Unconstrained Evolutionary and Gradient Descent-Based Tuning of Fuzzy-partitions for UAV Dynamic Modeling

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In this paper, a novel fuzzy identification method for dynamic modelling of quadrotors UAV is presented. The method is based on a special parameterization of the antecedent part of fuzzy systems that results in fuzzy-partitions for antecedents. This antecedent parameter representation method of fuzzy rules ensures upholding of predefined linguistic value ordering and ensures that fuzzy-partitions remain intact throughout an unconstrained hybrid evolutionary and gradient descent based optimization process. In the equations of motion the first order derivative component is calculated based on Christoffel symbols, the derivatives of fuzzy systems are used for modelling the Coriolis effects, gyroscopic and centrifugal terms. The non-linear parameters are subjected to an initial global evolutionary optimization scheme and fine tuning with gradient descent based local search. Simulation results of the proposed new quadrotor dynamic model identification method are promising.

Keywords: fuzzy identification method, dynamic modelling, quadrotor UAV, Christoffel symbols, genetic algorithms, non-linear parameters, global evolutionary optimization.

1. INTRODUCTION

Autonomous quad-rotor helicopters increasingly attract the attention of potential researchers. A wide area of robotics research is dedicated to aerial platforms. The quad-rotor architecture has low dimensions, good manoeuvrability, simple mechanics and payload capability. The electrically powered four-rotor quad-rotor helicopter architecture has been chosen for this research (Figure 1).

Figure 1. Quad-rotor helicopter

This structure can be attractive in several applications, in particular for surveillance, for imaging dangerous environments and for outdoor navigation and mapping. The study of kinematics and dynamics helps to understand the physics of the quad-rotor and its behaviour.

Together with modelling, the determination of the control algorithm structure is very important [1-6]. The quad-rotor UAV is controlled by angular speeds of four motors. Each motor produces a thrust and a torque, whose combination generates the main trust, the yaw torque, the pitch torque, and the roll torque acting on the quad-rotor. Motors produce a force proportional to the square of the angular speed and the angular acceleration; the acceleration term is commonly neglected as the speed transients are short thus exerting no significant effects.

Soft computing methods can be efficiently applied together with and also instead of conventional controllers. Fuzzy modelling [7-10] can be conducted as black-box modelling where all the system knowledge is mere input-output data. However when expert knowledge is readily available, we should take advantage of it – fuzzy grey-box modelling is a rational choice.

Identification of linear parameters is a well-studied area, with efficient matrix algebra and singular value decomposition based reliable tools. Non-linear parameters can also be simply traced to their local optimum with well-studied gradient descent methods, but we should always keep in mind that gradient descent methods are trapped by local optimum areas. Evolutionary algorithms are robust global optimum search engines, capable of multi-objective search as described in [8-10].

The paper is organized as follows:

In Section 1 the Introduction is given. In Section 2 the quad-rotor dynamic model is presented. In Section 3 the Fuzzy-Logic systems are illustrated. In Section 4 the Multi-Objective Genetic Algorithms are illustrated.

Section 5 presents the simulation setup and results. Conclusions are given in Section 6.

2. DYNAMIC MODEL OF THE QUAD-ROTOR HELICOPTER

Dynamic modelling [11-17] of the quad-rotor helicopter is a well elaborated field of aeronautics. The model of the quad-rotor helicopter [18] and the rotational directions of the propellers can be seen in Figure 2.
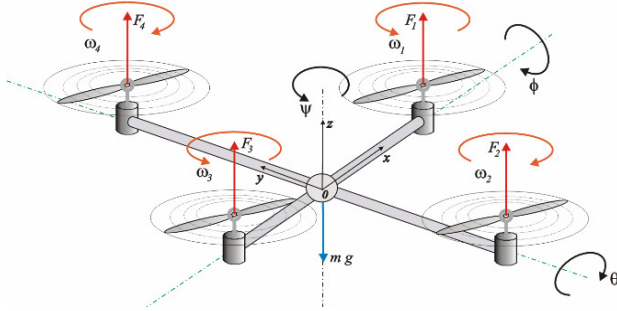

Figure 2. The model of the quadrotor helicopter

The rotor pair 2 and 4 rotates clockwise direction and the rotor pair 1 and 3, anticlockwise direction. A quad-rotor helicopter has fixed pitch angle rotors and the rotor speeds are controlled in order to produce the desired lift forces.

The quadrotor helicopter has four actuators - brushless DC motors which exert lift forces $\mathbf{F}_1$, $\mathbf{F}_2$, $\mathbf{F}_3$, $\mathbf{F}_4$ proportional to the square of the angular velocities of the rotors. Actually, four motor driver boards are needed to amplify the power delivered to the motors. Their rotation is transmitted to the propellers which move the entire structure.

The main thrust is the sum of individual trusts of each four motor. The pitch torque is a function of difference in forces produced on one pair of motors, while the roll torque is a function of difference in forces produced on other pair of motors. The yaw torque is the sum of all four motor reaction torques due to shaft acceleration and blades drag. The motor torque is opposed by a general aerodynamical drag. The complete dynamics of an aircraft, taking into account aero-elastic effects, flexibility of wings, internal dynamics of the engine, and the whole set of changing environmental variables is quite complex and somewhat unmanageable for the purpose of autonomous control engineering.

For a full dynamic model of a quad-rotor system both (1) the center of mass position vector of (x, y, z) in fixed frame coordinates and (2) the orientation Euler angles: roll, pitch, yaw angles (Φ, θ, ψ) around body axes X, Y, Z are considered for the vector of generalized coordinates q. Using the Euler-Lagrange approach it can be shown how the translational forces $\mathbf{F}_\xi$ applied to the rotorcraft due to main trust can be full decoupled from the yaw, pitch and roll moments For a full dynamic model of a quad-rotor system both (1) the center of mass position vector of (x, y, z) in fixed frame coordinates and (2) the orientation Euler angles: roll, pitch, yaw angles (ϕ, θ, ψ) around body axes x, y, z are considered for the vector of generalized coordinates q. Using the Euler-Lagrange approach it can be shown how the translational forces $\mathbf{F}_\xi$ applied to the rotorcraft due to main thrust can be full decoupled from the yaw, pitch and roll moments $\boldsymbol{\tau}$:

$$m\begin{bmatrix}\ddot{x}\\\ddot{y}\\\ddot{z}\end{bmatrix}+mg\begin{bmatrix}0\\0\\1\end{bmatrix}=F_\xi \tag{1}$$

where m is the quadrotor mass and g is the gravitational constant.

$$J\begin{bmatrix}\ddot{\phi}\\\ddot{\theta}\\\ddot{\psi}\end{bmatrix}+C\left(\begin{bmatrix}\dot{\phi}\\\dot{\theta}\\\dot{\psi}\end{bmatrix},\begin{bmatrix}\phi\\\theta\\\psi\end{bmatrix}\right)\begin{bmatrix}\dot{\phi}\\\dot{\theta}\\\dot{\psi}\end{bmatrix}=\tau \tag{2}$$

where J is a 3x3 matrix, called the inertia matrix and C is also a 3x3 matrix that refers to Coriolis, gyroscopic and centrifugal terms. Further on, for the scope of this paper we shall address only equation (2) as the quadrotor dynamic model to be identified.

Equation (2) can be analyzed as three resultant torques τ_i acting along the ith axes respectively as $i\in$ (ϕ, θ, ψ), which using Christoffel symbols of the first kind can be defined as a function of the state vector of Euler angles $q = [\phi, \theta, \psi]$, their velocities ($\dot{q} = dq/dt$) and accelerations ($\ddot{q} = d\dot{q}/dt$) as:

$$\sum_j\left(D_{ij}(q)\cdot\ddot{q}_j\right)+\sum_j\sum_k\left(\dot{q}_j\cdot D_{ijk}(q)\cdot\dot{q}_k\right)=\tau_i, \\ i,j,k=1,2,3. \tag{3}$$

The first component of equation (3) is shortly referred to as $J\ddot{q}$ the inertia matrix part, while the second as $C\dot{q}$ the Coriolis matrix term for which components are defined as:

$$J_{ik}=D_{ik}(q),\ \ C_{ik}=\sum_{j=1}^{p}\dot{q}_j\cdot D_{ijk}(q) \tag{4}$$

where D_{ik}, D_{ijk} are in general, highly non-linear scalar functions of the state vector q. They contain $sin(\cdot)$ and $cos(\cdot)$ functions of q, and their products and sums defined by the geometry of the system.

There are general relations that can be used for reducing the number of unknown elements of J and C, like: (1) J is symmetric and (2) D_{ijk} are Christoffel-symbols of D_{ij} [12] thus further properties are inherently defined as:

$$D_{ik}=D_{ki}, \\ D_{ijk}=\frac{1}{2}\left(\frac{\partial D_{ij}}{\partial q_k}+\frac{\partial D_{ik}}{\partial q_j}-\frac{\partial D_{jk}}{\partial q_i}\right), \\ D_{ijk}=D_{ikj}, D_{kij}=-D_{jik}, D_{kjk}=0, \\ \forall i,k\geq j \tag{5}$$

It should be noted that direct measurement of any single component from equation (4) is not possible; the only measurable data, on the output of the system, is the resultant torque of equation (3). Identification of all non-linear functions (4) under these terms is a considerable problem.

3. FUZZY-LOGIC SYSTEMS

The Takagi-Sugeno-Kang (TSK) type Fuzzy-logic systems (FLSs) having n inputs and 1 output are defined in [19] as:

$$f(q) = \sum_{l=1}^{M} \omega_l(q) \cdot y_l(q) \Big/ \sum_{l=1}^{M} \omega_l(q) \qquad (6)$$

where M is the number of rules, q is the vector of n input variables, y_l is a scalar function of n input variables, defined by $(n+1)$ c parameters as in equation (8). The antecedent, the premise part of a fuzzy rule is:

$$\omega_l(q) = \prod_{i=1}^{n} \mu_{F_{l(i)}}(q_i) \qquad (7)$$

where $\mu_{F_{l(i)}}(q_i)$ is the membership function (MF) of the ith input variable in the lth rule that defines the linguistic value $F_{l(i)}$. The linguistic form of the lth rule from the previously described first order TSK FLS is defined in [20] as:

IF (q_1 is $F_{l(1)}$) AND (q_2 is $F_{l(2)}$) AND …(q_n is $F_{l(n)}$)

$$\text{THEN } y_l = \sum_{j=1}^{n} c_{l(j)} \cdot q_j + c_{l(0)}, \qquad (8)$$

Zadeh-formed MFs are the z-, the s-, and π-functions (named after their shape) defined respectively as:

$$mfz(q,b_1,b_2) = \begin{cases} 1 & q \le b_1 \\ 1 - 2((q-b_1)/(b_2-b_1)) & b_1 < q \le \frac{1}{2}(b_2+b_1) \\ 2((q-b_1)/(b_2-b_1)) & \frac{1}{2}(b_2+b_1) < q \le b_2 \\ 0 & q > b_2 \end{cases}$$

$$mfs(q,b_1,b_2) = 1 - mfz(q,b_1,b_2) \qquad (9)$$

$$mf\pi(q,b_1,b_2,b_3,b_4) = \begin{cases} mfs(q,b_1,b_2) & q \le b_2 \\ 1 & b_2 < q \le b_3 \\ mfz(q,b_3,b_4) & q > b_3 \end{cases}$$

where $b_1 \le b_2 \le b_3 \le b_4$ are parameters defining MFs. In case there is more than one value q such that the degree of membership of q is equal to one, the interval where $\mu_k(q,b) = 1$ (the interval $[b_2, b_3]$ for $mf\pi$ type μ_k) is called the plateau of the μ_k MF. When having for example 3 naturally ordered linguistic values $l \in \{a, b, c\}$ (a = low, b = medium, c = large) constraints on parameters to preserve this ordering are:

$$\begin{aligned} b_{a1} &< b_{b1} < b_{c1} \\ b_{a2} &\le b_{a3} < b_{b2} \le b_{b3} < b_{c2} \le b_{c3} \\ b_{a4} &< b_{b4} < b_{c4} \end{aligned} \qquad (10)$$

A linguistic variable can be assigned K different linguistic values, each described by a MF $\mu_k(q,b)$ such that for every input q it holds that $\sum_{k=1}^{K} \mu_k(q,b) = 1$, the MFs are said to form a fuzzy-partition. Forming fuzzy-partitions by antecedent membership functions ensures that there cannot be a numerical input within the defined input range that will not result in firing at least one rule consequent of the fuzzy model, which means that there is a defined output for all possible input states. Keeping specific properties of fuzzy-partitions imposes a set of hard constraints on membership function parameters as detailed in [20]. By imposing these restrictions on all linguistic variables of the FLS, and additionally assuming that the rule base is complete in the sense that it covers the whole input domain, it immediately follows that the TSK model structure of equation (6) simplifies to:

$$f(q) = \sum_{l=1}^{M} \omega_l(q) \cdot y_l(q) \qquad (11)$$

Automatic fine tuning FLS parameters that satisfies all of above listed constraints is a significant problem.

In [21] a method is introduced that simplifies parameter optimisation of equation (11) while preserving all required constraints. Fuzzy-partitions can be simply formed from Zadeh-typed MFs by making equal the last two parameters of each preceding MF to the first two parameters of the succeeding MF. This way a fuzzy partition of K MFs is defined by $2(K-1)+1$ parameters. Let our input space be normalised ($q_{min} = 0$ and $q_{max} = 1$). If we do not want to allow any plateaux, parameter b_2 must be equal to b_3 in equation (9) this way the number of parameters is further reduced to $K-2$.

$$b_1 < b_2 < \ldots < b_{K-1} \qquad (12)$$

Let us add two more constraints:

$$0 < b_1 \text{ and } b_{K-1} < 1 \qquad (13)$$

Let us define the first MF to be:

$$mfz(q,0,b_1) \qquad (14)$$

Let the Kth, the last MF concluding the fuzzy partition be:

$$mfs(q,b_{K-2},1) \qquad (15)$$

Let us define intermediate k^{th} MFs to be:

$$mf\pi(q,b_{k-1},b_k,b_k,b_{k+1}) \qquad (16)$$

for $k = 1, \ldots, K-2$, where $b_0 = 0$ and $b_{K-1} = 1$. This way the ordered series of $K-2$ b_i parameters together with constants 1 and 0 are the minimal number of parameters to define a fuzzy-partition of Zadeh-formed MFs.

This minimal number of non-linear parameters is a very important issue for optimisation as over parameterised systems are hard to optimise [22-23]. The only problem is that when tuning the non-linear parameters of a FLS having an n dimensional input space, we must comply with $\sum_{i=1}^{n} K_i$ pieces of hard constraints.

Although there are a number of constrained optimisation methods it is obvious that an unconstrained optimisation method would be more efficient. Let us consider *K-1* pieces of rational, positive or zero parameters as proposed in [10]:

$$a_\kappa \in R_0^+, \kappa = 1,...,K-1 \qquad (17)$$

When we define b_k as:

$$b_k = \sum_{j=1}^{k} a_j \Big/ \sum_{\kappa=1}^{K-1} a_\kappa \qquad (18)$$

for every $k = 1, …, K-2;$ all the constraints of equation (12) and equation (13) are automatically fulfilled for every a_κ from equation (18) without any further restrictions on any a_κ, other than $0 \le a_\kappa$.

An ANFIS like optimisation, defined in [23] or any other efficient unconstrained nonlinear numerical method can be applied to minimise equation (11) error along the a_κ parameters. For calculating all linear parameters a linear least square (LS) method can be applied to $c_{l(j)}$ parameters of the consequent part. To avoid traps of local optimal solutions for a_κ, a preliminary global search should be applied.

4. MULTI-OBJECTIVE GENETIC ALGORITHMS

A genetic algorithm (GA) is constructed on the basis of imitating natural biological processes and Darwinian evolution [24]. GAs are widely used as powerful global search and optimization tools [25]. Real life optimization problems often have multiple objectives. To establish ranking of chromosomes for Gas the comparison of two objective vectors is required. Often a simple weighted sum is used, but its drawbacks are widely known [9]. Pareto based comparison is the bases of a few popular methods like Non-dominated Sorting GA (NSGA) [7] and Multi-Objective GA (MOGA).

A general multi-objective optimization problem consists of n number of scalar minimization objectives where every scalar objective function fi(x) is to be minimized simultaneously, where x is an n-dimensional vector of parameters. As maximization can be easily transformed to minimization, the generality of the previous statement stands.

A vector x1 Pareto-dominates x2, when no scalar component of x2 is less than the appropriate component of x1, and at least one component of x1 is strictly smaller than the appropriate component of x2. Since no metrics can be assigned to Pareto-dominance, there have been two different attempts to define a GA ranking method, which can be used for Pareto-dominance vector comparison: (1) "Block-type" ranking is defined as: Rank is equal to 1 + (number of individuals that dominate the ith individual) (2) "Slice-type" ranking is defined in [7] as: Rank is equal to 1 + (number of turns when the non-dominated individuals are eliminated, needed for the ith individual to become non-dominated).

Quantity-dominance, as proposed in [10] is defined as: vector a=[ai] Quantity-dominates vector b=[bi] if a has more such ai components, which are better than the corresponding bi component of vector b, and a has less such aj components, which are worse than the corresponding bj. A metrics can be defined as: the measurement of the extent of Quantity-dominance is the difference between the number of better and the number of worse components. For a measurement based ranking method the Rank of the ith objective vector can be simply defined as the sum of Quantity-dominance measurements for every individual measured from the ith vector. This ranking method can be readily applied with Quantity-comparison.

The proposed vector comparison method provides more information when comparing two vectors than the classic Pareto-based comparison, thus the GA is faster, more efficient in its search. The MMNGA algorithm is computationally less expensive, and more efficient compared to the classical methods, and its results analyzed on a number of GA hard problems are at least equally good [10].

A simple method for realistic training data acquisition is to define the desired state position vector (x, y, z) with the desired yaw rotation angle ψ. As the quadrotor dynamics is very sensitive to jerks, sudden changes in the third derivatives of state variables, the desired state variables will be defined through $\ddddot{q}$ jounce (the fourth derivatives of state variables) with continuous functions $mf\pi$ from equation (9), like:

$$jounce\pi(t,a,8b)$$
$$= \begin{cases} a*mf\pi(t,0,b,b,2b), & t < b \\ -a*mf\pi(t,2b,4b,4b,6b) & 2b \le t < 6b \\ a*mf\pi(t,6b,7b,7b,8b) & 6b \le t < 8b \end{cases} \qquad (19)$$

$$\bar{q}_i(t,a,b,c) = \begin{cases} jounce\pi(t,a,b), t < b \\ 0, b \le t < b+c \\ -jounce\pi(t,a,b), b \le t < 2b+c \end{cases}$$

A general basic smooth jounce function setup to minimise jerk and thus results in smooth torque transitions is presented in Figure 3.
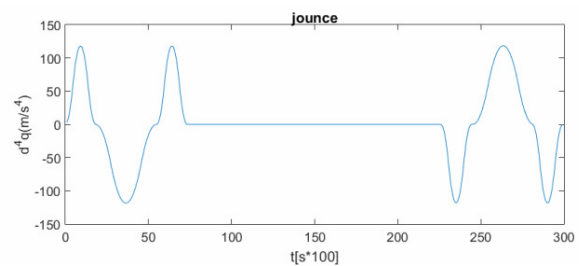

Figure 3. A basic jounce function setup

State variables *(x,y,z)* and ψ can be calculated by four time integration of their jounces. The roll and pitch is equal to:

$$\phi = a\sin\left(\frac{\dot{x}\sin\psi - \dot{y}\cos\psi}{\ddot{x}^2 + \ddot{y}^2 + (\ddot{z}+g)}\right)$$
$$\theta = a\tan\left(\frac{\dot{x}\cos\psi - \dot{y}\sin\psi}{(\ddot{z}+g)}\right) \qquad (20)$$

The proposal of this paper is to identify D_{ij} inertia matrix components of the dynamic model in equation

(4) as FLSs defined by equations (11) to (18), where the FLS general input variable q will be substituted for the appropriate state variables of (ϕ, θ, ψ). When the D_{ij} inertia matrix components are constructed in this way, forming the D_{ijk} components as Christoffel symbols is to be expressed by partial derivatives of equation (11) like:

$$\frac{\delta f(q)}{\delta q_i} = \sum_{l=1}^{M} (\frac{\delta \omega_l(q)}{\delta q_i} \cdot y_l(q) + \omega_l(q) \cdot \frac{\delta y_l(q)}{\delta q_i}) \quad (21)$$

The unknown inertia matrix components of equation (2) to be identified are:

$$D_{13}(\theta), D_{22}(\phi), D_{23}(\phi,\theta), D_{33}(\phi,\theta) \quad (22)$$

Based on quadrotor system structure and inertia matrix symmetry the remaining inertia components are known to be:

$$D_{11} = I_X, D_{12} = 0, D_{21} = D_{12}, D_{31} = D_{13}, D_{32} = D_{23} \quad (23)$$

Based on equation (5) the following Coriolis term matrix components can be calculated by equations (22):

$$D_{122} = -\frac{1}{2}\frac{\delta D_{22}}{\delta \phi}, D_{123} = \frac{1}{2}\left(\frac{\delta D_{13}}{\delta \theta} - \frac{\delta D_{23}}{\delta \phi}\right),$$

$$D_{322} = \frac{\delta D_{23}}{\delta \theta}$$

$$D_{133} = -\frac{1}{2}\frac{\delta D_{33}}{\delta \phi}, D_{223} = -\frac{1}{2}\frac{\delta D_{33}}{\delta \theta}, D_{312} = \quad (24)$$

$$= \frac{1}{2}\left(\frac{\delta D_{23}}{\delta \phi} + \frac{\delta D_{13}}{\delta \theta}\right)$$

Remaining D_{ijk} components are trivial identities defined by equation (5).

5. SIMULATION SETUP AND RESULTS

The proposed method is tested for a quad-rotor system simulation [26-33] from [1] with parameters as in Table I.

Table 1. Quad-Rotor parameters

Quad-rotor parameters		
parameter	value	unit
gravity constant, g	9.81	m/s^2
mass, m	6	kg
torque lever, l	0.3	m
trust factor, k	121.5e-6	
drag factor, b	2.7e-6	
body inertia along axes x, I$_x$	0.6	kgm^2
body inertia along axes y, I$_y$	0.6	kgm^2
body inertia along axes z, I$_z$	1.2	kgm^2
simulation time, T	3	s

The training data set is collected from a simulation along a trajectory with jounce for (x,y,z) and ψ defined so that position changes simultaneously along a unit cube main diagonal $(0,0,0) - (1,1,1)$, while performing a full circle rotation in jaw motion $0 - 2\pi$.

The calculated roll, pitch and yaw motions are as presented on Figures 4, 5 and 6. The simulated resultant torque training data is as presented on Figure 7.
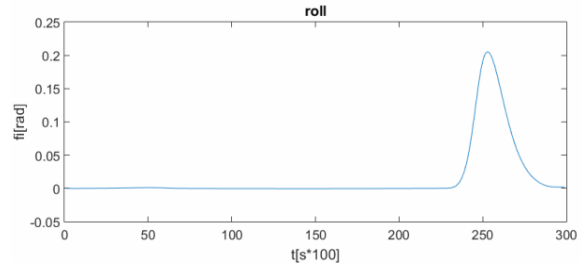

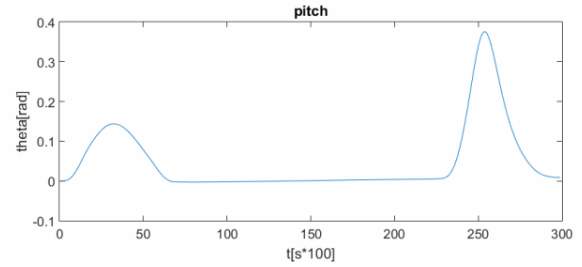
Figure 4. Roll training data for input
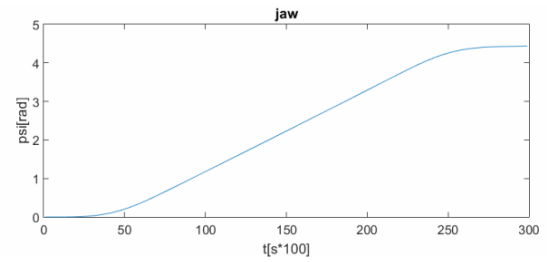

Figure 5. Pitch training data for input
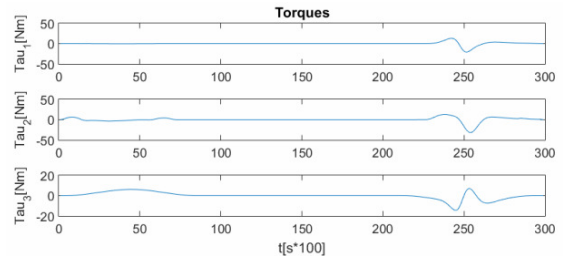

Figure 6. Yaw training data for input

Figure 7. Torque training data set for input

Non-linear a_K parameters of the system are identified in a manner that first the input space is normalised to the unit hyper-cube. A set of non-linear parameters consists of six times four a_K integer parameters for defining six fuzzy-partitions of five MFs each, where each partition consists of one z-type MF, three π-type MFs and one s-type MF as in (9)-(18). These six fuzzy-partitions serve as antecedents for the four fuzzy-systems like in equation (11) and (21), used for identifying D_{ij}, ij=(13, 22, 23, 33) as defined in equations (22)-(24) and (5).

Two unknown linear parameters D_{11} and D_{12} of the quadrotor model as in equation (23), together with 170 linear parameters of the four TSK FLSs (2 FLSs with 5 MFs on one input, each rule with 2 c parameters, plus 2 FLSs with 5 MFs on both of the 2 inputs, each rule with 3 c parameters) of equations (22) and equations (24) are determined by the SVD-based LS method as used in [21].

Concluded from equation (17) six fuzzy-partitions (antecedent part of 2 FLSs with 1 input, plus 2 FLSs with 2 inputs are covered by 6 independent fuzzy-partitions) are represented by a vector of six times four a_K parameters, which are optimized by a multi-objective hybrid genetic algorithm as detailed in [10]. Each chromosome evaluation is extended to include an additional round of nonlinear LSQ optimization of a_K parameters. Chromosomes are updated before applying further GA operators, so the GA does not waste time on local optimization; only global search capabilities of the GA are utilized. Three objectives are set for minimization: (1) the root mean square of the torque identification error, (2) the maximum absolute error for any given training data input-output pair, and (3) the condition number of the linear system of equations used for LS calculation of linear parameters.

The GA is set to work on a population of 125, divided into 5 subpopulations with migration rate 0.2 taking place after each 5 completed generations. Crossover rate, generation gap and insertion rate is 0.8, selection pressure is 1.5. In each generation 4% of individuals are subject to mutation, when 1% of the binary genotype is mutated. Individuals, chromosomes are comprised of 24 Gray-coded integers, each consist of 16 bits. The initial population is set up in a completely random manner.

Matrix of the linear equation is pre-processed from equation (3), where FLSs like equation (11) and their partial derivatives like equation (21) are inserted as described in equations (22)-(24). Unknown linear parameters are D_{11}, D_{12} and the 170 c parameters of fuzzy-rule consequents.

Evaluation of each individual is done as follows:
(1) Convert the coded a_K values from the chromosome to b_k by equation (18).
(2) Evaluate all MFs, which will comprise six fuzzy-partitions from each of six b_k quadruplets by equations (14)-(16). Also evaluate derivatives of equations (14)-(16).
(3) The pre-processed matrix of the linear equation is evaluated with the MFs.
(4) Linear components of equations (11) and (21) are calculated by SVD decomposition as described in [21].
(5) Next the a_K parameters are fine-tuned by the Matlab "lsqnonlin" function,
(6) MFs are re-calculated for the optimised a_K parameters and all linear parameters are re-calculated.
(7) Resulting optimised a_K parameters are re-assigned into the chromosome of the evaluated chromosome.

For the multi-objective rank assignment described in [10], the objective vector is created from:
(i) the mean square of the identified torque error,
(ii) the maximum absolute torque identification error and
(iii) the condition number of the matrix of the linear equation.

Stochastic universal sampling is used for selecting the next generation without explicit elitism. To speed up the GA processing, a database of evaluated chromosomes and their objective vectors is created, so only unique new individuals are evaluated in each generation.

Convergence is achieved in some 50 generation evaluations, when the mean square error is in order of $5e^{-7}$, the maximum torque error is <0.005 Nm. For non-dominated chromosomes the condition number of the used matrix of linear equation is in order of $1e^{+38}$.

One typical non-dominated chromosome and the corresponding torque identification error are presented on Figures 8 to 12. The numerical value of this chromosome is:

[61029   8550   10175   18348   6668   22470   11993 57404   608   18024   25310   39946   26698   53573 39807   47476   1909   46   52007   47288   3712   920 50956   5174],

which defines fuzzy-partition MF parameters as:
b_i for J_{13}: [0.6221, 0.7093, 0.8130].
b_i for J_{22}: [0.0677, 0.2957, 0.4174].
b_i for J_{23}: [0.0072, 0.2221, 0.5238; 0.1593, 0.4791, 0.7167].
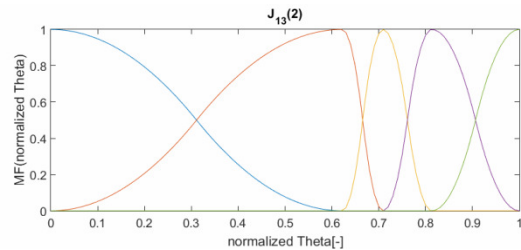b_i for J_{33}: [0.0189, 0.0193, 0.5330; 0.0611, 0.0762, 0.9148].

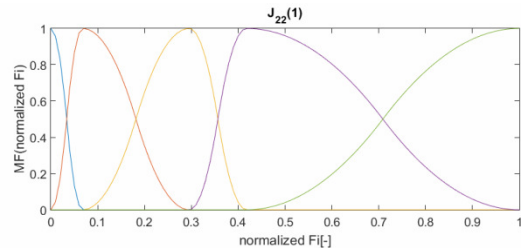Figure 8. Fuzzy-partition for J_{13} antecedents

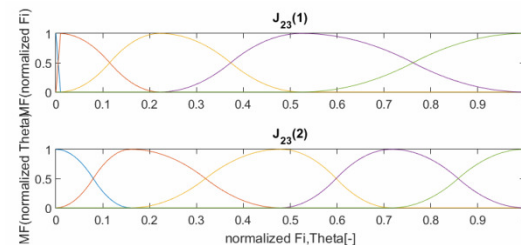Figure 9. Fuzzy-partition for J_{22} antecedents

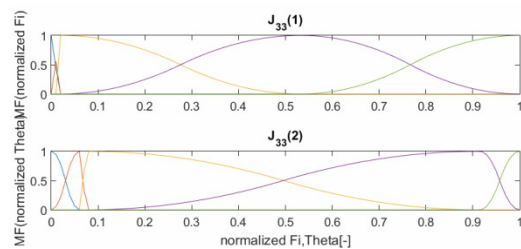Figure 10. Fuzzy-partition for J_{23} antecedents

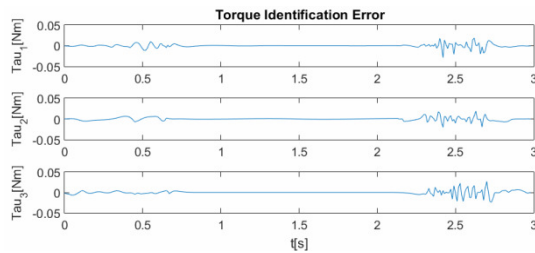Figure 11. Fuzzy-partition for J_{33} antecedents

Figure 12. Torque identification error

6. CONCLUSIONS

Simulation results of the proposed new quad-rotor dynamic model identification method are promising.

The quality of identification with the relative torque error being uniformly <0.1% is excellent, suitable for taking part in a model based control algorithm.

The typical condition number for used linear parameter evaluations is very high for the used training data setup, so a more advanced trajectory has to be planned with sufficient inertia excitation along the complete input domain.

Also the FLS structure is to be made flexible, in terms that the GA should be able to turn off unnecessary MFs and thus reduce the number of unnecessary rules and linear parameters.

REFERENCES

[1] Lozano, R., Unmanned Aerial Vehicles, ISTE Ltd, London, ISBN 978-1-84821-127-8, 2010.

[2] Stengel, R., Flight Dynamics, Princeton University Press, Cloth, ISBN 0-691-11407-2, 2004.

[3] Rodic, A., Mester, G., Stojković, I., Qualitative Evaluation of Flight Controller Performances for Autonomous Quadrotors, Intelligent Systems: Models and Applications, Endre Pap edit., Topics in Intelligent Engineering and Informatics, Vol. 3, Part. 2, ISBN 978-3-642-33958-5, DOI 10.1007/978-3-642-33959-2_7, Springer-Verlag, Berlin Heidel-berg, pp. 115-134, 2013.

[4] Mester, G., Rodic, A., Modeling and Navigation of an Autonomous Quad-Rotor Helicopter, E-society Journal: Research and Applications, Vol. 3, No. 1, pp. 45-53, ISSN 2217-3269, July 2012.

[5] Nemes, A., Dynamic Modelling of Robot Manipulators by Zadeh-type Fuzzy Partitions, Proceedings of the 4th International Symposium of Hungarian Researchers on Computational Intelligence, Budapest, 2003, pp. 1-9.

[6] Balázs, K., Botzheim, J., Kóczy, T., L., Comparative investigation of various evolutionary and memetic algorithms, Rudas, I. J., Fodor, J., Kacprzyk, J. edit., Computational Intelligence in Engineering, Vol. 313, pp. 129–140, Studies in Computational Intelli-gence, Springer-Verlag, Berlin-Heidelberg, 2010.

[7] Srinivas, N., Deb, K., Multiobjective Optimisation Using Nondominated Sorting in Genetic Algorithms, Evolutionary Computation Vol. 2, No. 3, pp. 221-248, 1994.

[8] Botzheim, J., Toda, Y., Kubota, N., Bacterial memetic algorithm for offline path planning of mobile robots, Memetic Computing, Vol. 4, No. 1, pp. 73–86, 2012.

[9] Balázs, K., Botzheim, J., Kóczy, T., L., Hierarchical fuzzy system modelling by genetic and bacterial programming approaches, Proceedings of the IEEE World Congress on Computational Intelligence, WCCI 2010, Barcelona, Spain, July 2010, pp. 1866–1871.

[10] Nemes, A., New Genetic Algorithms for Multi-objective Optimisation, Proceedings of the 1st International Symposium of Hungarian Researchers on Computational Intelligence, Budapest, 2000, pp. 1-15.

[11] Mester, G., Improving the Mobile Robot Control in Unknown Environments, Proceedings of the Conference YUINFO' 2007, ISBN 978-86-85525-02-5, March 11-14, 2007, Kopaonik, Serbia, pp. 1-5.

[12] Mester, G., Modeling of the Control Strategies of Wheeled Mobile Robots, Proceedings of The Kandó Conference 2006, ISBN 963-7154-42-6, January 12-13, 2006, Budapest, Hungary, pp. 1-3.

[13] Mester, G., Distance Learning in Robotics, Proceedings of the 3rd International Conference on Informatics, Educational Technology and New Media in Education, ISBN 86-83097-51-X, April 01-02, 2006, Sombor, Serbia and Montenegro, pp. 239-245.

[14] Mester, G., Introduction to Control of Mobile Robots, Proceedings of the Conference YUINFO' 2006, ISBN 86-85525-01-2, March 06-10, 2006, Kopaonik, Serbia & Montenegro, pp. 1-4.

[15] Mester, G., Intelligent Mobile Robot Controller Design, Proceedings of the 10th Intelligent Engineering Systems, INES 2006, ISBN: 0-7803-9708-8, DOI: 10.1109/INES.2006.1689384, June 26-28 2006, London, United Kingdom, pp. 282-286.

[16] Mester G., Adaptive Force and Position Control of Rigid Link Flexible Joint Scara Robots, Proceedings of the 20th IEEE Annual International Conference on Industrial Electronics, Control and Instrumentation, IECON'94, Vol. 3, ISBN: 0-7803-1328-3, DOI: 0.11 09/IECON.1994.398059, September 5-9 1994, Bologna, Italy, pp. 1639-1644.

[17] Kasac, J., Milic, V., Stepanic, J:, Mester, G., A Computational Approach to Parameter Identification of Spatially Distributed Nonlinear Systems with Unknown Initial Conditions, Proceedings of the IEEE Symposium on Robotic Intelligence in Informationally Structured Space RiiSS (2014), DOI: 10.1109/RIISS.2014.7009170, Vol. 1, ISBN: 978147 9944637, December 9-12, 2014, Orlando, Florida, USA, pp. 55-61.

[18] Rodic, A., Mester, G., The Modeling and Simulation of an Autonomous Quad-Rotor Microcopter in a Virtual Outdoor Scenario, Acta

Polytechnica Hungarica, Journal of Applied Sciences, Vol. 8, Issue No. 4, ISSN 1785-8860, pp. 107-122, 2011.

[19] Wang, L., Adaptive Fuzzy Systems and Control, Design and Stability Analysis, PTR Prentice Hall, ISBN 0-13-099631-9, 1994.

[20] Hellendron, H., Driankov, D., Fuzzy Model Identification, Selected approaches, Springer, 1997, ISBN 3-540-62721-9

[21] Nemes, A., Function Identification by Unconstrained Tuning of Zadeh-type Fuzzy Partitions, Proceedings of the 2nd International Symposium of Hungarian Researchers on Computational Intelligence, Budapest, 2001, pp. 1-10.

[22] Stevanovic S., Kasac J., Stepanic J., Robust tracking control of a quadrotor helicopter without velocity measurement. Annals of DAAAM for 2012 & Proceedings of the 23rd International DAAAM Symposium, Vol. 23, No. 1, ISSN 2304-1382, ISBN 978-3-901509-91-9, Vienna, Austria, 2012, pp. 595-600.

[23] Jang, J., Sun, C., Mizutani, E., Neuro-Fuzzy and Soft Computing, A Computational Approach to learning and Machine Intelligence, Prentice-Hall, 1997, ISBN 0-13-287467-9.

[24] Goldberg, D., Genetic Algorithms in Search, Optimization and Machine Learning, Addison Wesley Publishing Company, 1989, ISBN 0-201-15767-5.

[25] Goldberg, D., et all. Genetic Algorithms: A Bibliography, IlliGAL Report No.97002, University of Illinois at Urbana-Champaign, 1997.

[26] Mester, G., Pletl, Sz., Nemes, A., Mester, T., Structure Optimization of Fuzzy Control Systems by Multi-Population Genetic Algorithm, Proceedings of the 6th European Congress on Intelligent Techniques and Soft Computing, EUFIT'98, Vol. 1, 7-10 September 1998, Aachen, Germany, pp. 450–456.

[27] Nemes, A., System Identification Based on Multi-Objective Optimisation and Unconstrained Tuning of Zadeh-type Fuzzy Partitions, Proceedings of the IEEE SISY Conference, 2003, pp. 1-12.

[28] Mester, G., Modeling of Autonomous Hexa-Rotor Microcopter, Proceedings of the IIIrnd International Conference and Workshop Mechatronics in Practice and Education, MechEdu 2015, ISBN 978-86-91881 5-0-4, May 14-16, 2015, Subotica, Serbia, pp. 88-91.

[29] Mester, G., Rodic, A., Simulation of Quad-rotor Flight Dynamics for the Analysis of Control, Spatial Navigation and Obstacle Avoidance, Proceedings of the 3rd International Workshop on Advanced Computational Intelligence and Intelligent Informatics, IWACIII 2013, ISSN: 2185-758X, October 18 to 21 in 2013, Shanghai, China, pp. 1-4.

[30] Rodic, A., Mester, G., Control of a Quadrotor Flight, Proceedings of the ICIST Conference, ISBN: 978-86-85525-12-4, 03-06.03.2013, Kopaonik, Serbia, pp. 61-66.

[31] Mester, G., Rodic, A., Navigation of an Autonomous Outdoor Quadrotor Helicopter, Proceedings of the 2nd International Conference on Internet Society Technologie and Management, ICIST, ISBN: 978-86-85525-10-0, 1-3.03.2012, Kopaonik, Serbia, pp. 259-262.

[32] Rodic, A., Mester, G., Ambientally Aware Bi-Functional Ground-Aerial Robot-Sensor Networked System for Remote Environmental Surveillance and Monitoring Tasks, Proceedings of the 55th ETRAN Conference, Section Robotics, Vol. RO2.5, ISBN 978-86-80509-66-2, Banja Vrućica, Bosnia and Herzegovina, Jun 6-9, 2011, pp. 1-4.

[33] Rodic, A., Mester, G., Modeling and Simulation of Quad-Rotor Dynamics and Spatial Navigation, Proceedings of the 9th IEEE International Symposium on Intelligent Systems and Informatics, SISY 2011, ISBN: 978-1-4577-1973-8, DOI:10.110 9/SISY.2011.6034325, 8–10 September, 2011, Subotica, Serbia, pp. 23-28.

СЛОБОДНО ЕВОЛУЦИОНО И ГРАДИЈЕНТНО ОПАДАЈУЋЕ УСКЛАЂИВАЊЕ ФАЗИ ПАРТИЦИЈА КОД ДИНАМИЧКОГ МОДЕЛИРАЊА БЕСПИЛОТНИХ ЛЕТЕЛИЦА

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У раду се представља једна нова фази метода идентификације за динамичко моделирање квадротора. Метода је заснована на специјалној параметризацији претходника фази система који резултира фази поделом претходника. Овај метод представљања параметара претходника фази правила обезбеђује уважавање редоследа претходно дефинисаних лингвистичких вредности и осигурава да фази подела остаје непромењена за сво време неограниченог хибридног еволуционог, градијентно опадајућег оптимизационог процеса. У једначинама кретања, одговарајућа компонента дериватива првог реда се срачунава на бази Кристофел симбола, деривативи фази система се користе за моделирање Кориолисових ефеката, жироскопских и центрифугалних израза. Нелинеарни параметри су подвргнути иницијалној општој еволуционој оптимизационој шеми а фино подешавање градијентно опадајућем локалном претраживању. Симулациони резултати предложеног новог идентификационог метода динамичког модела су обећавајући.