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Research Article

Visual-based quadrotor control by means of fuzzy cognitive maps

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ABSTRACT

By applying an image-based visual servoing (IBVS) method, the intelligent image-based controlling of a quadrotor type unmanned aerial vehicle (UAV) tracking a moving target is studied in this paper. A fuzzy cognitive map (FCM) is a soft computing method which is classified as a fuzzy neural system and exploits the main aspects of fuzzy logic and neural network systems; so it seems to be a suitable choice for implementing a vision-based intelligent technique. An FCM has been employed in implementing an IBVS scheme on a quadrotor UAV, so that the UAV can track a moving target on the ground. For this purpose, by properly combining the perspective image moments, some features with the desired characteristics for controlling the translational and yaw motions of a UAV have been presented. In designing a vision-based control method for a UAV quadrotor, there are some challenges, including the target mobility and not knowing the height of UAV above the target. Also, no sensor has been installed on the moving object and the changes of its yaw angle are not available. Despite all the stated challenges, the proposed method, which uses an FCM in controlling the translational motion and the yaw rotation of a UAV, adequately enables the quadrotor to follow the moving target. The simulation results for different paths show the satisfactory performance of the designed controller.

1. Introduction

Owing to their unique capabilities, quadrotor type unmanned aerial vehicles (UAVs) are appropriate machines to use in covered environments with numerous obstacles. To effectively execute their missions (route finding, obstacle avoidance, path tracking, etc.), these vehicles need to know their exact positions in different environments. Unfortunately, a global positioning system (GPS) [1] cannot be used in interior or covered spaces that do not have a sufficient field of view of the sky [2]. In this paper, we intend to design a vision-based control scheme for a flying quadrotor, so that by using a camera installed under it, the quadrotor is able to track a target moving on the ground and within the field of view of the camera. The nonlinear nature of the quadrotor and the existence of uncertainties in image equations, which are produced as a result of target mobility, led to the use of intelligent methods to control the quadrotor. For this purpose, a fuzzy cognitive map (FCM), which is a soft computing method and similar to human reasoning, was employed to control the position and the yaw angle rotation.

In general, the control schemes that use a vision sensor are divided into image-based visual servoing (IBVS) and position-based visual servoing (PBVS) control methods. The authors in [5] have considered the vision-based control of an unmanned aerial vehicle. The problem of controlling a UAV with under-actuated dynamics has been comprehensively explored. Perspective image features and the virtual spring control concept have been used. Some of the works that have applied the IBVS approach on a quadrotor UAV, but have overlooked the UAV dynamics, include (in which the classic IBVS method has been implemented on a quadrotor), [9] (in which an adaptive method has been employed for determining the vision loop control gain factors), and [10] (in which the IBVS has been used for landing a quadrotor on a moving plate). The use of image moments in IBVS control has been evaluated in [11,12]. It has been demonstrated in [13] that the image equations have reactive properties in the oriented image plane. The authors have dealt with a vision-based control scheme involving the takeoff and landing of a vertical-takeoff-and-landing (VTOL) type UAV, which allows the UAV to track a moving target.

An FCM is a soft computing method, which is classified as a fuzzy neural network capable of incorporating and adapting

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human knowledge [15]. We can also say that an FCM is a technique of modeling complex systems by using the existing knowledge and human experience. It is capable of learning and it has certain features that help improve its structure and computational behavior [16–18]. As a knowledge representative and a method of reasoning, an FCM expresses a system in a form that closely resembles human cognition. It can also combine the knowledge of the experts and the existing knowledge of data in the form of rules [17–20]. This method presents knowledge by emphasizing the causal relationships and using a map structure.

The cognitive map (CM), which is the precedent to the FCM, was first introduced in 1976 by Robert Axelrod [21]. The CMs were presented as a tool for analyzing the systems formed of concepts connected through complex relationships. Then in 1986, FCM was introduced by Kosko [22]. In the FCM, instead of using just a sign, each edge is accompanied by a number (weight), which indicates the intensity of the causal relationship. The FCM model can be easily understood, even by non-technical individuals; and each of its parameters has an understandable meaning [23]. The FCM model has been developed and it is used in various research fields such as engineering [24], medicine [3,25,26], business [27], software engineering [28,29], environmental science [30] and politics [31].

The current generalizations performed on the FCMs are usually intended to solve three problems: modeling of uncertainties, solving dynamic problems, and presenting rule-based knowledge [32]. The ability of FCMs to improve their performance via experience constitutes a vital modeling issue. The connection matrix can either be adapted, without supervision, based on the Hebbian method [33–36] or by supervised methods which use the evolutionary computations [37], or by means of gradient-based techniques [38]. In one of the earlier attempts in this regard, the researchers proposed a simple method called the differential Hebbian learning (DHL), which was based on the Hebbian theory [39]. The improved version of the DHL, introduced as the balanced differential algorithm (BDA) [40], eliminated one of the limitations of the DHL method by considering the values of all the concepts which were continually changing during the updating of weights. Then the nonlinear Hebbian learning (NHL) algorithm and the active Hebbian learning (AHL) algorithm were introduced. Based on a training principle similar to that of NHL, an improved version of the NHL method called the data-driven nonlinear Hebbian learning (DD-NHL) [41] was introduced, which uses the advantages of historical data. The use of a genetic strategy (GS) for training the FCM model from data, i.e., training the weight matrix, was introduced in [42]. The particle swarm optimization (PSO) method, belonging to the group of swarm intelligence algorithms, was proposed in [15]; and another method based on swarm optimization, called the memetic particle swarm optimization (MPSO), was presented in [43].

One of the fields in which the FCMs are employed is robotics. The use of FCMs to describe a system with one agent has been proposed in [44,45]. Modeling the movement in autonomous and robotic agents by means of FCMs has been investigated in [46,47]. In [48], an FCM has been applied as a support tool to find the optimal path between the start and end positions in a special maze designed for a mobile robot. Another application for an FCM in robotic systems has been presented in [49]. They have used this technique to simulate a robot's position and perform simple moves by the robot. A mobile robot equipped with several sonar sensors and an odometer has been described in [50] and its navigation by means of a cognitive map has been tested. An FCM has been designed in [51] for balancing a legged robot. An FCM trained by the PSO training algorithm has been employed in [52] for controlling the ball passing and kicking by a bipedal robot.

In the rest of this paper, first, the considered FCM and its relevant equations are presented in Section 2, and a brief description of the NHL algorithm is given in Section 3. The NHL algorithm is applied to train the FCMs used for controlling the translational motion and the yaw of the UAV. The quadrotor UAV, its manner of movement and kinematic and dynamic equations and also the uncertainty that may exist in its dynamics are described in Section 4. In Section 5, the method of projection on a virtual plane is presented, and image features are introduced. In Section 6, FCM is employed for the IBVS control of a moving object. The results of the simulations for investigating the performance of the designed scheme are presented in Section 7. And finally, the conclusion of this work is presented in Section 8.

2. Fuzzy cognitive maps

Fuzzy cognitive map, an extension of the CM, has inherited the major features of the fuzzy logic and neural networks. FCMs are tools for obtaining ideal causal knowledge by signed fuzzy graphs, which can be introduced as a single-layer neural network [22]. They describe special regions by using nodes (i.e., variables, states, inputs and outputs) and the signed fuzzy relationships between the nodes. The fuzzy part allows us to have a degree of causality, which is presented as a link between the nodes (also known as concepts) of this graph. In other words, the edges (an edge is an arrow connecting two concepts together) of the graph are assigned weights with a real value from the interval $[-1, 1]$; with each weight expressing the strength of the connection between two concepts. For example, the position of a valve in a tank system can be in a state of "low", "medium" or "high" and an edge can indicate the relationship between the liquid level in the tank and the state of one of the valves. In other words, the level of liquid in the tank is affected by the condition of the valves. Also, a positive value for the edge relating the valve condition to the level of liquid in the tank indicates that the liquid level increases with the increase in the degree of valve, while a negative value shows the reduction of the liquid level with the increase of the valve state. The weights are normally determined by defuzzifying the fuzzy opinions of several experts [24].

In an FCM structure, the concepts are modeled as a set of linguistic variables $C = \{C_1, C_2, ..., C_M\}$, in which each linguistic variable is presented by means of fuzzy sets $L_k^{C_i}$ (where $k = 1, ..., n$) over U_i. The global set U_i depends on the area where C_i has been defined. The linguistic variables indicate the degree of occurrence of each concept. The relationship between concepts is described by means of "if-then" rules. If a change A occurs in the concept value of C_j, then a change B will occur in the concept value of C_i. $E : (C_i, C_j) \to e_{i,j}$ relates $e_{i,j}$ to a pair of concepts (C_i, C_j), $e_{i,j}$ denotes the weight of an edge from C_i to C_j, and $e_{i,j} \in [-1, 1]$. When an FCM is formed, it can receive data from its input concepts, perform the logical reasoning operation and produce the results as the output concept values. During the logical reasoning process, the FCM repeatedly computes its states until convergence occurs. A state is presented by a state vector $S(t)$, which includes the node values $s_i(t) \in [0, 1], \quad i = 1, 2, ..., M$ at iteration time t (discrete time). The value of each node is determined from the following equation:

$$s_i(t+1) = W\left(s_i(t) + \sum_{\substack{j=1 \\ j \neq i}}^{M} s_j(t) e_{j,i} \right) \tag{1}$$

And in the matrix form, it is written as follows:

$$S(t+1) = W(S(t) + S(t)E) \tag{2}$$

The initial state vector $S(0)$, indicative of the user input and including the observations, measurements and the extension of results, is mapped over the $[0, 1]$ interval by using the membership