteristics to overcome this difficulty is highly desirable. Neural-fuzzy combined with the highly transparent and compact form of fuzzy rules makes dynamic systems candidate against disturbances and/or noises as closed-loop method for autonomous vehicles [3, 4].

Millary and Zachari applied the theory of partially Markov decision processes to design guidance algorithms for the motion of unmanned aerial vehicles. They used on-board sensors for tracking ground targets [5]. Han and Bang investigated proportional navigation guidance to avoid collision based on the optimal method [6]. In 2006, autonomous operation was demonstrated for unmanned air vehicle by Ma and Stepangan [7]. Also, autonomous guidance system based on receding horizon optimization was described by Mettler and Dadkhan [8]. In 2010, Paw and Balas presented an integrated framework for small unmanned aerial vehicles' flight control development. Moreover in reference [9], software-in-the-loop and flight testing are conducted with a synthesized controller [9]. There has not been complete investigation into MAVs like Samarai with one wing and radio controller that made by Lockheed Martin's Intelligent Robotics Laboratories [2]. Therefore, Kellas investigated the design and development of controllable single-blade autorotation vehicles in 2007. Simulation results were examined to provide insight into selecting the best control concept and hardware for the final guidance of Samarai design. The free-flight simulation results predicted approximately 10% of experimentally observed performance while the coning angle was predicted to be 25% of the observed angle [1].

An efficient strategy was proposed by Babaei and Mortazavi to design the autopilot for a UAV which was non-minimum phase, and its model included both parametric uncertainties and unmodeled nonlinear dynamics. Babaei's work had been motivated by the challenge of developing and implementing an autopilot that was robust with respect to these uncertainties. By combination of classic controller as the principal section of the autopilot and the fuzzy logic controller to increase the robustness a new methodology was developed [10].

Challenges uniquely associated with developing this type of vehicle are identified and a dynamic modeling and control synthesis procedure [11]. Therefore, this paper focuses on the optimal control and designing closed-loop trajectories.

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This paper describes a principled framework to design a novel algorithm to guide a MAV for civil applications. Also, this research suggests a neural-fuzzy guidance based on the trained optimal trajectories from open-loop solutions. Thus optimal trajectories are achieved through optimal control theory with a novel algorithm and GA-PSO optimizer for many scenarios, to train neural-fuzzy method. In this way, new system dynamic is utilized to consider wind effects for increasing the robustness of the mentioned unstable vehicle.



II. BRIEF REVIEW TO THE OPTIMAL CONTROL THEORY

Dynamic optimization of dynmic system may be considered as optimal control theory. Calculus of variation is the most important method in the optimal control theory. Optimal path or value of the control variable is the key point in the optimal control solution. In other hand, if the control variable is found, the optimal solution for the state variables are derived. Optimal control problem can be stated in the complex vector form $\vec{x} = f(\vec{x}, \vec{u}, t)$ to minimize or maximize cost function like $J = \int_{0}^{t_f} L(t, \vec{x}) dt$ where optimal controller

belongs to time domain [0, T]. T is the final time of optimal process and it may be free or fixed based on the problem. Also, for optimal control problems boundary conditions such as initial conditions or final conditions are emphasized as $\vec{x}(t_0) = \vec{x}_0$ and $\vec{x}(t_f) = \vec{x}_f$ or $x_f = free$. Above discussion yields to the two point boundary value problem (TPBVP). Many methods are introduced to solve TPBVP [3]. However, in this work based on the basic phenomena of the optimal control theory, new method is introduced to solve the problems of these field and overcome difficulties of usual method such as variation of external, shooting method, pseud-spectral method and etc.

III. NOVEL METHODTO SOLVE OPTIMAL CONTROL PROBLEMS

In the optimal control theory m equations are derived with respect to the dynamic of the main problem to illustrate the behavior of the system, however, the optimal dynamic system encounters with more than n unknown. These unknown parameters are optimal controls. In this novel algorithm, system equation is re-derived based on variation of optimal control with respect to time. Therefore, number of equations and unknown parameters will be equal and one can solve this system equation as ordinary system equations with initial boundary conditions. In this novel method that proposed, optimal control derivatives are obtained by new method to construct new system dynamic

$$\begin{array}{l}
\left(\dot{x}_{1} = f_{1}(\vec{x}, t, u) \\
\dot{x}_{2} = f_{2}(\vec{x}, t, u) \\
\vdots \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{New Method}{\vdots} \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{Method}{\vdots} \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{Method}{\vdots} \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{Method}{\vdots} \\
\overset{Method}{\vdots} \\
\overset{K_{1} = f_{1}(\vec{x}, t, u) \\
\vdots \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{Method}{\vdots} \\
\overset{K_{1} = f_{1}(\vec{x}, t, u) \\
\overset{K_{2} = f_{2}(\vec{x}, t, u) \\
\vdots \\
\dot{x}_{n} = f_{n}(\vec{x}, t, u) \\
\overset{Method}{\vdots} \\
\overset{K_{1} = f_{1}(\vec{x}, t, u) \\
\overset{K_{2} = f_{2}(\vec{x}, t, u) \\
\overset{K_{2} = f_{2}(\vec{x}, t, u) \\
\vdots \\
\overset{K_{n} = f_{n}(\vec{x}, t, u) \\
\overset{K_{1} = g(\vec{x}, t, u) \\
\overset{K_{2} = f_{2}(\vec{x}, t, u) \\
\overset{K_{2} = f_{2}(\vec$$

An important point is "How $\frac{d\vec{u}}{dt}$ is obtained based on optimal control theory". The second point in this new method belongs to achieve suitable conditions for these augmented equations for integrating $\frac{d\vec{u}}{dt}$. When these two mentioned questions are answered, this new method for solving optimal control problems is achieved. To answer these two equations about achieving $\frac{d\vec{u}}{dt}$ and $\vec{u}_0(t_0)$, new mathematical method is proposed an considered the mathematical new phenomena. Solution of the first question belongs to mathematical methods. Therefor at first, states and co-state relations of the system dynamic are achieved $\dot{\vec{x}} = \frac{\partial H}{\partial \vec{\lambda}}$ and $\dot{\vec{\lambda}} = -\frac{\partial H}{\partial \vec{x}}$ where x is state vector, λ is co-state vector and H is the Hamiltonian of the system. Next when co-states are achieved (without integration) in this method, one can use derivative of $\lambda(\vec{x}, \vec{u})$ with respect to time. Achieving co-states without integration is belonged at the optimality condition like $\frac{\partial H}{\partial \vec{u}} = 0$. From $\frac{\partial H}{\partial \vec{u}} = 0$ one can obtain n co-state of the system analytically. It should be noted that n is the number of control variables. So $d\lambda_i = \frac{\partial \lambda_i}{\partial \vec{x}} (d\vec{x}) + \frac{\partial \lambda_i}{\partial \vec{u}} (d\vec{u}) + \frac{\partial \lambda_i}{\partial t}$ and $\frac{d\lambda_i}{dt} = \frac{\partial\lambda_i}{\partial\vec{x}}(\frac{d\vec{x}}{dt}) + \frac{\partial\lambda_i}{\partial\vec{u}}(\frac{d\vec{u}}{dt}) + \frac{\partial\lambda_i}{\partial t}$ in this way

$$\frac{d\vec{u}}{dt} \text{ is achieved as } \frac{d\vec{u}}{dt} = \frac{\frac{d\lambda_i}{dt} - \frac{\partial\lambda_i}{\partial\vec{x}}(\frac{d\vec{x}}{dt}) + \frac{\partial\lambda_i}{\partial t}}{\frac{\partial\lambda_i}{\partial\vec{u}}}$$

and new equations for dynamic system in this new method is obtained. It should be noted $\frac{d\lambda_i}{dt}$, $\frac{d\vec{x}}{dt}$ are achieved form the basic phenomena of the optimal control theory. Also when co-states are achieved analytically in this method $\frac{\partial\lambda_i}{\partial\vec{u}}$ and

1.

 $\frac{\partial \lambda_i}{\partial \vec{x}}$ are derived simply. Moreover when dynamic system

isn't dependent of time explicitly $\frac{\partial H}{\partial t} = 0$. The next question is about initial conditions for this new system equations.

Hence, these unknown conditions for equations $(\frac{d\vec{u}}{dt})$ are

achieved by intelligent methods. Therefor optimization algorithms are used to obtain these unknown conditions with respect to minimize or maximize the main cost function based on optimal control criterion. Finally, when new augmented equations based on mathematically the derivative of the optimal controls are obtained and also their unknown initial conditions are obtained by optimization algorithm, new optimal system dynamic is achieved and it can be solved analytically or numerically simply. Bellow chart illustrates the main idea of this new method to simplify understanding mentioned novel algorithm.



Fig. 1, Main chart of the novel algorithm

IV. INVESTIGATING OPEN-LOOP SOLUTIONS

To obtained results and derived equations for co-states, last discussions about achieving new system dynamic are considered. Hence, the system dynamic for three dimensional motion with respect to wind effects are as bellow.

$$\frac{dx}{dt} = V \cos(\varphi) \cos(\psi) + u$$

$$\frac{dy}{dt} = V \cos(\varphi) \sin(\psi) + v \qquad (2)$$

$$\frac{dz}{dt} = V \sin(\varphi) + w$$

Where u, v, w are non-dimensional wind velocity as $u = \frac{x}{x_w}, v = \frac{y}{y_w}, w = \frac{z}{z_w}$ and V is relative velocity of

Samarai. Also x_w , y_w and z_w are non-dimensionlized parameter regarding to wind characteristic. To construct optimal control solution, Hamiltonian of the system should be obtained.

$$H = L + \lambda_x \left(V \cos(\varphi) \cos(\psi) + u \right) + \lambda_y \left(V \cos(\varphi) \sin(\psi) + v \right)$$
(3)
+ $\lambda_z \left(V \sin(\varphi) + w \right)$

Main cost function is considered as minimum-time so, L = 1.

Also, formulas for obtaining co-states equations regarding to optimal control theory are:

$$\frac{d\lambda_x}{dt} = -\frac{\partial H}{\partial x} = -\frac{\lambda_x}{x_w}$$

$$\frac{d\lambda_y}{dt} = -\frac{\partial H}{\partial y} = -\frac{\lambda_y}{y_w}$$

$$\frac{d\lambda_z}{dt} = -\frac{\partial H}{\partial z} = -\frac{\lambda_z}{z_w}$$
(4)

Regarding to optimal controls as two angles $\varphi(t), \psi(t)$ optimality conditions are introduced as follows:

$$\frac{\partial H}{\partial \varphi} = 0$$

$$\frac{\partial H}{\partial \psi} = 0$$
(5)

Based on the above equations, one can obtain two unknown variables such as two co-states analytically. Moreover, for min-time cost function that final time is free and explicit terms for time are not seen in the system equations the Hamiltonian is equal to zero. Hence, three co-states can be determined such as:

$$\lambda_{x} = \frac{-\dot{x}}{V\left(u\,\dot{x} + v\,\dot{y} + w\,\dot{z}\,\right)}$$

$$\lambda_{y} = \frac{-\dot{y}}{V\left(u\,\dot{x} + v\,\dot{y} + w\,\dot{z}\,\right)}$$

$$\lambda_{z} = \frac{-\dot{z}}{V\left(u\,\dot{x} + v\,\dot{y} + w\,\dot{z}\,\right)}$$
(6)

Now, proposed algorithm is utilized based on analytical solutions for co-states. Therefore, with respect to bellow

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equation, $\frac{d\varphi}{dt}$ and $\frac{d\psi}{dt}$ are obtained to construct new optimal system equation regarding this poyal algorithm

optimal system equation regarding this novel algorithm.

$$\frac{d\vec{u}}{dt} = \frac{\frac{d\lambda_i}{dt} - \frac{\partial\lambda_i}{\partial\vec{x}}(\frac{dx}{dt})}{\frac{\partial\lambda_i}{\partial\vec{u}}} \quad i = x, y, z \tag{7}$$

The key point of the mentioned method is referred to initial and final conditions for new augmented equations (see above equation) that tuned by optimizer to maximize or minimize the main cost function. In this problem, main cost function is considered as min-time criteria. In the next part, simulations and results are sketched to show the accuracy of the work. At first, comparison between this method and pseudo-spectral method is investigated to valid the results of the new algorithm.



Fig. 2, Comparison Novel Algorithm (line) and pseudo-spectral method (circle) for z direction (meter)



Fig. 3, Comparison Novel Algorithm (line) and pseudo-spectral method (circle) for x direction (meter)



Fig. 4, Comparison Novel Algorithm (line) and pseudo-spectral method (circle) for *y* direction (meter)



Fig. 5, Comparison Novel Algorithm (line) and pseudo-spectral method (circle), three dimensional



Fig. 6, Comparison Novel Algorithm (line) and pseudo-spectral method (circle) for the *first controller* (deg)



Fig. 7, Comparison Novel Algorithm (line) and pseudo-spectral method (circle) for the *first controller* (deg)

V. AN INTRODUCTION TO FUZZY SYSTEMS

Fuzzy systems are accurately-defined systems. Although fuzzy systems describe uncertain and unspecified phenomena, the fuzzy theory itself is an accurate theory. In operational systems, important data are resulted from two sources. One source is the expert whose knowledge and wisdom on system is defined using a natural language. Another source is the mathematical model and measurement emanating laws. Hence, combining these two types of information is an important issue in systems design. A Fuzzy system is composed of four sections including recognition database or fuzzy rules, fuzzy-maker unit, decision-making or deduction unit and fuzzy-remover unit. Input signals are converted into fuzzy language variables in the fuzzy-maker unit. Then system output is produced in the fuzzy form by decision-making unit which uses the existing rules and combines them with recognition database information. Finally, the output passes through the fuzzy-remover unit and becomes quite non-fuzzy.

a More advanced method, neural-fuzzy training method was used to overcome the weaknesses of the fuzzy method. These weaknesses could be enumerated as follow:

- Limited rule definition
- Limited membership function over the specified range
- Non optimal membership functions

Noteworthy is that, neural-fuzzy method could be used to define optimal membership functions. In other words, smart neural logic tries to optimize the specified range of the membership functions leading to reduced errors in definition of the membership functions which itself contributes to optimization. *Sugeno* deduction rule has been used in the neural-fuzzy training in this work where the number of inputs and outputs are 3 and 1, respectively for states and divided

controls $\frac{d\varphi}{d\psi}$. As it is clear from these figures, behavior is

highly complex and quite nonlinear denoting the fact that it is a complicated and difficult task to train a smart system with such non-linear behaviors for autonomous optimal guidance.



Fig. 8, Comparison Novel Algorithm (line) and neural-fuzzy method (circle) for *z* direction (meter)



Fig. 9, Comparison Novel Algorithm (line) and neural-fuzzy method (circle) for y direction (meter)



Fig. 10, Comparison Novel Algorithm (line) and neural-fuzzy method (circle) for *x* direction (meter)



Fig. 11, Comparison Novel Algorithm (line) and neural-fuzzy method (circle), three dimensional



Fig. 12, Comparison Novel Algorithm (line) and neural-fuzzy method (circle) for the *first controller* (deg)



Fig. 13, Comparison Novel Algorithm (line) and neural-fuzzy method (circle) for the *second controller* (deg)

In the next part to examine the robustness of optimal neural-fuzzy guidance, noises are exerted on the system. Therefore, from figures it is concluded that autonomous optimal guidance policy can direct samarai with respect to noises such as navigation system.



Fig. 14, Comparison open-loop solution and closed-loop solution with noise, z direction (meter)

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Fig. 15, Comparison open-loop solution and closed-loop solution with noise, y direction (meter)

Above figure show the higher impact is acted on y direction and red line is open-loop solution with noise that non-autonomous system can not damp the exerted noises.



Fig. 16, Comparison open-loop solution and closed-loop solution with noise, x direction (meter)



Fig. 17, Comparison open-loop solution and closed-loop solution with noise, three dimensional



Fig. 18, Comparison open-loop solution and closed-loop solution with noise, the *first optimal controller* (deg)



Fig. 19, Comparison open-loop solution and closed-loop solution with noise, the *second optimal controller* (deg)

VI. CONCLUSION

In this paper, new and novel algorithm based on the optimal control theory is achieved for *Samarai* micro aerial vehicle autonomous guidance policy. In this way, wind effects in the system dynamic equations are considered to increase the robustness of this optimal guidance. In this work not only open-loop guidance but also closed-loop guidance is obtained by new method based on the intelligent methods. Intelligent methods such as GA-PSO optimizer and neural-fuzzy are utilized in the proposed new algorithm. Results of the new algorithm are compared with pseudo-spectral optimal control solver to show high accuracy of results against wind effects and noises.

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