UNMANNED GROUND VEHICLES MODELING AND CONTROL

Meparishvili Badri, Janelidze Gulnara
Georgian Technical University

Summary

The main goal of the paper is elaboration of new approach based on artificial intelligence methods, particularly on concept of collective intelligence in respect to behavioral modeling, to physical or environmental risk monitor and assessment, to adaptive control of UGV team, including Unmanned Ground Vehicle (UGV) system for navigation in undefined condition in time of autonomous scouting missions, cooperatively environmental monitoring and performing different emergency-maintenance and military tasks in aggressive conditions or hostile environment. One of the newest branches of AI is field of Multi-agent systems (MAS), which are communities of problem-solving entities that can perceive and act upon their environments to achieve their individual goals as well as joint goals. Everywhere, where there is some group of alive or technical objects which should joint efforts to perform some work or to solve some task, there is a problem of group control. As an example of multi-agent systems we can consider particular case of an intellectual UGV team.

Keywords*:* Unmanned ground vehicle. Collective intelligence. Entropy.

1. Introduction

Relevance of problems and Novelty of research. The key technologies, which are based on the paradigm usually called *Team Intelligence (SI),* focus on *collective behaviors* of UGV team, in which the system properties emerge from local interactions between elementary actions of single agents. Group control of reconfigurable UGV networks is fundamentally a difficult problem, which can be based on use of principles of evolutionary programming in a collective control within a studied area, allowing to lower computing complexity of the given task is offered.

The use of Unmanned Ground Vehicles allows for cooperation, coordination, and tight or loose collaboration related to multiple missions. UAVs can provide a global perspective of the surrounding environment, obstacles, and possible threats, broadcasting goals, sub-goals and alterations to the overall mission of the team.

Our approaches are emerging as a new engineering computational paradigm, based on entropy and synergy of dynamic systems. If we consider complex system as an interactive, multi-agent, heterogeneous chaotic system of a multidimensional, complicated hierarchic structure, then its modeling is a very complicated problem. This is conditioned by the existence of a human being as nonlinear and fuzzy factor, respectively with very high degree of freedom of behavior.

The basic idea is that all the system use relate to groups of related entities. Any change or evolution of the system can be described as a transition from one state to another one, which is closely related with the changing of (increasing or decreasing) of entropy. In view of the aforesaid we introduced a new conception of entropy as an internal behavioral incompatibility (resistibility) or antagonism, certain contradiction between disoriented components behavioral vectors.

2. UGV's behavior modeling and control in aggressive conditions or hostile environment.

UGVs, are mostly supervised, autonomous ground vehicles which are purposed to perform military tasks in place of soldiers with minimizing the human oversight. These military UGVs are capable to work outdoors on a variety of grounds. UGVs are the successful combination of Artificial Intelligence, computer technology and advanced processor developments. The proposed paper investigates the behavioral modeling of multi-UGV systems, especially the case of decentralized group control strategy, when each UGV defines its own vector of control singly with a glance of its own position, the state of environment, and the control actions of others UGVs, that is UGV group make decision cooperatively.

Swarm intelligence (PSO) is a population-based method, a variant of evolutionary algorithms with moving towards the target rather than evolution, through the search space. In PSO algorithm, the problem solution emerges from the interactions among many simple individual agents called particles [1]. It's easy to know that the canonical PSO model consists of a team of particles, which are initialized with a population of random candidate solutions. Each particle has a position represented by a position-vector x_i (i is the index of the particle), and a velocity represented by a velocity-vector v_i.

The swarm is defined as a set: $X = \{x_1, x_2, \cdots, x_N\}$, of N particles or individuals (candidate solutions), defined as: $x_i = (x_{i1}, x_{i2}, \cdots, x_{in})^T \in A, \quad i = 1,2,\cdots,N$ where A is the searching space. The particles are assumed to move within the search space, A, iteratively. This is possible by adjusting their *position* using a proper position shift, called *velocity*, and denoted as:

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{in})^T, \quad i = 1,2,\cdots,N$$

Velocity is also adapted iteratively to render particles capable of potentially visiting any region of A. If t denotes the iteration counter, then the current position of the i-th particle and its velocity will be henceforth denoted as $x_i(t)$ and $v_i(t)$, respectively. Velocity is updated based on information obtained in previous steps of the algorithm.

This is implemented in terms of a memory, where each particle can store the *best position* it has ever visited during its search. For this purpose, besides the team, X, which contains the current positions of the particles, PSO maintains also a *memory* set: $P = \{P_1, P_2, \cdots, P_N\}$

which contains the best positions: $P_i = (P_{i1}, P_{i2}, \cdots, P_{in})^T \in A, \quad i = 1,2,\cdots,N$

ever visited by each particle. These dynamic parameters are defined as:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 (P_{ij} - x_{ij}(t)) + c_2 r_2 (P_{gj} - x_{ij}(t)) \qquad (1)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad i = 1, 2, \cdots, N, \quad j = 1, 2, \cdots, n \qquad (2)$$

where t stands for the iteration counter; r_1 and r_2 are random variables uniformly distributed within [0,1]; c_1, c_2 are weighting factors, also called the *cognitive* and *social* parameter, respectively.

At each iteration, after the update and evaluation of particles, best positions are also updated. Thus, the new best position of x_i at iteration t+1 is defined as follows:

$$P_i(t+1) = \begin{cases} x_i(t+1), & if \quad f(x_i(t+1)) \le f(P_i(t)), \\ P_i(t), & otherwise \end{cases} \tag{3}$$

There are some approaches to estimate the UGV team control that can be used to evaluate coherence of the multi-UGV system. Entropy, order, and average angular velocity metrics can be defined to measure the alignment, positional order and energy consumption of the group, respectively. The average forward velocity metric is also utilized as a secondary measure of the energy consumption, and is more convenient to use in some cases.

Entropy-based metrics in UGV control. Entropy measures the positional disorder of the team. Entropy is used in a number of classical approaches to clustering, as a means to drive the clustering process. This metric is calculated by finding every possible cluster combination, finding Shannon's information entropy of these clusters and then sum them up.

Several approaches in metrics are directly applicable to the problem of team clustering. They include the *entropy* (*S*) measures as the positional disorder of the swarm. It is calculated by finding every possible cluster via changing the maximum distance (*h*) between the position vectors of UGVs in a same cluster. Shannon's information entropy H*(h)* of a cluster with a maximum distance *h* is defined as [2].

$$H(l) = -\sum_{k=1}^{K} P_k \log_2(P_k) \tag{4}$$

where P_k is the proportion of the individuals in the *k*-th cluster and *M* is the number of clusters for a given *h*. The rate of change of the entropy (dS/dt) is considered as metrics. These entropy values are integrated over all possible *h*'s ranging from 0 to ∞ to find the total entropy (*S*):

$$S = \int_0^\infty H(l)dl \tag{5}$$

The angular order. The order (coherence or synergy) measures the angular order of the sensors.

$$\psi(t) = \frac{1}{M}\left|\sum_{k=1}^{M} e^{i\theta_k}\right| \tag{6}$$

where M is the number of sensors in the cluster and θ_k is the heading of the *k*-th sensor at time *t*. Team order can be estimated by the value between 0 and 1 and is calculated by collecting the heading value of the distributed sensors. When the group in an *ordered* state, the order parameter approaches to 1, and inversely, when the group is unaligned, the system is in a *disordered* state and the order parameter is close to 0.

The swarm velocity as metrics. This metric, which is the average velocity of the geometric center of the team during the whole course of its motion, can be calculated by dividing the displacement of the geometric center of the team by the duration of flocking.

$$\vec{V}_s(t) = \frac{1}{N}\left|\sum_{i=1}^{N} \vec{V}_i(t)\right| \tag{7}$$

This approach is based on vector algebraic addition of the velocity-vectors $\vec{v}_i(t)$ of mobile UGVs at time *t*. Metric of whole UGV group in time *t* can be measured as:

$$H(t) = -\sum_{k=1}^{K} P_k(t)\log_2(P_k(t)) \tag{8}$$

where:
$$p_k(t) = \frac{\sum_{i=1}^{N} \vec{v}_i(t)}{\sum_{i=1}^{N} |\vec{v}_i(t)|} \tag{9}$$

3. Collective Behavior Modeling

One of the main sources for the emerging theory of physical team systems is groups of interacting autonomous UGVs in engineering. We discuss collective UGVs, where researcher have attempted to think up ways to let UGVs cooperate with each other. A very concrete physical application area of collective intelligence is *collective UGVs*. Generally there are two control strategies (a centralized one and a decentralized one) dedicated for two different types of the behavior. In centralized strategies, there exists a single agent that controls the UGVs [3].

This section presents a formalization of the group control problems complexity estimation. The state of integrated system "UGV group - Environment" is a tuple [4].

$$S(t) \in \langle \mathfrak{R}(t), E(t), T(t), A(t) \rangle \tag{10}$$

where there is a group $\mathcal{R}$ of N mobile UGVs R_i $(i = 1, N)$ functioned in environment *E.* We can define the complete group of UGVs $\mathcal{R}$ under study as the vector-function:

$$\mathfrak{R}(t) = f_R(\mathbf{R}_1(t), \mathbf{R}_2(t), ..., \mathbf{R}_N(t)) \,. \tag{11}$$

where N is the number of UGVs.

The condition of $R_i \in \mathcal{R}$ UGV in point of time t can be described by the vector:

$$R_i(t) = [r_1(t), r_2(t), ..., r_n(t)]^T \,,$$

The elements of vector $R_i(t)$ are represented by the values of parameters (reserve of energy resources, linear or angular velocity and acceleration, coordinates of position, angles of orientations such as course, turn, trim difference and etc.) of UGVs condition $R_i \in \mathcal{R}$ at time *t.*

The condition of environment around the UGV $R_i \in \mathcal{R}$ in point of time t can be described by the vector:

$$\mathbf{E}_i(t) = [e_1(t), e_2(t), ..., e_n(t)]^T \tag{12}$$

and the condition of environment for all group of UGVs is determined by the vector-function:

$$\mathbf{E}(t) = f_E(\mathbf{E}_1(t), \mathbf{E}_2(t), ..., \mathbf{E}_N(t)) \tag{13}$$

where the elements $\mathbf{E}_i(t)$ are the values of parameters of environment measured by UGV-sensors.

The set of target tasks **T**, emerged under the influence of the environment, can be decomposed on some subtasks *M*:

$$\mathbf{T} = [\mathbf{T}_1, \mathbf{T}_2, ..., \mathbf{T}_M] \tag{14}$$

where each subtask $\mathbf{T}_l$ $(l = \overline{1, M})$ has its own coefficient of priority k_l of performance.

In addition, there is certain weight coefficient or estimation of effectiveness d_{il} between every pair of subtask $\mathbf{T}_l$ $(l=\overline{1,M})$ and UGV $R_i \in \mathcal{R}$ $(i=\overline{1,N})$.

In every point of time $t\in[0, t_f]$ the executing control action (or control response) for each UGV $R_i \in \mathcal{R}$ $(i=\overline{1,N})$ we can formulate as $A_i(t)=\sum_{l=1}^{M} d_{i,l}\cdot k_l \cdot c_{i,l}$ (15)

with some constraints on control: $\sum_{l=1}^{N} c_{i,l}=1, \quad i=\overline{1,N}$ (16)

$$\sum_{i=1}^{N} c_{i,l}=1, \quad l=\overline{1,M} \qquad k_l \ge 0, \qquad c_{i,l}\ge 0 \tag{17}$$

and where
$$c_{i,l}=\begin{cases}1, & if \text{ robot } i\ choosed\ \ task\ \ l\\ 0, & othervise\ .\end{cases} \tag{18}$$

The total executing control action for UGV group will be

$$A(t)=\sum_{i=1}^{N} A_i(t) \tag{19}$$

The main problem of group control consists in determination such control parameters A_i for UGVs $R_i \in \mathcal{R}$ on interval $[t_0, t_f]$, where t_0 – initial point of time or before functioning of group $\mathcal{R}$ and t_f – final moment of functioning of group $\mathcal{R}$, when the extremum of functional (1), estimating the quality of group control $\mathcal{R}$, will be realized

$$S(t)=\int_{t_0}^{t_f} F\big(t,\Re(t),\mathbf{E}(t),A(t)\big)dt \to Optimum \tag{20}$$

with respect the following conditions (that the states of environment, UGV system and control actions must belong to set of admissible states):

$$E(t)\in\{E^p(t)\}\subset\{E\}$$
$$\Re(t)\in\{\Re^p(t)\}\subset\{\Re\}$$
$$A(t)\in\{A^p(t)\}\subset\{A\}$$

For the case of decentralized group control strategy, each UGV $\mathbf{R}_i(t)$ defines its own vector of control singly with a glance of its own position, the state of environment $\mathbf{E}_i(t)$, and the control actions of others UGVs

$$A_i(t)=f_a(A_1(t),\ldots,A_{i-1}(t),A_{i+1}(t)\ldots,A_N(t)) \tag{21}$$

making sure the extremum of functional (13).

In conclusion we can add, that collective control is always decentralized.

As mentioned above, in the case of decentralized group control strategy, the main target task can be decomposed on some subtasks, which are as a main goal for UGV group.

$$S(t)=f_s(s_1(t),s_2(t),\ldots,s_N(t)) \tag{22}$$

Each UGV $\mathbf{R}_i(t)$ defines its own vector of control action, when the given extremum of functional will be realized. From viewpoint of multi-objective or vector optimization , we can note, that this kind of problems can be resolved successfully using Artificial Intelligence techniques.

In the case of Artificial Neural Network method application, we are required to calculate the estimation of the weight coefficients of the neural synapses $w_i(t)$ each UGV $R_i \in \Re$ as [5]:

$$w_i(t) = \frac{s_i(t)}{\sum_{i=1}^{N} s_i(t)} \tag{23}$$

A sigmoidal neuron computes an output value according to:

$$S(t) = \sum_{i=1}^{N} A_i(t) w_i(t) \geq S^{Opt} = \sum_{i=1}^{N} A^{*}{}_i(t) w_i(t) \tag{24}$$

And finally we introduce the formulation of entropy, an application of Shannon's information entropy metric to UGV groups that provides a quantitative measure of UGV group collective behavior.

$$H_m = -\sum_{i=1}^{N} P\left(\frac{S^{Opt}}{\sum_{i=1}^{N} s_i(t)}\right) \log_2\left(\frac{S^{Opt}}{\sum_{i=1}^{N} s_i(t)}\right) \tag{25}$$

4. Conclusion

This work is motivated by the idea of collective behavioral modeling, to physical or environmental risk monitor and assessment, to adaptive control of UGV team, including Unmanned Ground Vehicle (UGV) system for navigation in undefined condition in time of autonomous scouting missions, cooperatively environmental monitoring and performing different emergency-maintenance and military tasks in aggressive conditions or hostile environment.We have discussed different kind of metrics to robotic groups behavior. We defined some number of metrics such as order and entropy, which will help us in evaluation of performance of the swarming behavior. We discuss also collective UGVs, where researcher have attempted to think up ways to let UGVs cooperate with each other.

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უპილოტო მიწისზედა ტრანსპორტის მოდელირება და მართვა

ბადრი მეფარიშვილი, გულნარა ჯანელიძე

საქართველოს ტექნიკური უნივერსიტეტი

რეზიუმე

სტატიის მთავარი მიზანია სოციალური სისტემების კოლექტიურ ქცევებთან დაკავშირებული ახალი სამეცნიერო მიდგომების შემუშავება. მიუხედავად იმისა, რომ მრავალმიზნობრივი ევოლუციური ალგორითმები, გადაწყვეტილების მიღების თანამედროვე პროცედურები ეფუძნება მულტი-აგენტურ მოდელირების მეთოდებს, ჩვენ მიერ შემუშავებული მიდგომები შეიძლება განვიხილოთ როგორც ახალი საინჟინრო გამოთვლითი პარადიგმა, რომელიც ემყარება დინამიკური სისტემებისათვის დამახასიათებელ ენტროპიისა და სინერგიის ცნებებს. თუ განვიხილავთ რთულ სისტემას როგორც ინტერაქტიულ, მულტი-აგენტურ ჰეტეროგენულ ქაოტურ სისტემას მრავალგანზომილებიანი, რთული იერარქიული სტრუქტურით, მაშინ მისი მოდელირება წარმოადგენს ურთულეს პრობლემას. ეს განპირობებულია ადამიანის, როგორც არაწრფივი და არამკაფიო ფაქტორის, არსებობით, რაც შესაბამისად დაკავშირებულია სოციალური სისტემების ქცევის თავისუფლების მეტად მაღალ ხარისხთან.

МОДЕЛИРОВАНИЕ И УПРАВЛЕНИЕ БЕСПИЛОТНОГО НАЗЕМНОГО ТРАНСПОРТА

Мепаришвили Б., Джанелидзе Г.

Грузинский Технический Университет

Резюме

Основной целью статьи является разработка новых научных подходов, связанных с коллективным поведением социальных систем. Несмотря на то, что многоцелевые эволюционные алгоритмы, а также современные процедуры принятия решений основываются на методе мульти-агентного моделирования, разработанные нами подходы можно рассмотреть как новую парадигму, основанную на понятиях энтропии и синергии. Если рассмотреть сложные систем в виде интерактивных, мульти-агентных, гетерогенных систем со сложной, многоразмерной, иерархической структурой, то их моделирование представляет собой сложнейшую задачу. Это обусловлено присутствием человека, как нелинейного и нечеткого фактора, что соответстенно связано с высокой степенью свободы поведения социальных систем.