Decentralized Autonomous Unmanned Aerial Vehicle Swarm Formation and Flight Control

Ihor Skyrda(✉)

National Aviation University, Kyiv, Ukraine
skyrda2@gmail.com

Abstract. Unmanned Aerial Vehicles (UAV) have become more popular for usage due to the low cost of deployment and maintenance. Single UAV employment allows remote area monitoring and transferring different payloads to inaccessible or dangerous zones for human. In order to deal with flight tasks that are more complex, UAV swarms are applied. The main challenge of UAV swarm formation and flight control is to avoid vehicle collisions. In this case, artificial intelligence is responsible for flight performance in the airspace in such way that collision is avoided. The main requirements to the method, which will provide conflict-free maneuvers, are safety (collision avoidance), liveness (decentralized control, destination area reachability) and flyability (UAV flight performance constraints are satisfied). Artificial force field method fulfills all of these demands. It allows to detect a potential conflict between multiple UAVs in a swarm and other static or moving obstacles found in airspace, to provide collision resolution by changing UAVs flight parameters through maintaining minimum separation distance, including cases when manned vehicles are found in the same airspace. There can be distinguished by a wide range of obstacles: static (buildings, restricted areas and bed weather conditions) and dynamic ones (other UAVs, manned aircraft). Method allows keeping UAV swarm shape on the flight path, taking into account ground speed and turn bank angle values restrictions according to UAV's flight performance characteristics.

Keywords: Autonomous unmanned aerial vehicle · Potential field · Vortex field · Swarm formation · Fixed wing · Three-dimensional space

1 Introduction

Unmanned Aerial Vehicles (UAV), also known as 'drones', are vehicles that fly without a pilot on-board with remote control or in an autonomous way. It is a part of Unmanned Aircraft System (UAS), which includes UAV, ground station (where an operator is located) and communication infrastructure.

A diverse range of systems and UAVs lies within the broad definition of UAS. Some differences between these UAS are immediately apparent features, such as size, weight or type of aerial platform (multi-rotor, fixed wing, single rotor) of UAVs. These systems have varying degrees of automation and autonomy, but usually include human remote operator controlling the vehicle from meters, kilometers or continents away.

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UAVs are mostly applied for domestic functions such as environmental monitoring, security, emergency response, surveillance and recreation.

The main technical peculiarity of UAV is defined by the extent of autonomy and automation delegated from the operator to the system. Automation levels vary from those that are fully piloted from a remote location to fully automated. There are also several points in-between, with some maneuvers triggered automatically through autonomous conditions monitoring. Depending upon system priorities, autonomous maneuvers may have the priority over, or to be overridden by, the commands of a remote operator. The International Civil Aviation Organization (ICAO) and current European Commission (EC) plans will only permit the autonomous maneuvers to override operator command in extraordinary circumstances such as communication failure or imminent collision risk, the main requirements for UAV integration into normal airspace. The UAV technologies beyond this definition, featuring a greater autonomy, are also quite well developed and, while integration is not currently planned, it could plausibly follow a successful period of development in the UAS sector [1].

The UAV swarm is a group of vehicles that perform the flight in a group, communicating with each other and assisting other UAV in tasks' accomplishment. Many applications for UAV swarm use there are foreseen, they may be search, rescue and payload (nonhomogeneous UAVs) transportation. A swarm could cover a big area, especially if where only small UAVs could be used and would require only one operator. In order to model UAV swarm motion and control it is better to use the bottom-up modelling approach and use the decentralized method for UAVs coordination. The main advantages of such principle are flexible, adaptive and efficient group organization of system with low autonomy, where the intelligence is distributed through all swarm participants, even in case of one UAV loss. Currently, an important challenge is the reduction of the number of operators required for performing a multi-UAV mission. This challenge can be addressed by increasing the autonomy of fleets and providing capabilities of operators to the interfaces. This article presents a proposal of control method for UAV swarm flight performance, so the multi-UAV system will be able autonomously perform shaping and maintain the expected formation with desired flight parameters.

2 Related Work

The results of analysis show that most of known methods for multi-UAV control have a number of significant limitations that are connected with multiple conflicts resolution and group formation. Particularly, the main disadvantage of such methods is connected with pairwise way (between two vehicles) of potential conflicts resolution, when this issue needs to be done in a global way. For example, the system called Traffic Alert and Collision Avoidance System (TCAS) that is already installed aboard uses a range of measurements and range-rate estimates to determine if a conflict exists in the horizontal plane. In case potential conflict presence TCAS searches through a set of climb or descent maneuvers (Fig. 1) and choose the best one accounting flight performance characteristics and flight plan of only two aircraft to provide safe conflict resolution [2, 3]. Methods developed for a group control in robotics do not include such feature, so UAVs must deal with constant movement and limited turning ability, which makes collision avoidance much more complicated [4].

Multiple conflicts can be resolved in pairwise and global way, where pairwise means that all conflicts will be resolved sequentially in pairs and global means analysis of general traffic situation. The first way refers to TCAS principle of operation where one conflict induces a new one until conflict free trajectory will be found, but there is a big probability that it leads to “domino effect”. That’s why the second way will be used in the combination with algorithms.

It is possible to define four main classes of algorithms:

– geometric approach;
– stochastic approach;
– linear programming approach;
– potential fields approach.

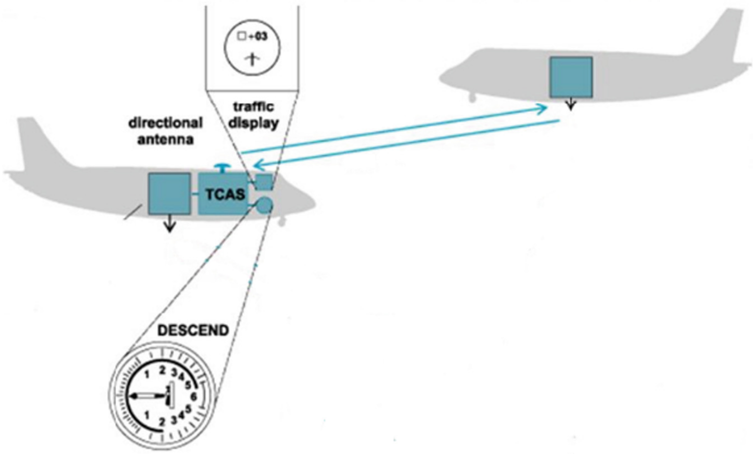

Fig. 1. TCAS Air part principal of operation

The classical approach is called geometric, where aircraft trajectory predictions are based on linear projections of the current vehicle states. Such projections can be computed efficiently, and prediction errors are negligible for short time periods, but it still cannot be used for multiple vehicle conflicts resolution due to computational complexity, so it requires time and space discretization [5]. In [6] presented idea for global conflict resolution with geometric approach by aggregation of vehicles in one artificial vehicle (Fig. 2) [6] with its center but for this more complicated algorithm is required, and from practical point of view the rate of updating surveillance information should be fast.

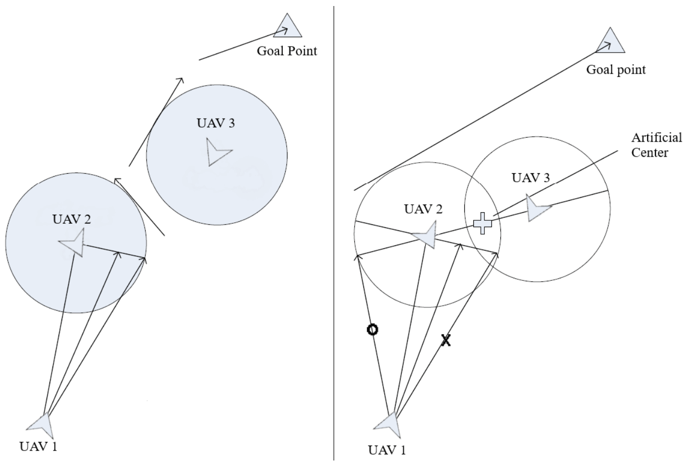

Fig. 2. Multiple conflicts resolution based on geometric approach

The class of stochastic approaches is related to the problem of probabilistic conflict detection in the presence of various uncertainties during the flight. The aircraft dynamics are described by using stochastic differential equations, and the future aircraft's trajectory is determined by solving the stochastic trajectory optimization task, it could be applied for the conflict definition at rather big distances (Fig. 3) [7], so stochastic approach can be hardly applied in order to control a group of UAVs flying close to each other.

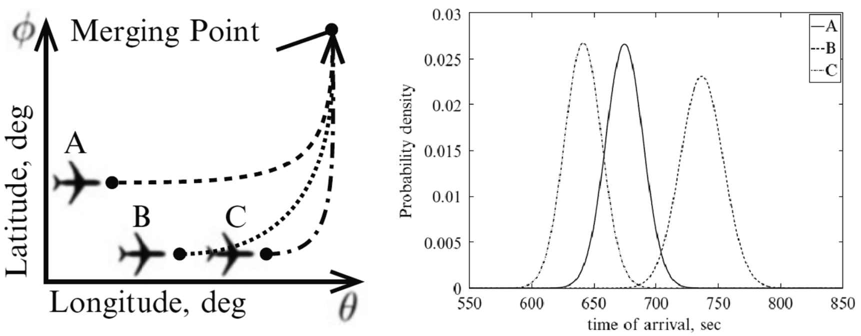

Fig. 3. Multiple conflicts resolution based on probabilistic approach

Linear programming is a mathematical method [8] where an optimal control problem lies in finding trajectories that minimize objective function. There distinguish two main approaches, where the first approach, the optimal control is converted to a finite dimensional Nonlinear Program (NLP) by using collocation on finite elements and by reformulating the disjunctions involved in modeling the protected zones by using continuous variables. In the second approach, the optimal control is converted to a finite dimensional Mixed Integer Linear Program (MILP) using Euler discretization and reformulating the disjunctions involved with the protected zones by using binary variables and Big-M techniques. The drawback of such approach is flyability of the optimal trajectories due to its safety and performance aspects. Also it's computationally expensive with the number of vehicles increasing and causing "the curse of dimensionality" (Fig. 4) [8].

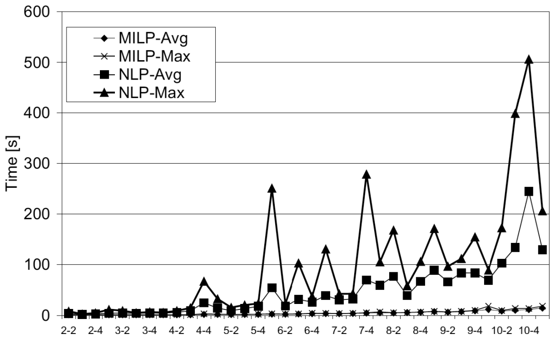

Fig. 4. Maximum and average computational times depending on number of UAVs for multiple conflicts resolution based on probabilistic approach

The common disadvantage of these methods is that they do not meet the main requirements with respect to autonomous UAVs: the absence of any communication links with the appropriate ground stations, with on-board computational and power sources being limited.

The summarized disadvantages of the analyzed methods make no possibility to simultaneously use a combination of such parameters as heading, speed and altitude change maneuvers to resolve multiple potential conflicts. Therefore, it is necessary to develop some new methods for multiple autonomous UAVs control in a group in a three-dimensional space. The method, developed in this article, is the evolution of potential field method proposed in article [9]. A potential fields approach is based on assigning magnetic or electrical charges of the same sign to UAVs, while the opposite charges are assigned to destinations, with the principle being based on the laws of physics according to which the like particles will repel each other, while the destinations having the opposite charges will attract them. The main feature of such approach is UAVs do not necessarily need to know the positions of all other aircraft, so artificial force generated by each UAV allows them to avoid each other spontaneously, at the same time keeping a group form [10]. According to [11], this approach is scalable and can be applied to a big number of UAVs, even in case of multiple conflicts without a ground control station (Fig. 5) [9].

The Artificial Potential Field (APF) approach was introduced in [12], it was used for collision avoidance where the robot is attracted by the destination position and is repulsed from obstacles or other objects. Last years, this method was extended and modified, in order to solve the task of autonomous vehicles path planning either in the stationary or dynamic environments. There are two methods called Formation Potential Field (FPF) and Modified Artificial Potential Field (MAPF). The first one is used for the multiple vehicles formation problem, combining multiple local attractive fields generated by other vehicles to keep the swarm shape with multiple local repulsive potential fields generated by obstacles and vehicles to prevent collisions. A global attractive potential is added to denote a destination area and virtual leader located in the formation center is introduced [13]. The second method - MAPF - is intended for multiple UAVs control and maintains a formation. It can deal with static and dynamic obstacles and differ from FPF by its ability to prevent destination area attractive potential field naturalization by other vehicles repulsive potential field [14].

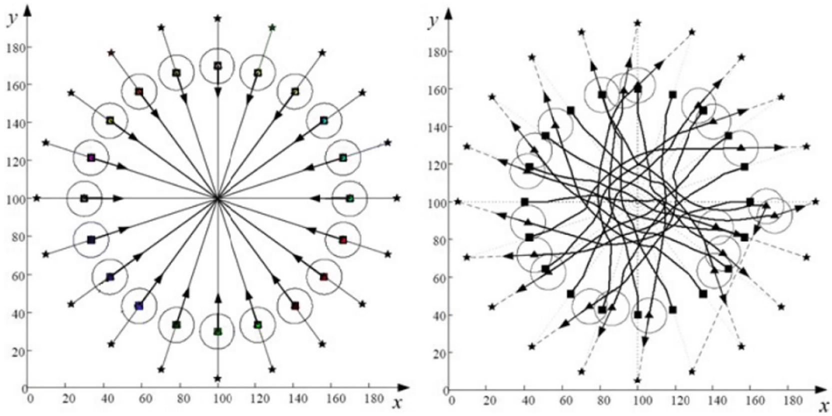

Fig. 5. Multiple conflicts resolution between dynamic objects based on potential fields approach

3 Problem Statement

To solve this problem, a potential field approach is used. This method uses the property of the real world charged particles generating a force field (electric or magnetic), caused attraction and repulsion forces when these particles interact. The matter itself is a typical example of the self-organization principle in our nature. UAVs are considered as the dynamic objects with the same sign, with the point of destination having the opposite sign, it is analogous to the free movement of the aircraft autonomous motion where they constantly have the potential conflicts, and it is required avoiding collisions with other dynamic objects or static/dynamic obstacles. In this case, the term ‘potential conflict’ is a situation, when the minimum separation standard between dynamic objects is violated. The protection zone of dynamic objects is generally defined as follows: the minimum allowed horizontal separation and the vertical separation requirement depending on the dynamic objects’ sizes. The dynamic objects collision is the process of interaction between the dynamic objects or obstacles at a distance in which the dynamic objects change their direction of motion and the speed module.

The dynamic objects interact similarly to the particles of substances that are found in other aggregate states of matter (solid, liquid). The forces act simultaneously. For the different dynamic objects, the general character of the gravity force from distance is qualitatively the same: the attraction force between dynamic objects dominates at large distance, while the repulsion force acts at a short distance. Figure 6 shows the qualitative dependence of forces interaction between two dynamic objects found at distance r between two dynamic objects is presented, where F^+ and F^- - are the dependence of the attraction and repulsion forces respectively, and $F^+ + F^-$ - is a resultant force. At a critical distance $r = r_{cr}$ the resultant force is equal to zero, i.e., the forces of attraction and repulsion are counterbalanced (Fig. 7). This distance r_{cr} corresponds to the equilibrium distance between the dynamic objects.

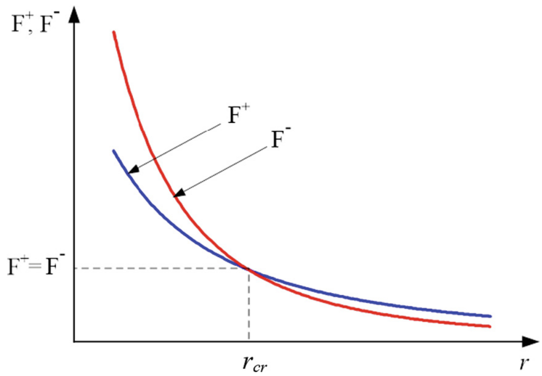

Fig. 6. The dependence attraction and repulsion forces between dynamic

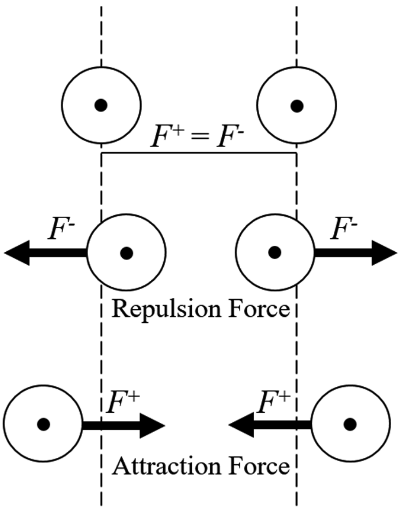

Fig. 7. Attraction and Repulsion forces action

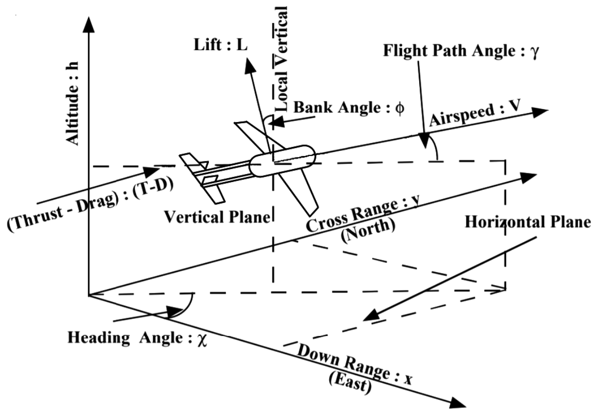

Fig. 8. UAV coordinate system

This article considers a group system consisting of n autonomous UAVs, with a point-mass model used to describe UAV formation movement. The related variables are defined with a respect to the inertial coordinate system and shown in Fig. 8.

The point-mass UAV model captures most of the dynamical effects encountered in the civil aviation aircraft. The point-mass equations of motion are formulated with a respect to a coordinate system shown in Fig. 8. The point-mass model assumes that the UAV thrust is directed along the velocity vector, and that the UAV always performs coordinated maneuvers. It further assumes a flat, non-rotating earth. These assumptions are reasonable for UAVs operating within different ranges, therefore, this method can be used in a conflict resolution between different types of UAVs, with the fidelity provided by the point-mass model being adequate for formulating these problems.

Point-mass models are applicable for the spherical earth approximations that can also be developed. The fuel expenditure is negligible, i.e., the center of mass is time-invariant [15]. Under these assumptions, the motion equations of the i-th UAV can be described as follows:

$$\begin{aligned}
\dot{x}_i &= V_i \cos\gamma_i \cos\chi_i;\\
\dot{y}_i &= V_i \cos\gamma_i \sin\chi_i;\\
\dot{h} &= V_i \sin\gamma_i;\\
\dot{\gamma} &= \tfrac{L_i \cos\varphi_i - g m_i \cos\gamma_i}{V_i m_i};\\
\dot{\chi} &= \tfrac{L_i \sin\varphi_i}{m_i V_i \cos\gamma_i};\\
\dot{V} &= \tfrac{T_i - D_i}{m_i} - g \sin\gamma_i;
\end{aligned} \tag{1}$$

where: $i = 1, 2, \ldots, n$ is the index of multiple UAVs under consideration. x_i, y_i, h_i denote the components of UAV gravity center position. For i-th UAV, x_i is down range; y_i is cross range; h_i is altitude; V_i is ground speed; γ_i is flight path angle; χ_i is heading angle; T_i is engine thrust; D_i is drag; m_i is mass; g is acceleration due to gravity; φ_i is bank angle; L_i is vehicle lift. Bank angle φ_i and engine thrust T_i are the control variables for an aircraft. A bank angle is commanded via combining rudder and aileron trims, thrust is commanded by engine throttle. The g-load $n_i = L_i/gm$ is controlled by elevator, though it refers only to UAV construction characteristics having higher limits due to the absence of crew on board an aircraft in comparison to traditional application. Throughout the UAV swarm control process, these control variables will be constrained to remain within their respective limits. The most common constraints considered are upper and lower bounds on ground speed (V_i), altitude (h_i), g-load (n_i), thrust (T_i), bank angle (φ_i) and climb or descent rates.

Heading angle χ_i and flight path angle γ_i are computed as:

$$\tan \chi_i = \frac{\dot{y}_i}{\dot{x}_i} \tag{2}$$

$$\tan \gamma_i = \frac{\dot{h}_i}{V_i} \tag{3}$$

In an air traffic, a conflict resolution is determined by separation constraints, forming the so-called conflict envelopes or 'protection zones' so that UAVs flight trajectories do not overlap during a flight. The conflict between two UAVs or an UAV with the above-mentioned obstacles implies that their altitude should differ in value h_{pr} given in UAV flight performance characteristics, or they should not get closer in the horizontal plane than indicated by value r_{pr}. The protection zone can be visualized for each UAV as shown in Fig. 9.

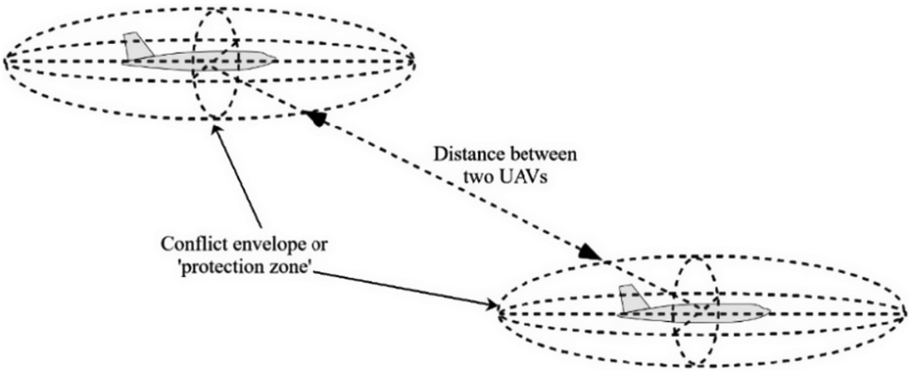

Fig. 9. Spheroidal conflict envelope or 'protection zone' and distance between two UAVs in the vertical plane

The model of UAV swarm formation and control is based on three characteristics: autonomy, which is provided by fully independent vehicle activity, localization, each vehicle is aware of local traffic situation and should not know about a whole air picture, decentralization, there is no any head of swarm.

It means that the UAV can receive information about another UAVs or vehicles by communication channels and it helps to estimate a range between them, and to use a different type of sensors to scan an environment for the obstacles presence. As a result, based on collected information, a decision about flight trajectory changes can be made. UAV collects the information about the coordinates and the flight parameters of other vehicles, the obstacles location and the shape. Then an autopilot system transfers it to the control command based on UAV flight dynamic model (Fig. 10). The difficulty of such model is connecting with the fixed-wing type vehicles considered in the paper, because they must keep a minimum velocity and have maneuverability limitations.

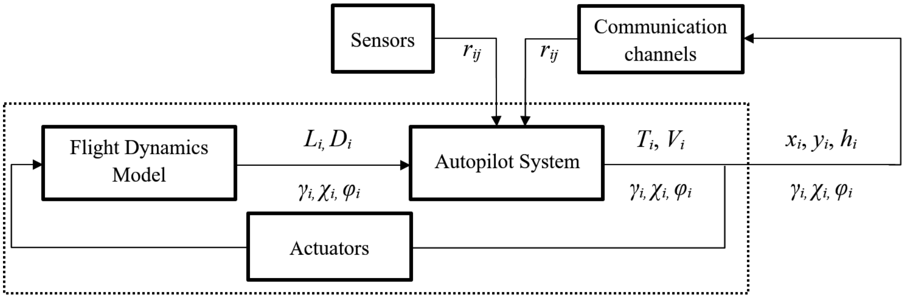

Fig. 10. Model of single UAV and parameters exchange mechanism

4 Method of the UAV Swarm Formation and Flight Control

In order to apply this approach, it is required to transfer the real world properties of UAVs and their position coordinates to the virtual world with its synergetic properties, with the potential conflicts that may occur on the flight path being taken into account [16].

This process includes the following steps:

- structural and parametric synthesis of the virtual world;
- structure formation and parameters of virtual measuring systems that provide conflict free trajectories calculation.

UAVs are transferred from the real to the virtual world as dynamic objects, with mass, attraction and repulsion potentials values being assigned to them [17]. So, the equilibrium state can be represented as:

$$F^{+}\left(m_i, m_j, G, r_{cr}^{\alpha}\right) = F^{-}\left(m_i, m_j, G, r_{cr}^{\beta}\right) \tag{4}$$

where m_i, m_j – masses of i-th and j-th dynamic bodies, G – gravitational constant,

Attraction and repulsion forces can be calculated as:

$$F_{ij}^{+} = \frac{Gm_i m_j}{r_{ij}^{\alpha}}; \qquad \alpha \in \{2, 3, \ldots\}; \tag{5}$$

$$F_{ij}^{-} = \frac{Gm_i m_j r_{\kappa p}}{r_{ij}^{\beta}} \qquad \beta \in \{3, 4, \ldots\}; \tag{6}$$

Projections of attraction and repulsion forces between i-th and j-th bodies on axes X and Y are calculated by the formulas:

$$\mathrm{F}_{\mathrm{ijx}}^{+} = \mathrm{F}_{\mathrm{ij}}^{+} \frac{|\mathrm{x_i} - \mathrm{x_j}|}{\mathrm{r_{ij}}} \quad \mathrm{F}_{\mathrm{ijx}}^{-} = \mathrm{F}_{\mathrm{ij}}^{-} \frac{|\mathrm{x_i} - \mathrm{x_j}|}{\mathrm{r_{ij}}} \tag{7}$$

$$\mathrm{F}_{\mathrm{ijy}}^{+} = \mathrm{F}_{\mathrm{ij}}^{+} \frac{|\mathrm{y_i} - \mathrm{y_j}|}{\mathrm{r_{ij}}} \quad \mathrm{F}_{\mathrm{ijy}}^{-} = \mathrm{F}_{\mathrm{ij}}^{-} \frac{|\mathrm{y_i} - \mathrm{y_j}|}{\mathrm{r_{ij}}} \tag{8}$$

$$\mathrm{r_{ij}} = \sqrt{(\mathrm{x_i} - \mathrm{x_j})^2 + \left(\mathrm{y_i} - \mathrm{y_j}\right)^2} \tag{9}$$

In Eqs. (5) and (6), the aggregate state of the virtual world environment (solid, liquid, gas) is chosen by the ratio α/β, which characterizes the self-organization degree of the dynamic objects. The aggregate state analogy of a virtual environment can serve as an aggregate state of matter - gaseous, liquid, crystalline, etc.

The resultant vector at each point of dynamic object location consists of the attraction and repulsion forces sum, $F_{ij}^{+} + F_{ij}^{-}$, but can perform a group formation, so to produce dynamic objects movement there should be present one more force which takes into account thrust force P_{ijx}, P_{ijy} direction with projection on axes X and Y (Fig. 11):

$$\mathrm{F_{ijx}} = \mathrm{F}_{\mathrm{ijx}}^{+} + \mathrm{F}_{\mathrm{ijx}}^{-} + P_{ijx} \tag{10}$$

$$\mathrm{F_{ijy}} = \mathrm{F}_{\mathrm{ijy}}^{+} + \mathrm{F}_{\mathrm{ijy}}^{-} + P_{ijy} \tag{11}$$

$$\mathrm{F_{ij}} = \mathrm{F}_{\mathrm{ij}}^{+} + \mathrm{F}_{\mathrm{ij}}^{-} + P_i(\chi_i) \tag{12}$$

The main condition for dynamic object motion should be satisfied in the following way: $F_{ij}^{+} + F_{ij}^{-} < P(\chi_i)$. The group consists of n dynamic objects and each of them can be described by the system of equations:

$$\frac{d^2 x_i}{dt^2} = \frac{1}{m_i} \sum\nolimits_{i \neq j}^{n} \left(\mathrm{F}_{\mathrm{ijx}}^{+} - \mathrm{F}_{\mathrm{ijx}}^{-} + P_{ijx}\right) \tag{13}$$

$$\frac{d^2 y_i}{dt^2} = \tfrac{1}{m_i} \sum\nolimits_{i \neq j}^{n} \left(\mathrm{F}_{\mathrm{ijy}}^{+} - \mathrm{F}_{\mathrm{ijy}}^{-} + P_{ijy}\right) \\ i \in n, j \in n. \tag{14}$$

The main advantage of the formed virtual world is when the dynamic objects approach the critical distance r_{pr}, the resultant force acting on them is zero, i.e., the forces of attraction and repulsion balance each other. Thus, r_{pr} allows to set the size of the dynamic objects protection zone.

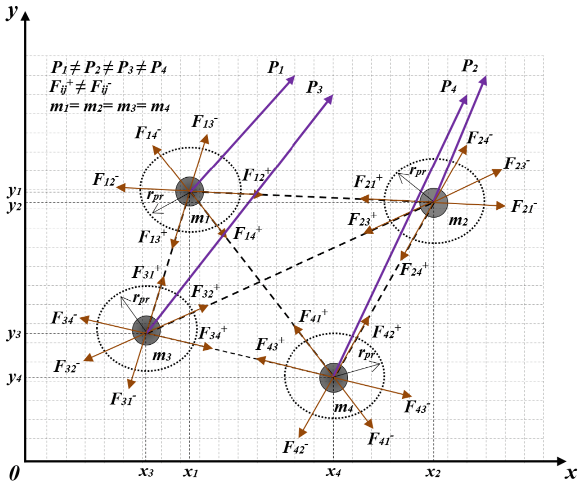

Fig. 11. The forces scheme with four dynamic objects in the original position

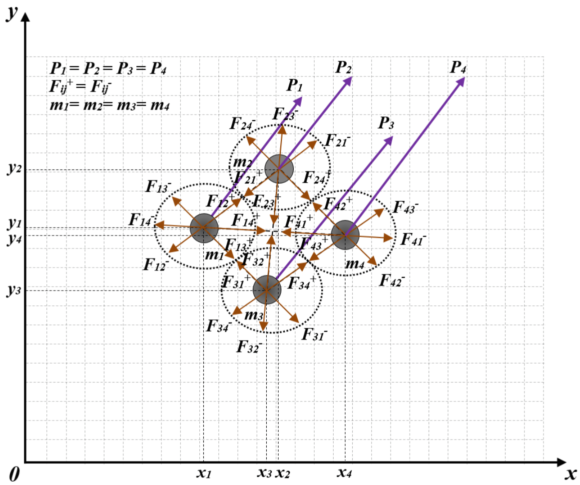

Fig. 12. The forces scheme with four dynamic objects after group formation

$$\mathrm{F}_{\mathrm{ij}}^{+} = \mathrm{F}_{\mathrm{ij}}^{-} \tag{15}$$

The absence of such zones intersections, taking into account the forecasted position of the dynamic objects uncertainty, allows maintaining a guaranteed level of traffic safety in the UAV swarm flight control (Fig. 12).

If a static obstacle occurs on a multi-UAV path, the group interacts with it through applying attraction F_O^+ and repulsion F_O^- forces (Fig. 13). This type of maneuver can be conducted provided F_O^- is neglected, because the obstacle is static:

$$F_O^+ < \mathrm{F}_{ij}^+ + \mathrm{F}_{ij}^- + P_i(\chi_i) \tag{16}$$

In order to satisfy the condition (16) the resultant vector at each point of dynamic object location (12) should be changed according to the form (17), where a and b are user-defined weighting factors. In a such way, it is possible to regulate a virtual connection strength between dynamic objects and regulate their state from solid to liquid in case of collision avoidance with obstacles.

$$\mathrm{F}_{ij} = \mathrm{aF}_{ij}^+ + \mathrm{bF}_{ij}^- + P_i(\chi_i) \tag{17}$$

The forces F_O^+ and F_O^- created by obstacles are directed from geometric centers (point O) (Fig. 13). It can lead to 'stop' effect occur, when attraction and repulsion forces vectors lies on one line with the opposite directions, which is not allowed in case of fixed-wing UAVs application.

To solve such issue, obstacle forces vectors should start at a boundary line and directed with tangent according to the rule, where δ point the angle of victor direction:

$$\mathrm{F}_{oj}^+ = \mathrm{acos}(\delta)\mathrm{F}_{ij}^+ \tag{18}$$

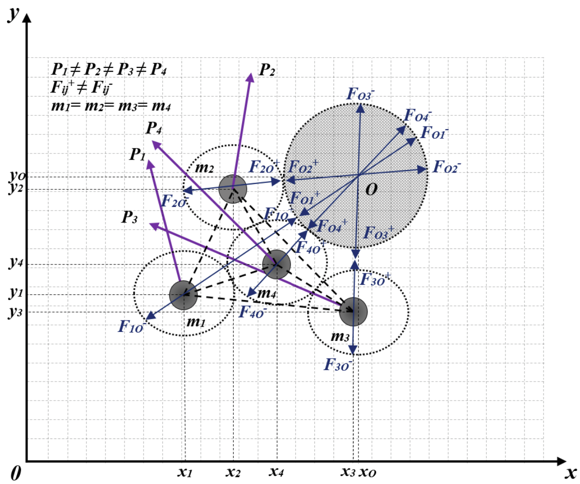

Fig. 13. The scheme of forces with four dynamic objects in a group obstacle avoiding

The values of heading angle χ_i and ground speed V_i may change depending on dynamic objects location relative to the obstacle and destination point.

5 The UAV Swarm Formation and Flight Control Simulation

In order to find out if the potential field approach can be applied for decentralized UAV swarm formation and flight control problem solution, Matlab simulators were used. All in all, 3 cases were simulated with 8 of dynamic objects, with UAV being referred to as a dynamic object.

The flight path was divided into 3 main stages of flight: (1) swarm aggregation; (2) obstacle avoidance; (3) straight line flight in a group to the destination. Figures represent dynamic objects movement trajectory in 2D (a), change in ground speed V_i (b), heading angle χ_i (c) and distance between moving dynamic objects, with dotted line showing protection zone with radius 3 m (d).

$$\tan\chi_i = \frac{\dot{y}_i}{\dot{x}_i} \text{or} \tan\chi_\mathrm{i} = \frac{\mathrm{F_{ijy}}}{\mathrm{F_{ijx}}} \tag{19}$$

$$V_i = \sqrt{\dot{x}_i + \dot{y}_i} \tag{20}$$

The dynamic objects are in their original positions with the starting speed being equal to zero. At the first stage of modelling, due to the attraction action (5) and repulsion (6) forces the process of group formation begins, which depends on the distance between them (9). Heading angle χ_i has the same direction as vector F_{ij}, which is projected on axes X (10), Y (11) and is formed by their sum, including thrust force (12). Simultaneously, the shape of group formation is regulated be the equilibrium state (4), (15).

In Experiment 1, 8 dynamic objects were considered with the point-mass of 1 kg and protection radius 3 m, with two 6 m-radius obstacles to overcome and the swarm state was considered as liquid. On Fig. 14 shown projections of attraction and repulsion forces vectors with the condition that obstacles only repulse dynamic object $F_o^- = 0$ and destination zone only attract $F_d^+ = 0$, at the same time on dynamic objects act both forces in order to provide swarm aggregation and keep its shape during flight performance. On Figs. 15 and 16, 8 equal dynamic objects (considered as fixed-wing UAVs) move from the initial positions to destination area in swarm where they are being pushed away from each other and settle at their equilibrium distance of so called 'non-conflict'. This figure also demonstrates the swarm moving and accurately performing collision avoidance in three dimensions.

The UAVs were placed at the random initial positions, but under influence of attractive and repulsion forces UAVs have to move as a swarm to a destination area, thereby demonstrating velocity matching as well as swarm aggregation (Fig. 17) and avoiding two obstacles (Fig. 18) placed between the starting points and destination area. Result of simulation, destination area was reached in 1650 s.

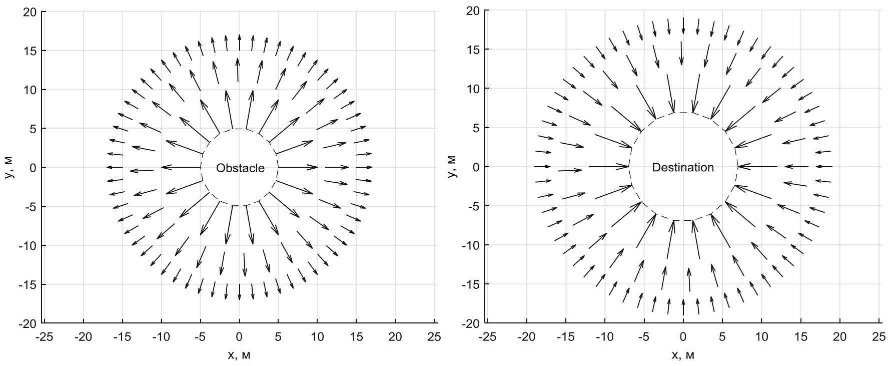

Fig. 14. Experiment 1. Attraction and Repulsion forces vectors projection for obstacles and destination area

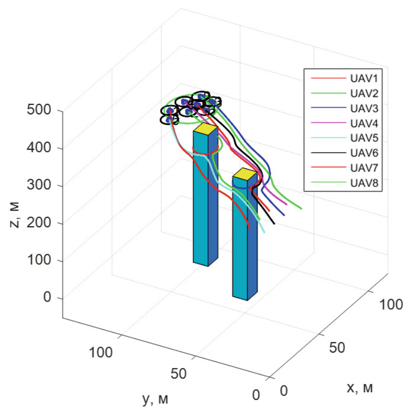

Fig. 15. Experiment 1. UAV swarm movement to destination area in 3D with t = 1650 s

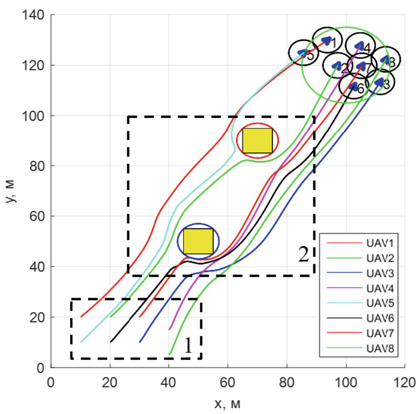

Fig. 16. Experiment 1. UAV swarm trajectory of movement in 2D

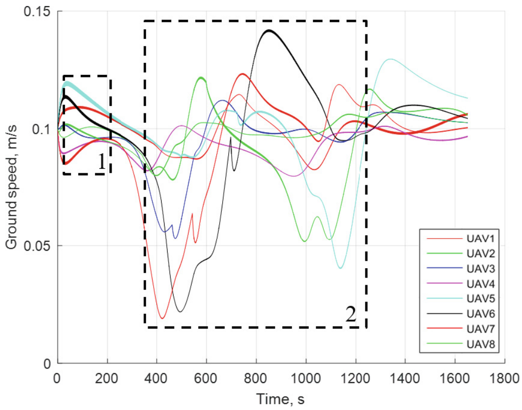

Fig. 17. Experiment 1. UAVs ground speed on time dependence

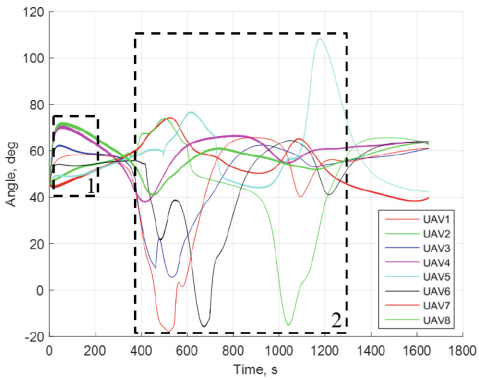

Fig. 18. Experiment 1. UAVs heading angles change

The Experiment 1 results prove the potential field method applicability for UAV swarm aggregation and control. Small differences were observed between theory and simulation results because it requires the mathematical model of concrete UAV type and implementation of stabilization control laws.

In Experiment 2, 8 dynamic objects were considered whose point-mass was 1 kg and protection radius was 3 m, with two obstacles in the way whose radii 6 m and the swarm state was considered as solid but left side rule was applied for conflict resolution. The experiment's aim is to show the swarm acting in case of non-standard obstacle shape and it will require group motion in one direction in order to keep the aggregate state. In comparison with previous one, obstacle repulsion force directed not perpendicular, but on tangent line clockwise (Fig. 19). Multi-UAV movement shown in 3D (Fig. 20) with various height obstacles and destination zone. UAVs trajectories represent the real dynamic objects behavior in a flight (Fig. 21) and verify the applicability. Verification is based on a ground speed (Fig. 22), heading angle (Fig. 23), and distance between UAVs taking into account protection zone. Intersection of protection zones leads to immediate change of heading angle and ground speed depending on the obstacle size and shape.

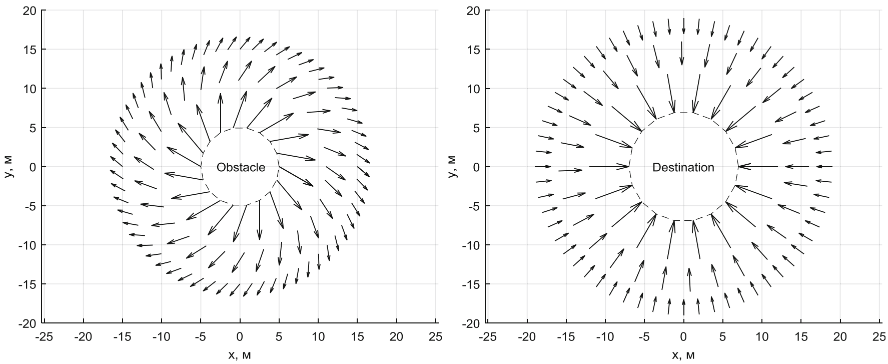

Fig. 19. Experiment 2. Attraction and Repulsion forces vectors projection for obstacles and destination area

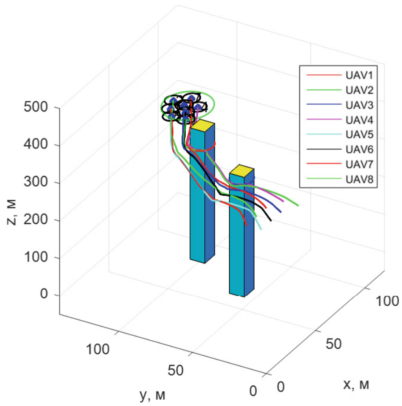

Fig. 20. Experiment 2. UAV swarm movement to destination area in 3D with t = 1550 s

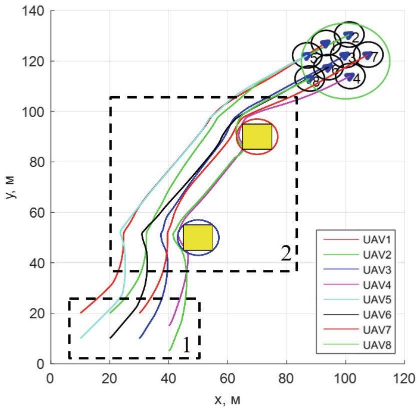

Fig. 21. Experiment 2. UAV swarm trajectory of movement in 2D

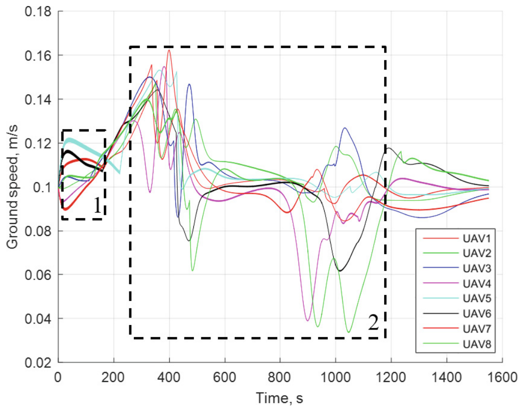

Fig. 22. Experiment 2. UAVs ground speed on time dependence

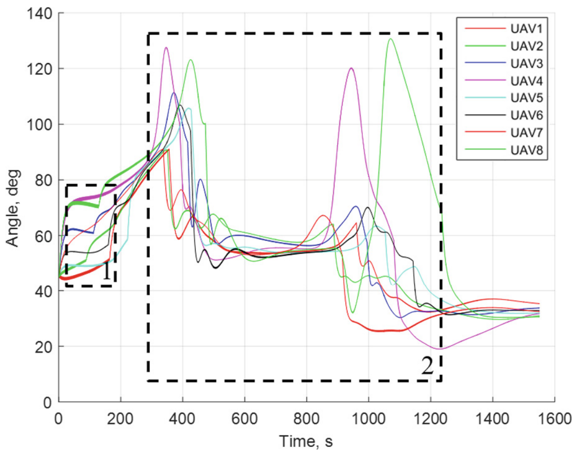

Fig. 23. Experiment 2. UAVs heading angles change

In Experiment 3, 8 dynamic objects were considered, whose point-mass was 1 kg and protection radius was 3 m, with two obstacles in the way, whose radii 6 m and the swarm state was considered as a solid, but a right side rule was applied for a conflict resolution. Obstacles repulsion force directed on a tangent line counterclockwise (Fig. 24). Simulation in 3D (Fig. 25) proves algorithm applicability and gives the opportunity to consider conflict resolution in vertical plane, even in case of low obstacles detection range, fixed-wing UAVs due to their aerodynamic characteristics will not have enough time and space for maneuver. UAVs in case of potential conflict detection will change both heading angle and flight altitude (Fig. 26).

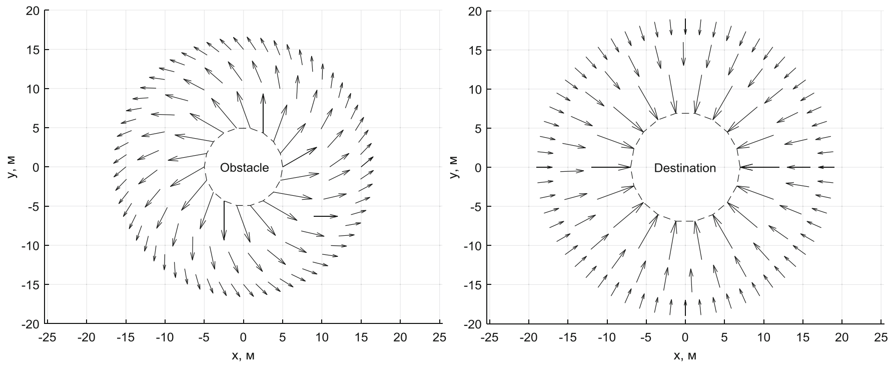

Fig. 24. Experiment 3. Attraction and Repulsion forces vectors projection for obstacles and destination area

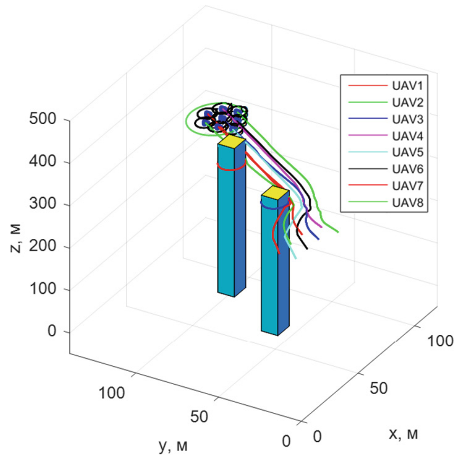

Fig. 25. Experiment 3. UAV swarm movement to the destination area in 3D with t = 1500 s

The Experiment 3 result is analogous to previous experiments, where all flight performance parameters are in an allowable range (Figs. 27 and 28). During such flight observed uneven power consumption, which will lead to decrease of flight time, to solve this issue may be considered the case of uniform motion with constant speed where heading angle changes only, or in the combination with altitude. It may require a bigger detection range, so to provide enough time and space for a conflict resolution. The time spent for destination zone achievement is the smallest in comparison to other experiments and alert about potential conflict detection appears on the time basis criterion because UAVs move with different speeds in order to achieve artificial protection zone of obstacle.

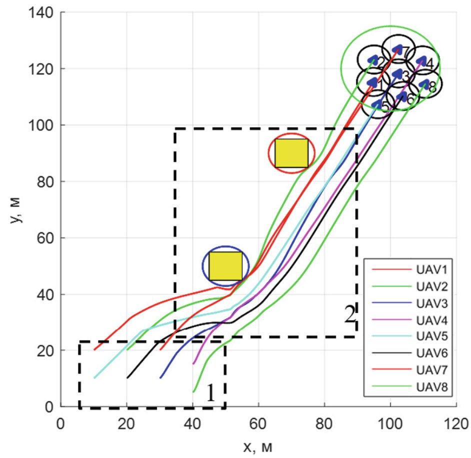

Fig. 26. Experiment 3. UAV swarm trajectory of movement in 2D

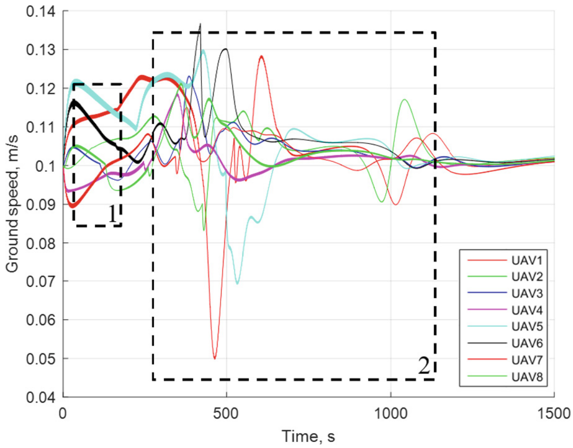

Fig. 27. Experiment 3. UAVs ground speed on time dependence

All experiments were performed with the same initial data: UAVs, obstacles, destination zone coordinates. The results of simulations shown the time required to reach destination zone in Experiment 1 t = 1650 s, Experiment 2 t = 1550 s, Experiment 3 t = 1500 s.

The artificial potential field based method can efficiently obtain the conflict-free results. They lead to small deviations from the nominal paths and the additional flight distances. The solution obtained by the UAV swarm control algorithm is time varying. Each UAV should keep on calculating conflict free results according to the outer environment. The distributed decentralized algorithm of autonomous UAVs control is also fast. The provided trajectories are smooth and low-cost results. The results show

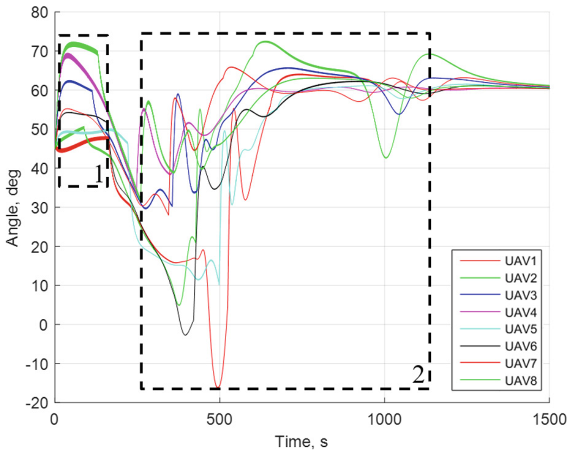

Fig. 28. Experiment 3. UAVs heading angles change

that proposed method is efficient in solving the multiple conflicts problem in the dynamic environment.

Artificial Potential Field (APF), Formation Potential Field (FPF), Modified Artificial Potential Field (MAPF) and Evolutionary Artificial Potential Field (EAPF) methods described in [12–14, 18] are solving the problem of multiple vehicles formation and control, mostly devoted to the robot path-planning problem. These methods are associated with robots or flying objects without maneuverability limitations and in some cases they require a central control station for trajectory optimization. APF allows only prevent collisions with obstacles, FPF devoted to multiple vehicles formation control, EAPF provides smooth and optimal paths and MAPF is decentralized and does not require a high computational capability. Proposed method composes all advantages of methods listed above. It allows in decentralizes way to control a big formation of UAVs that act independently, to modify a flight trajectory when the unexpected obstacles detected, to avoid collisions with different size obstacles without any loss of swarm shape, and to provide optimal path based on an environment. The main breakthrough of proposed method is a fixed wing UAV aerodynamic and the flight characteristics integration to MAPF with an excessive robustness in a dynamic environment and it can guarantee a mission performance.

6 Conclusions

UAVs are widely used in different areas of human activity, and UAV swarm performance has many advantages compared with the performance of an individual UAV. Research institutions and groups are currently developing an algorithm for a group of UAV autonomous control since manual control is not available.

For multi-UAV formation control, the artificial potential field approach is used, where UAVs are denoted as the interacting dynamic objects influenced by attraction and repulsion forces. The movement of each dynamic object is described by a system of equations, with the direction of movement coinciding with a thrust force angle projected on each of axes.

The algorithm allows to accurately steer UAV fixed-wing type swarm to user defined positions. The applied method has a number of limitations related to such flight performance parameters: ground speed, turn rate, bank angle, distance between UAVs in swarm and obstacles. UAV swarm control method is effective in creating stable multi-UAV group and it was checked using simulation. It includes 3 experiments with 8 UAVs and 2 obstacles located at the different positions with the same mass and protection zone around. The tasks were to form a group, avoid the obstacles, and continue a movement into the destination area with no change in the shape of the group. The results show that in this form the approach can be applied to a group aggregation and multi-UAV flight control. All dynamic objects moved within the allowable range determined by heading angle χ_i and ground speed V_i keeping within the protection zones.

The simulations have shown that potential field approach is an adequate method to control swarms of fixed-wing UAVs. The functionality of method can be extended by checking the maximum number of UAVs in swarm that could be controlled, loss of UAVs in swarm and its influence on the flight task performance, collision avoidance with dynamic obstacles, and collision avoidance between swarms by the conflict resolution in the horizontal and vertical planes.

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