Autonomous rerouting flight path planning using Gaussian-mixture-based artificial potential field method

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Abstract: As air transportation traffic increases, Free Flight has been considered a possible solution for future challenges in air traffic management (ATM). Autonomous navigation and guidance system can be used for a free flight of a UAV or assist a pilot in path planning to avoid flight into an unsafe area or collision with other aircrafts (or UAVs) in dense air traffic environments. To implement the collision avoidance and guidance function, we use a Gaussian-mixture-based artificial potential field method. In this paper, we introduce the gaussian-mixture based APF method which improves traditional APF problem and can be applied to air traffic routing scenarios. This APF method can be easily extended to air traffic modeling such as weather condition, traffic density, Special Use Airspace (SUA) as well as path planning for collision avoidance. This indicates that the APF approach can be applied effectively in the field of civil aviation air traffic management. The proposed collision avoidance algorithm generates a path for multi-UAVs, with each UAV considering of the other UAVs as obstacles. We also apply the developed algorithm to a possible scenario and demonstrate its performance through simulation using multicopter-type UAVs and obstacles.

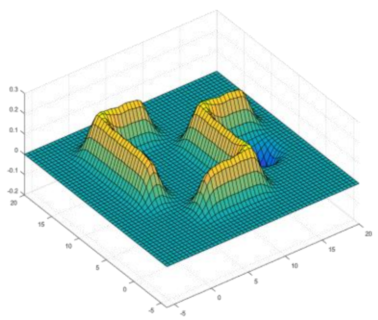
Keywords: Air Traffic Management (ATM), Air Traffic Control (ATC), Free Flight, Collision Avoidance, Artificial Potential Field (APF), Gaussian Mixture Model (GMM), Path Planning, Unmanned Aerial Vehicles (UAVs)

1. INTRODUCTION

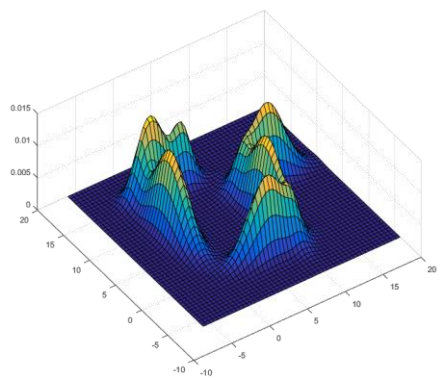
As air transportation traffic increases, Free Flight has been considered as a possible solution for future challenges in air traffic management (ATM)[1]. It is believed that the problems in en-route air traffic, among various flight phases defined in free flight, need to be dealt with to comply to traffic flow management. Therefore, development of fully autonomous flight path planning methods become one of the crucial steps in autonomous air traffic control. For this purpose, various support tools have been developed and suggested for different directions and levels. Among these, the approach using artificial potential field (APF) would be of noteworthy interest to consider, thanks to its flexibility for application and, relatively, simplicity for implementation. Despite of the inherent drawbacks such as getting stuck in the local minima**,** The APF approach has been popularly utilized in field robot path planning [2,3] and recently applied also to the guidance of a multicopter-type UAV including collision avoidance [4,5].

Ref.[1] firstly, as far as the authors knew, introduced a series of methods to apply the APF approach to ATM area for flight route planning, conflict detection and resolution, and local trajectory generation. Especially, the authors modeled various objects and situations in airspace being encountered during flight such as weather, Special Use Airspace (SUA), etc., using potential functions with different attributes in an object-oriented fashion. In Ref.[6], an improved APF model (IAPFM) was introduced by additionally including a gravitation point in order to resolve the inherent local minimum solution problem. The performance of the IAPFM was numerically demonstrated using a rerouting planning of an aircraft according to thunderstorm cloud forecasts modeled by IAPFM. This method was also modified to include the impact of air wind to the aircraft in Ref.[7]. More recently, Ref.[8] suggested a new method that mixes search-based motion planning with inverse reinforcement learning to build an autonomous ATC in which an APF is used as a penalty in order to avoid potentially unsafe states.

Although this paper can also be categorized as an APF-based method, the current APF does have some different attributes than the traditional APF. First, within the current APF framework, the possible two-dimensional location of various objects or situations during flight are modeled as a mixture of several two-dimensional gaussian distribution function. The number of functions in a mixture is dependent upon the level of complexity of the object shape. Generally, the more complex the shape the more bivariate functions in a mixture. The height of the mixture does not represent the physical size of a three-dimensional object but indicates the level of possibility of the object's existence. Figure 1 shows an example of a complex object together with a mimicking gaussian-mixture model consisting of six two-dimensional gaussian functions with different parameters (mean, variance, participation factor).



(a) Given objects



(b) Mimicked APF model of the object

Figure 1 Gaussian Mixture Model [4]

Second, the shape of a constructed gaussian-mixture model of an artificial potential function can be updated upon getting new observed measurement data or other forms of information on the location of the target object, which is enabled via the Expectation-Maximization algorithm. By using a recursive type of the algorithm, the update can be quickly implemented.

Finally, using the derivative of the final potential function which adds the effect of the obstacle potential, the destination potential, and the global converging potential, we can automatically generate the possible flight path avoiding the possible obstacles and aiming at the destination.

In the next section, the gaussian-mixture model (GMM) is briefly introduced and how the GMM is updated is discussed. Then, in Section 3, a numerical simulation result using two multicopters is presented. Finally, Section 4 concludes the study.

2. GAUSSIAN-MIXTURE-BASED ARTIFICAIL POTNETIAL FIELD

As introduction in Section 1, the artificial potential function consists of the obstacle potential, the destination potential, and the global converging potential functions. The obstacle potential function is implemented using a GMM by adding as many bivariate functions as the given object can be reasonably approximated. The destination potential function is included to indicate the final location at which the aircraft must arrive. To attract the aircraft, the value of this function is taken to the opposite sign (usually negative) of the obstacle potential function (usually positive). In addition to the destination potential function, the global converging potential function is considered to guide the aircraft to the destination location of the aircraft. Usually, a two-dimensional, smooth and gentle, concave surface function is used for this effect. Figure 2 shows an example of an artificial potential function consisting of these three components from which the artificial potential field (Figure 3) is generated by taking the spatial derivative of the potential function.

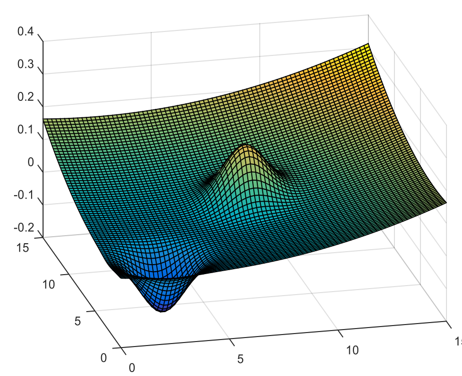


Figure 2 Artificial Potential Function Example [4] (upward: obstacle, downward: destination, concave: global converging potential function)

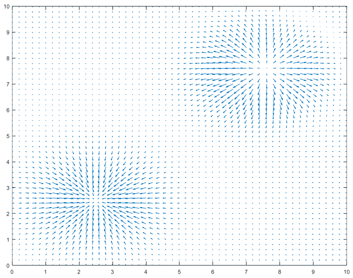


Figure 3 Generated Artificial Potential Field from the Artificial Potential Function of Figure 2 [4]

The obstacle potential function $p(\mathbf{x}\,|\,\theta)$ can be expressed as a mixture of gaussian distributions with different participation (weight) factors α_i and the parameters θ_i as (1) and (2)

$$p(\mathbf{x}\,|\,\theta)=\sum_{i=1}^{N}\alpha_i p\left(x_i\,|\,\theta_i\right) \tag{1}$$

where,

$$\sum_{i=1}^{N}\alpha_i=1,\qquad 0\le\alpha_i\le 1\cdot \tag{2}$$

The parameters $\theta_i=\left\{\mu_i^x,\mu_i^y,\sigma_{x,i}^2,\sigma_{y,i}^2\right\}$ denote the mean and variance of each gaussian distribution and the participation (weight) factors α_i can be obtained by the Expectation-Maximization (EM) algorithm which evaluates probabilistic conformity using the log-likelihood function as [9, 10]:

$$\theta^*=\arg\max\ Q(\theta,\theta') \tag{3}$$

$$Q(\theta,\theta')=\sum_{i=1}^{M}\log\left(\sum_{j=1}^{N}\alpha_j p_i\left(x_i\,|\,\theta_j\right)\right)$$

where

N: number of classes
M: number of data
θ' : previous data
Q : log-likelihood about all data
θ^* : maximum likelihood estimation

The EM algorithm repeats the Expectation step (E-step) and the Maximization step (M-step) to produce an optimized model from an initial model.

In the E-step, the expectation value of the log likelihood is calculated as the estimated value of the parameter θ_i, and the variable that maximizes this expectation value is obtained in the M- step. The variable calculated in the M-step is used as the estimated value of next E-step. If we take advantage of the process of updating the obstacle's GMM using the EM algorithm, it also can be applied to avoiding dynamic obstacles.

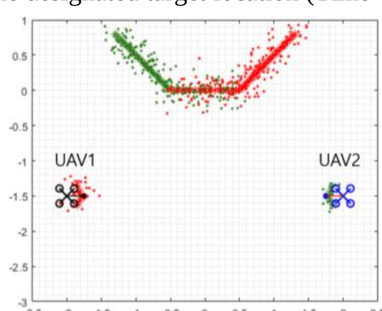
For more details about the EM algorithm applied to the GMM-based APF construction, please refer to Ref.[4,5].

3. NUMERICAL SIMULATION

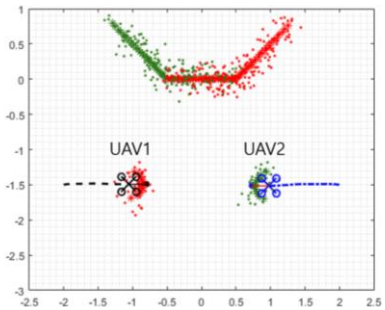
Using a numerical simulation, performance of the introduced GMM-based APF approach is demonstrated for two multicopter-type UAVs flying near a U-shaped obstacle. It is assumed that each of UAV is equipped with a LiDAR sensor to detect obstacles around the UAV. Figure 4 describes the results of a simulation scenario in which two UAVs horizontally approache each other, UAV1 from left to right and UAV2 from right to left. In the upper region of the UAVs, there is a fixed U-shaped obstacle. The thick (green and red) solid lines represent the true location of the obstacle and the dots around the lines represent the LiDAR data measured by each of the UAVs: Green and red dots indicate the LiDAR data obtained by UAV1 and UAV2, respectively. Each UAV also obtains LiDAR data of the other UAV which is denoted as dots around each UAV with different colors. In order to mimic the effect of some noises when measuring the obstacles via LiDARs, we artificially scattered the data by adding random noise to each data points.

Each of UAV observes the other UAV and the U-shaped object as obstacles which are modeled as a Gaussian Mixture consisting four gaussian distributions, three for the U-shaped object and one for the other UAV. From the constructed potential function, we can generate a corresponding APM from which we can guide each UAV to each destination point while avoiding collision with the other UAV and with the U-shaped obstacle.

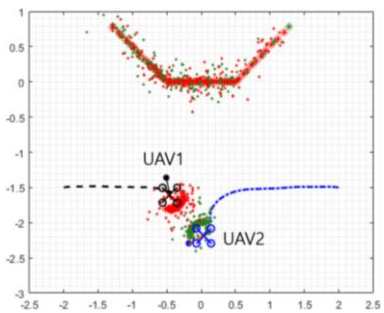
At the begging period (Time =0, 1) the two UAVs fly relatively in straight lines and after detecting the other UAV, the flight paths change (Time = 2, 3). Finally, each of UAV arrives at the designated target location (Time = 4).



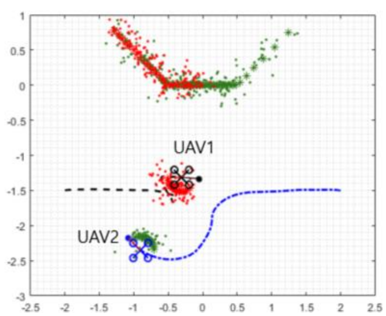
(a) Time = 0



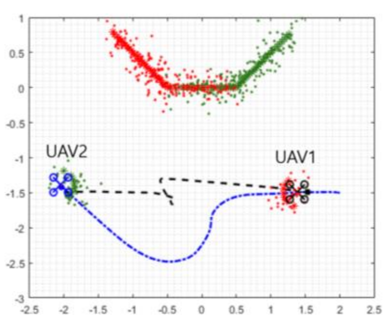
(b) Time = 1



(c) Time = 2



(d) Time = 3



(e) Time = 4

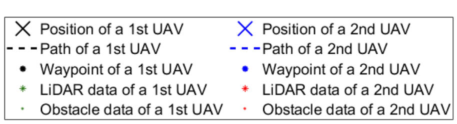


Figure 4 Simulation Result of Collision Avoidance and Rerouting Flight Path Planning: Two-UAV and one U-shaped Obstacle

4. CONCLUSION

In this paper, we have introduced a new artificial potential field approach, based on Gaussian mixture model, for autonomous rerouting flight path planning. This algorithm is relatively simple to implement and flexible to approximately mimic complex objects that may be encountered during flight. Although a simple simulation scenario including two UAVs and a near object is used to demonstrate the performance, it is expected that after considering more specific information of ATM and implementing more detailed algorithms this GMM-based APF approach can be considered as a support tool in free maneuvering flight phases in free flight.

5. ACKNOWLEDGMENTS

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