Multicriteria Analysis of the Robotic Systems Autonomy Using Fuzzy Calculations

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Abstract: Against the background of the ever-increasing needs for robotic systems (RS) with an increased degree of autonomy and the emerging transition to their widespread use, the need for technologies for quality assessment and multi-criteria analysis of the autonomy degree of such devices is becoming more urgent. The article describes the current state of issues assessing and comparing the degree of autonomy of unmanned systems using the vector criterion. Well-known estimates of the degree of autonomy are given. The existing classification system distinguishes between informational and intellectual autonomy, which are considered in close connection. Solutions are proposed that make it possible to formulate estimates of the autonomy degree of robots in various areas of economics based on the theory of fuzzy sets. Based on the method of fuzzy areas of preference, it becomes possible to obtain estimates of the degree of autonomy, taking into account the judgments of the decision-maker. One of the positive consequences of this approach is the unification of formulations and solutions in the tasks of information support in the RS, which, in turn, facilitates interaction between users, customers and developers.

1 INTRODUCTION

The International Federation of Robotics (IFR) defines a robot as a working mechanism that is programmable along several axes with some degree of autonomy and is capable of moving within a defined environment to perform assigned tasks (IFR, 2015). From this definition, it follows that the essential features of the concept of "robot" (i.e., criteria for the analysis of mechanisms created in different historical periods) are: autonomy, which means that "a robot is able to interpret the environment in which it is located and adapt to the assigned tasks "(Kaysner et al., 2016); and the ability to program it in several directions. Another common definition among scientists and practitioners is the following: a robot is "any machine capable of perceiving the environment and reacting to it based on independently made decisions" (Nesmelov, 2022). Thus, the key difference between robots and other machines is considered to be "autonomy": the robot is able to interpret the environment in which it is located and adapt to the assigned tasks. Robots are evolving from programmed automation to semi-autonomous and more autonomous complex systems. Fully autonomous systems will be able to independently make "decisions" in their intended environment and perform tasks without human assistance. In general, we can say that the trends in modern robotics are increasing their autonomy and the ability to solve various problems through the use of artificial intelligence. Among the known types of autonomy of technical devices such as logistical, informational, and intellectual (Ermolov, 2012), it is intellectual autonomy that stands out, closely related to informational autonomy, and necessary for solving problems in a previously unknown, changeable environment.

What should RS have in order to be classified as autonomous, and what should it be able to do execute what algorithms? Experts predict that in development work to create special-purpose robots, in accordance with existing trends, the following should be implemented (Murphy, 2020):

- increased resource autonomy;
- modularity of construction and reconfigurability;

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• constructive and technological unification of samples and their key functional components;
• noise-resistant multi-channel means and systems of information and control interaction and identification;
• intelligent software and algorithmic tools that allow for recognition of objects and the working environment, reflexive forecasting of the development of events, planning of rational (optimal) behavior, and, as a consequence, adaptively controlled functioning of special-purpose robots in uncertain, dynamically changing heterogeneous application conditions;
• intelligent software and algorithmic tools that allow for the integration of different types of special-purpose robots into a single group with subsequent control of their joint actions in similar, heterogeneous, and mixed combat formations;
• intelligent systems for human-machine interface and decision support for operators controlling special-purpose robots when solving combat (strike, fire), support and special tasks.

Various criteria for autonomy are found in publications, for example, the Society of Automotive Engineers (SAE). To help automotive engineers, governments, and insurance companies better understand this new technology, SAE has defined six (including no autonomy) levels of automotive autonomy (SAE, 2023):

• Level 0: Not at all autonomous; the driver has sole control of the vehicle.
• Level 1: One function is automated, but does not necessarily use information about driving conditions. A vehicle operating with simple cruise control will qualify as Level 1.
• Level 2: Acceleration, deceleration, and steering are automated and use sensory data from the environment to make decisions. Modern cars with cruise control automatic lane keeping, or collision mitigation braking fall into this category. The driver remains solely responsible for the safe operation of the vehicle.
• Level 3: At this level, all safety functions are automated, but the driver must still take control in an emergency that the car cannot handle. An example would be Tesla cars with the Autopilot feature enabled. This is the most controversial level because it requires the human driver to remain alert and focused on the driving task even though the car is doing most of the work. People would naturally find this situation more tedious than simply driving a car, and many in the autonomous vehicle community worry that the driver's attention could be diverted from the task at hand, leading to disastrous results. Some automakers choose to skip Level 3 and go straight to Level 4.
• Levels 4 and 5: These are fully autonomous levels where the car makes all driving decisions without human intervention. The difference is that Level 4 cars are limited to a specific set of driving scenarios, such as city, suburban, and highway driving, while Level 5 cars can handle any driving scenario, including off-road driving.

A similar autonomy scale has been adopted among drone developers (PROXIMA, 2023). There are five levels of UAV autonomy, based on the principles of self-driving vehicle autonomy.

• Level 0: No autonomy.
• Level 1: Some systems are automated, such as altitude control, but a human controls the UAV.
• Level 2: Multiple simultaneous systems are automated, but a human still controls the UAV.
• Level 3: The UAV operates autonomously under certain conditions, but a person monitors its movement.
• Level 4: The drone is autonomous in most situations; a person can take over control, but this is not necessary.
• Level 5: The drone is completely autonomous.

Currently, the development of UAV technology is between levels 3 and 4, where the drone can make some decisions autonomously, but a person still needs to observe the operation process of the device. The main challenge in reaching level 5 is solving technical problems and overcoming laws, regulations, and even social acceptance in different regions.

Through the efforts of this ALFUS group, a clear diagram has been proposed of what constitutes an idea of the autonomy of a system and by what indicators the autonomy of a particular system can be assessed (ALFUS, 2004).

Autonomy indicators (sets of metrics) for a detailed model that determines the level of autonomy are summarized in the “space” of autonomy.

Mission complexity can be measured using indicators such as levels of subtask completion, decision-making and collaboration, knowledge and perception requirements, planning and execution efficiency, etc.

The level of human dependency can be measured using indicators such as interaction time and frequency, operator workload, skill levels, robot initiation, etc.

Environmental complexity can be measured by the size of obstacles, density and traffic, terrain types, urban traffic characteristics, ability to recognize friends, enemies, bystanders, etc. The detailed model of the ALFUS framework contains the following defining concepts:

- Unmanned systems (UMS) autonomy touches many technical areas. Task complexity and adaptability to the environment are some of the key aspects.
- The nature of UMSs' collaboration with human operators, such as levels of involvement and types of interactions, is important to the possibility of autonomy.
- Performance factors such as mission success probability, response time, accuracy, resolution, and latency tolerance influence UMS autonomy levels (Huang et al., 2003).

Work is currently underway to determine measurement scales for the proposed metrics. Decision-makers may be guided by some complex algorithms, as opposed to simple weighted averages, to determine the resulting levels of vehicle autonomy.

It is recognized that the level of autonomy is an extremely complex issue. There are a number of problems that require resolution. These include:

1. Clarification of quantitative indicators and prioritization. Identification of coincidences and conflicts between them along the three axes of the proposed space.
2. Development of standard measuring scales for metrics.
3. Create high-level definitions of levels of autonomy for the summary or executive model.
4. Development of methods and plans for testing and confirming the levels of autonomy of unmanned vehicles.
5. Defining and installing a domain-specific autonomy level model for selected programs.

In addition, it is necessary to note the following disadvantages of the proposed scheme:

• Assessments based on indicators (criteria) are often assigned by experts, but the method does not take into account the degree of confidence of the expert in the assigned assessment.

• Criteria weights may also have a fuzzy (blurry) character.

• The use of weighted summation leads to implicit mutual compensation of criteria, which means that unsatisfactory scores for one criterion will be offset by good scores for others.

Suggestions for overcoming some of these problems will be discussed below.

2 METHOD

Based on experience in the development of robotic systems (Sokolov, 2022) and analysis of methods of applied mathematics in various fields (Sudakov and Zhukov, 2023), methods for developing a generally very productive and promising scheme of the ALFUS group based on replacing the weighted summation of point estimates with fuzzy judgments are proposed.

Let a vector of fuzzy values for autonomy assessment criteria be given:

$$X = (\tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m), \tag{1}$$

where $\tilde{x}_j$ - the value of the fuzzy j-th criterion is characterized by the membership function:

$$\mu_j(x_j),\ x_j \in D_j, \tag{2}$$

where D_j is the domain (set of possible values) of the j-th criterion.

If the value of the criterion cannot be determined, this is complete uncertainty:

$$\forall x_j \in D_j,\ \mu_j(x_j) = 0.5 \tag{3}$$

If the criterion is “not fuzzy”, then $\mu_j(x_j)$=1, for some $x_j = x_j^*$ and $\forall x_j \neq x_j^*$ $\mu_j(x_j)$=0.

Any other $\mu_j(x_j)$ specified on the coordinate grid with the required degree of detail are acceptable.

Let the permissible levels of autonomy for objects O_i, $i = \overline{1,n}$ be given. The solution to the problem of determining the level of autonomy is based on the construction of expert rules for the product type:

If some subset $\tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m$ takes certain fuzzy values, then $X \in O_i$.

This rule does not clearly assign an object to one level of autonomy. It only redistributes the object’s membership function to the set of all numbers of autonomy levels. In fuzzy form, this implication looks like this:

$$p(i, \tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m) = \min_j \inf_x \langle \lambda_{ij}(x), \mu_j(x) \rangle, \tag{4}$$

where $\lambda_{ij}(x)$ belongs the value x to level O_i for variable j.

Next, we can move to a “not fuzzy” statement by choosing the most possible level of autonomy:

$$i^* = \operatorname*{argmax}_i p(i, \tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m) \tag{5}$$

If the values of the characteristics are listed in products through a fuzzy disjunction, then formula (4) will take the form:

$$p(i, \tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m) = \max_j \inf_x \langle \lambda_{ij}(x), \mu_j(x) \rangle \tag{6}$$

This method of specifying fuzzy membership requires specifying expert judgments at the time of estimating RS.

In addition to fuzzy class affiliation, it is necessary to determine the degree of interest in the corresponding levels of autonomy. This assessment depends on the current environment in which the RS operates, as well as on the priorities of the decision-maker.

If the criteria are independent in preference, then the standard fuzzy weighted summation procedure is applied.

The level of autonomy is calculated using the standard weighted sum formula:

$$P_i^* = \sum_{k=1}^{n} W_k X_{ik}, \qquad (7)$$

where X_k is the fuzzy estimate of the i-th RS according to criterion k, and W_k is the fuzzy importance of criterion k, P_i^* is the final interest in objects of class i.

The rules for summing and multiplying fuzzy numbers are carried out based on the principle of communication. Membership function corresponding to the operation:

$$\mu(y^*) = \sup_{\substack{y_1, y_2, \dots y_n: \\ \eta(y_1, y_2, \dots y_n) = y^*}} \left(\underset{i}{\Theta}\, \mu_i(y_i) \right), \qquad (8)$$

where η is the operation that needs to be applied (in the case of calculating $W_k X_{ik}$ is the product, and for calculating $\sum_{k=1}^{n} W_k X_{ik}$ is the sum), y_i are the values to which the required operation is applied, $\mu_i(y_i)$ is the membership function of fuzzy values, $\mu(y^*)$ is the membership function for the result of applying the operation η. Θ is the intersection operation for membership functions. In this work, this is min, but there are other varieties of this operation. Let us denote the membership function of the resulting fuzzy weighted sum as $\varphi_i^*(y)$.

To calculate the final level of autonomy, the clip function is calculated for all possible levels, taking into account their priorities, and their further fuzzy combination:

$$\rho(y) = \max_i \min\langle p(i, \tilde{x}_1, \tilde{x}_2, \tilde{x}_3 \dots \tilde{x}_m), \varphi_i^*(y) \rangle \qquad (9)$$

If fuzzy estimates of autonomy levels are obtained for several RSs that need to be compared, then a fuzzy comparison procedure is constructed or defuzzification is performed:

$$\tilde{y} = \frac{\int y\rho(y)\, dy}{\int \rho(y) dy} \qquad (10)$$

This approach will allow:

- provide decision makers with tools for formalizing qualitative judgments about the degree of autonomy in tasks with a high dimension of the criterion;
- allows further assessment of the degree of autonomy in automatic mode, i.e., the RS ranking process will occur quickly and, possibly, without the involvement of the decision maker, but taking into account his preferences;
- take into account preference dependencies between the components of the vector criterion. As a result, it is possible to identify and eliminate situations where RS with an unacceptable level according to one criterion receives a high integral assessment at the expense of other criteria;
- ensure the distinguishability of RS in the case when criterion scales are subjected to artificial discretization in order to replace continuous scales with point scores.

To the complex “autonomy space” proposed by the ALFUS group, we add scalar indicators:

qualification (mandatory program - admission to evaluation, comparison or competition) of a robot: what does a qualified device have?

statement of the problem: division into classes: which class of problems can be solved (with what amount of a priori information);

quality of problem solution (consumed computing resources, time, accuracy, reliability (response to an unforeseen situation)).

In terms of developing methods and plans for testing and confirming the levels of autonomy of unmanned vehicles, we are preparing an approximate program and methodology for testing technical vision systems in the task of providing information support for targeted movements of autonomous vehicles.

To set the mission of an unmanned vehicle with subsequent decomposition and automatic translation into functional tasks, we create lists of tasks - basic, typical scenarios, or precedents for the use of unmanned vehicles. In our work, we focus on ground mobile robots (Sokolov, 2022). An example of use cases for an autonomous mobile robot:

- surveillance of the area or object;
- reconnaissance of a given area;
- search for specific objects of interest, their identification and precise localization;
- work with detected objects of interest.

The basic list of technological operations (TO) of a robot is determined by the above precedents. TO include:

- TO robot safety systems (preventing collisions with obstacles and robot overturning);

- calculated TO (construction of trajectories, localization of objects of interest, construction and correction of the map);
- TO practice commands or information-motor actions (ensuring the fulfillment of specified modes of operation of the robot).

One of the most challenging issues in assessing and making comparisons of unmanned vehicle autonomy is defining or establishing a domain-specific level of autonomy model for selected programs. An equally complex problem is the problem of a weighted assessment of the totality of quantitative assessments in the space of "autonomy".

Assessing the combination of mission complexity and environmental complexity is subject to a high degree of uncertainty and complexity, which significantly limits the application of quantitative methods for comparative analysis. Therefore, in this part of autonomy assessments, the use of a well-developed cognitive modeling apparatus is proposed. Fuzzy cognitive maps are a way of representing real dynamic systems in a form that corresponds to the human perception of such processes.

3 CONCLUSIONS

The degree of autonomy depends on the tasks that ned to be performed. Qualitatively, the scope defined by a set of parameters within which the system can make decisions and act independently to achieve its goals can be called the degree of autonomy. Robots with full autonomy are preferred in many applications, such as space exploration, logistics, and others. As the analysis shows, an objective and constructive assessment of the degree of autonomy of RS requires the serious collective efforts of the entire robotics community.

The use of fuzzy logic, methods of multicriteria analysis of alternatives, and decision-making theory will allow us to take into account the vagueness of the judgments of experts and decision-makers in problems of comparing different RSs in terms of the degree of autonomy and other criteria, including economic and technical indicators. On this path, in particular, lies the construction of ontologies for subject areas - areas of application of RS. The use of ontologies will allow customers and users to unify coordinate units along the axes of the "autonomy space", objectively and quantitatively compare the degrees of intellectual and information autonomy of RS and RS designers to quickly assemble successful solutions among themselves.

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