DIGITAL INFANTRY BATTLEFIELD SOLUTION

INTRODUCTION TO GROUND ROBOTICS

DIBS project

Part I

Milrem in collaboration with

Estonian National Defence College
Latvian National Defence Academy
Latvian Institute of International Affairs
Riga Technical University
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Digital Infantry Battlefield Solution.
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The book consists of collection of opinions by various authors from different countries and diverse research backgrounds to provide a multi-faceted review of the development of unmanned ground systems (UGS) in military use from different perspectives – to cover both the retrospective and prospective development of UGS as well as the current issues and challenges from military, technical and legal perspectives.

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AUTONOMOUS SYSTEMS AND AUTONOMY QUANTIFICATION

Dr. Agris Nikitenko and Jeff Durst

This chapter presents several methods for autonomy assessment and quantification of intelligent Unmanned Systems (UMS). While the importance of UMS in civil or military application has a solid increasing trend over the past decade and the number of commissioned UMS in defence and security sectors has reached many thousands, still the question about their performance assessment before or during the mission is open. Since military operation planning and execution is related to complex risk assessments and resource estimations a simple metric number representing an expected UMS performance potential within the given mission would be more than welcome. This chapter provides a detailed outline of new methodology developed to address the performance estimation problem. The methodology proposes a single metric Mission Performance Potential (MPP) that characterises the expected performance of a given UMS for a defined mission within the specific environment. Thereby the novel method provides a tool for predictive performance estimation instead of retrospective ones proposed by other methods, which are outlined within the chapter.

INTRODUCTION TO PROBLEM DOMAIN

UMS – regardless of operation domain: water, underwater, ground or air – play an increasingly important role in modern warfare, which increases the overall mission planning and execution complexity especially in difficult environments. A key capability of future UMS will be a true autonomy enabling them to operate and cooperate to achieve a common goal and lead the mission to its success. The current scientific and industrial trend regardless of the application domain moves towards this future of truly autonomous systems. The future visioning concepts that highlight the main benefits and the key challenges are Industry 4.0[1] and Society 5.0[2]. While both of them are being developed in different contexts i.e. industrial and social, they have a lot of common:[3]

- Both emphasise the role of Big Data and artificial intelligence as the key enablers of future systems, building smart manufacturing plants and smart environments;
- Highly integrated and cooperative Internet of Things (IoT) devices will enable the gathering and accumulation of a wide range of data enabling agile control and management of systems;
- Cyber security and privacy have been identified as the main problems that have to be addressed for the coming years to form the necessary technological background of the future manufacturing and living environments;
- Decentralised control and management are among the concepts ensuring flexibility and greater reliability of future systems.

Both to a large extent rely on the assumption that higher autonomy of the systems will bring greater performance and effectiveness within a particular application domain.

Looking back to the military domain most of the operational systems deliver weak autonomy or are completely tele-operated (especially in ground domain). This does not apply to systems being under development and research. One of the reasons why systems are slow in bringing more autonomy is due to the simple fact that in complex missions not always more autonomy means higher performance. However, elaboration of a metric for autonomy levels estimation itself is rather complex.

Unfortunately, there are no common standards or methods providing a comparative measure of different UMS and methods for measuring parameters of the systems itself, mission and environment. Some of the most commonly known and used tools are described in the following sections.

AUTONOMY LEVEL ASSESSMENT FRAMEWORK FOR UNMANNED SYSTEMS

While there are several reference system architectures and development methodologies for autonomous systems, the assessment of their autonomy and performance is still weakly developed. One of the most developed performance assessment models is ALFUS – Autonomy Levels for Unmanned System, which was created and presented by ALFUS workgroup in 2004 at the international Society for Optics and Photonics[4]. The model is focused on autonomous ground vehicles (UGVs) and consists of several components[5]:

1. Terms and definitions;
2. Detailed model for autonomy levels;
3. Summary model for autonomy levels;
4. Guidelines, processes and uses cases.

The ALFUS framework lays the groundwork for how an UMS's performance evaluations could be combined into a single quantitative measure of a system's autonomy.

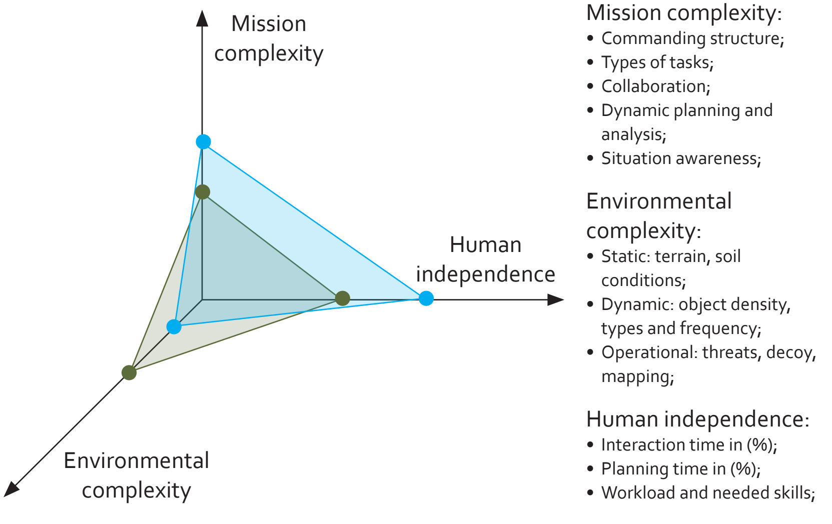

Figure 1. ALFUS scoring axes and parameter examples[6].

This detailed ALFUS model uses a three-axes method of Context Autonomous Capability (CAC) outlined in Figure 1. The scores for each axes are acquired through bench tests specific to particular test domain. Acquired scores are combined into a single autonomy level score. While the tests are specific to particular domain the CAC model itself is limited to these bench tests. Each of the UMS mission subtask is evaluated against the axes providing the autonomy estimation throughout the mission. The scores estimated afterwards are weighted and averaged providing a higher level task score thus providing an iterative method to calculate the score for the given UMS within the given environment and mission.

The summary model is a simpler version of the full model to be used for reference and further communication of the results to be compared with other systems. The model steps can be summarised as follows[7]:

1. Starting from the subtask autonomy scores they are summarised up to top level tasks using weighted sum;
2. For each autonomy level a human interpretable description is added;
3. Domain specific capabilities are described bringing the domain and mission context into the model.

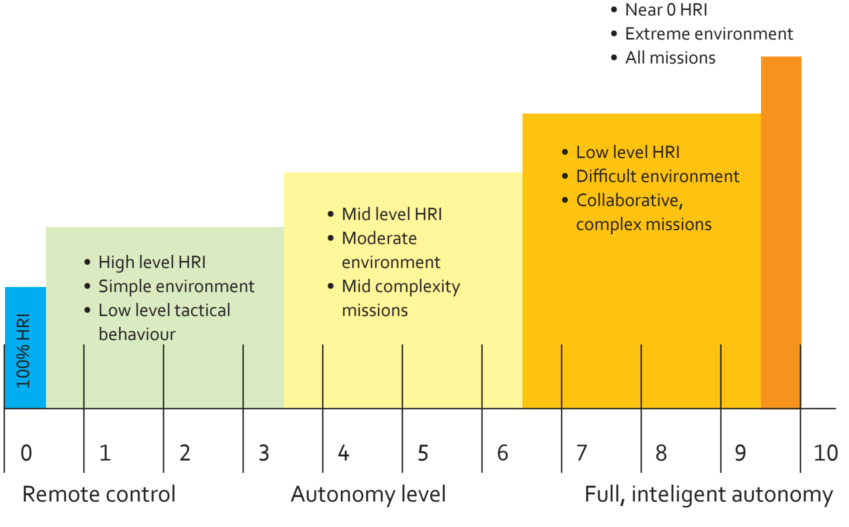

Figure 2. ALFUS summary model HRI – Human Robot Interaction[8].

As emphasised in[9] the ALFUS framework provides the capability of estimating the level of autonomy of one robot or a team of robots, but it still has some drawbacks that prevent its direct implementation:

- Lack of commonly agreed standards for task decomposition;
- Requires to conduct exhaustive tests for a given UMS;
- Lack of methods to assess the interdependency between the metrics, as some of the subtasks can apply to more than one metric;
- Uses subjective ratings instead of objective metrics decreasing potential of comparative measurements;
- Does not integrate the metrics into the final the autonomy level.

As mentioned above a fully autonomous mode of operation does not always deliver the highest performance. An example might be an inspection task of improvised explosive device, where a fully tele-operated asset would perform better due to various risk factors. Unfortunately, ALFUS suffers from the assumption that a higher level of autonomy is directly related to higher mission performance.

Other contextual-based measures of autonomy have been proposed, namely those focused on measures of human-robot interaction[10] and those designed to determine 'optimal' performance through adjustable autonomy[11]. While these methods provide the benefit of a rigid definition of UMS autonomy levels, they still suffer from many of the same drawbacks of the ALFUS. Specifically, any performance measure derived from human operator performance fails to produce a firm result that is comparable between systems and tests, especially for tests aimed at defining what sensor, hardware, and software requirements are 'optimal' for a given UMS.

NON-CONTEXTUAL PERFORMANCE ASSESSMENT

As illustrated previously context is one of the main drawback of the ALFUS approach since it brings a subjective component to the evaluation procedure. Even for the same UMS it might be difficult to re-establish the same environmental context. Therefore, a method, which could derive the performance just having parameters of the system itself would be more appropriate.

Moreover, most of the ALFUS inputs do not have commonly agreed methods or standards for their estimation, what makes it difficult to widely accept and apply in practical problems. Having these drawbacks highlighted a Non-Contextual Autonomy Potential (NCAP) has been developed, which draws the autonomy level from reference architecture model of a given UMS[12]. The NCAP provides a predictive measure of a UMS's ability to perform autonomously rather than a retrospective assessment of UMS autonomous performance. Furthermore, the UMS autonomy level is determined outside of a mission or environmental setting. The key difference is that the NCAP treats autonomy level and autonomous performance separately. A UMS that fails completely at its mission but does so autonomously still operates at the same autonomy level as another UMS that succeeds at the same mission.

The NCAP defines four Autonomy Levels (AL). The AL ranges from 0, no autonomy/fully-radio-controlled or tele-operated, to 3, fully autonomous. A UMS's AL is defined within the context of a generic UMS architecture model as follows. A UMS that only contains perception, i.e., a tele-operated Unmanned Ground Vehicle (UGV) with an onboard camera, has no autonomy. A UMS that generates some sort of world

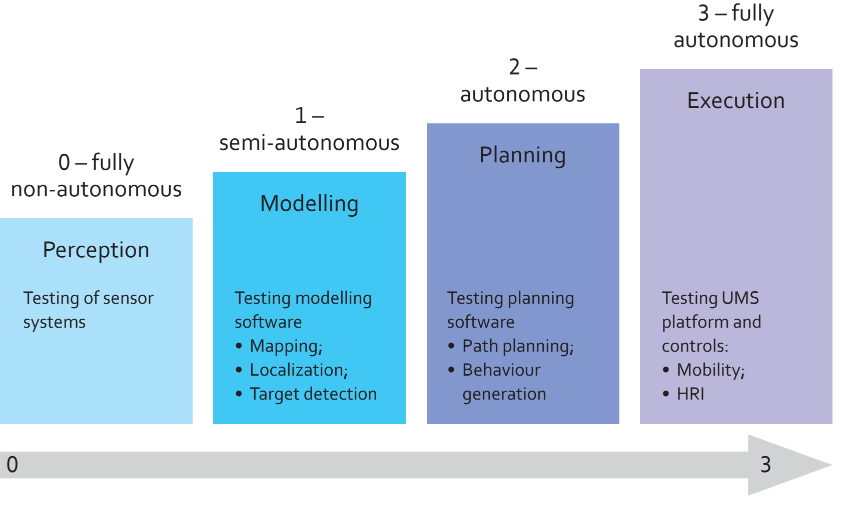

Figure 3. NCAP levels within generic UMS architecture model[13].

model or retains an internal knowledge base of its surroundings is considered semi-autonomous. At this level, the UMS is interpreting the raw sensor data on its own and has the beginnings of intelligence. A UMS that further uses its world model to form a plan of action is considered autonomous. At this level, the UMS is making a judgment based on its internal knowledge base. Finally, a UMS that chooses a best action based on its modeling and planning and performs that action without operator input is considered fully autonomous. The following figure shows the NCAP autonomy levels:

Figure 2 shows the NCAP AL along with the level of UMS architecture with which each AL is associated.

The NCAP is based solely on the UMS platform itself. Metrics based on component level testing of the UMS are combined to provide the final NCAP score, and the NCAP is meant to serve as a tool for predicting autonomous performance potential. According to the NCAP methodology the following table shows some examples of AL assigned by the model[14]:

Table 1. NCAP assessment examples

No.	UMS	Hardware	Software	NCAP autonomy level
1.	iRobot Roomba	caster-steered platform, IR sensor	edge detection, area coverage algorithms	3
2.	RC quad-rotor UAV	quad-rotor body	none	0
3.	NREC LAGR	wheeled platform, stereo camera, IR rangefinder, GPS, IMU, wheel encoders	obstacle detection, mapping, path planning	3
4.	CMMAD semi-autonomous counter-mine system	Talon UGV, camera, LIDAR, metal detector	obstacle detection, mapping, path planning	1

While the NCAP does offer some benefits over the ALFUS in terms of ease of implementation, it does not provide a complete solution to the problem of measuring mission performance or measuring the impact of autonomy on mission performance.

Therefore, a new metric for UMS performance is needed, i.e., one that fuses both contextual and non-contextual performance assessment methods into a single one.

MISSION PERFORMANCE POTENTIAL

The mission performance potential has been developed within NATO Research Task Group, which recommended the development of a new tool to address the lack of predictive measures of mission performance. To large extent the tool developed is a result of international cooperation among NATO alias demonstration not only a common interest but also a common commitment for future developments. Thereby the authors of this chapter are presented the work results and were only a part of the team.

As emphasised above a tool enabling predictive mission performance assessment without full scale testing would provide the critical tool missing in the UGV evaluation process. Unfortunately, for obvious reasons, without full scale testing in particular environments, or without mission context, the mission performance cannot be determined. However, if the mission context is known along with other critical data about the system and environment then it is possible to reason about performance potential that might be expected using the given asset. Specifically, a new tool should be developed that provides the following[15]:

1. A single, numeric value, comparable between UGV systems, that provides a predictive measure of UGV performance for a given mission, environment, and autonomy level;
2. A fixed UGV autonomy level and UGV performance is measured as a function of that autonomy level;
3. An input data set that can be evaluating using only the UGV system and mission description.

Thereby the MPP methodology having mission description, environment description and system description in terms of software, hardware and intelligence provides a single predictive number that describes the performance potential. Since the MPP measure is not based on retrospective tests analysis it describes the expectation level to be considered for mission planning or assets comparative analysis. The framework is presented in the following figure:

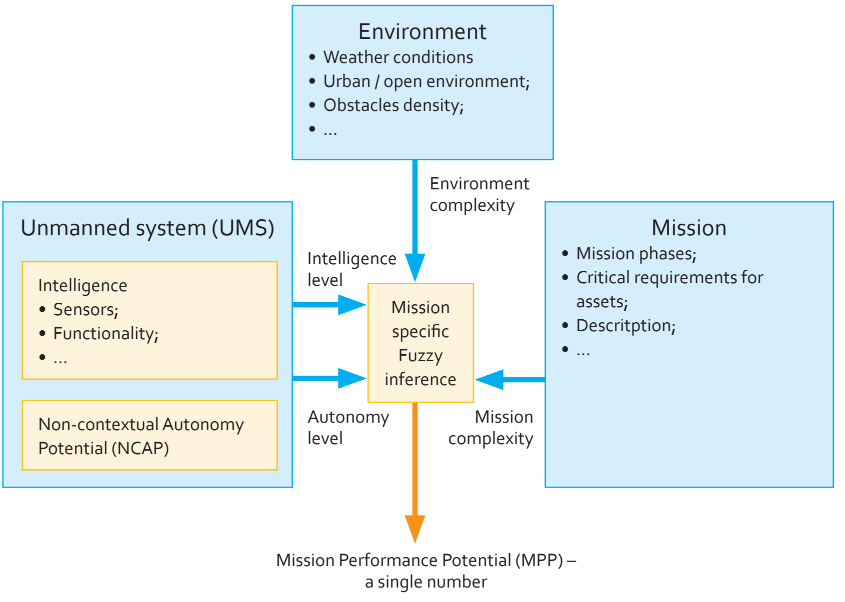

Figure 4. MPP framework – Mission specific fuzzy inference provides forms a core of the tool

MPP APPROACH

The MPP starts from an approach similar to the NCAP that fixes the UMS's autonomy level. This approach provides several benefits[16]:

- First and foremost, it fulfils the goal of assessing mission performance as a function of autonomy level enabling further comparison of the same asset under different operation modes, thereby increasing quality of mission planning;

- Second, these predefined autonomy levels provide users with a better understanding of the UMS's capabilities rather than an abstract number. Still it is and the assessment provided by the expert, but it limits the possible doubts about assignment of particular number;
- Lastly, this approach deals with the fact that for a given UMS, the autonomy level may vary between missions and environments. For example, a UMS may operate with some autonomy in urban environments but be fully tele-operated in off-road environments while having the same overall level of mission performance in each environment.

The MPP defines five levels of autonomy as follows[17]:

1. Radio-control: the operator is provided with a method of controlling the actuators of the vehicle directly. Sensory feedback is through human senses that are limited by visual range and noise.
2. Tele-operation: the operator is provided with a method of indirectly controlling the actuators on the vehicle, through control-by-wire or rates' control. He is also informed of the vehicle's status through communication subsystems and data visualisation techniques, i.e., visual animated gauges, maps, arrows, or heads-up displays.
3. Supervised Autonomy: the operator is provided with a method of controlling the vehicle's general behaviour. It is assumed the operator can maintain communications with the vehicle for task reallocation. This AL includes waypoint control, goal-based control, and scenario-based control.
4. Adaptive Autonomy: the operator is provided with a method for accepting the vehicle-initiated changes to the initial task, path, or goal. The vehicle is capable of suggesting, changing, or overriding previous operator commands, based on new situational awareness. It is up to the operator to manage the decision-making process in the UMS.
5. Higher Intelligence: the operator is provided with the vehicle's relevant information for decision making and tactical planning. The

operator does not need access to full vehicle's sensor readings or navigation sensors, and instead focuses on the mission sensitive data collection.

INPUT DATA

At its core as depicted in Figure 4, the MPP is similar to the previously proposed performance assessment frameworks. In particular, the MPP is an extended application of the basic ideas behind the NCAP that is built on the theoretical basis of the AFLUS. The MPP leverages the work already done in other efforts and reframes these ideas into a new framework that addresses mission-specific performance potential.

Similarly to the NCAP, the MPP framework ground its assessment on data provided by the field experts through answering a question about the mission and environment. The answers provide the 'filter' or 'masks' for minimum requirements to be met. If the 'mask' requirements are not met, then the MPP values are set to 0 automatically. For instance, if a given missions requires a particular positioning accuracy of the UGV and the given one cannot provide it, the MPP is 0, while all other aspect will not play any role for the MPP estimation. This is a major benefit of the MPP over previous methods.

Calculation of the MPP score requires three types of input data[18]:

1. Data about the system being estimated, i.e. the platform's physical parameters like weight, shape, dimensions, and sensing capabilities describing sensor types and their functional characteristics;
2. Data about the system's intelligence, namely the platform's decision making abilities including path planning, re-planning, obstacle avoidance, and other relevant qualities that demonstrate the system's active and reactive behaviours;
3. Data about the mission environment such as weather conditions, soil conditions, structured-ness (i.e. urban vs. cross-county), to name only a few.

Tables 2 provides a breakdown of the data as an example, including the values, ranges, and types of information needed to drive the MPP calculation. The main challenge behind the MPP calculation is the need for a reasoning procedure that allows the combination of input data that is different both in its nature and its value domains. As Tables 2 shows, data values fall within wide ranges and contain disparate types of information (binary, percentile, categorical, etc.). The only feasible solution for MPP calculation is therefore the use of fuzzy inference techniques allowing the combination of different information types into a unified inference mechanism. A full discussion of fuzzy logic and fuzzy aggregation operators is well beyond the scope of this work, and there is detailed review of these topics[19].

Using fuzzy logic, the MPP aggregates all the necessary data related to the UMS system (hardware, software, and intelligence) into a final MPP score. The rules and 'masks' mentioned above for the fuzzy aggregation are determined by the mission description. A brief description of some of the fuzzy aggregation methods used for the following example application of the MPP can be found in[20].

Table 2. Parameter example needed for MPP calculations: not all required are presented

Parameter	Description	Estimation approach	Comments
UMS platform parameters			
Physical parameters: Width, height, length	Size of the UMS	Numeric values	Different mission might need assets of different sizes
Locomotion schema	Categories list: skid-steered, Ackerman, Differential, …	Single value from the list	The locomotion type can affect the MPP, for example a tracked vehicle will have a higher MPP for cross-country applications.
VTOL	Categories list: Yes/no	Single value from the list	Some of the missions might require vertical take-off and landing capabilities
Other parameters…			

Parameter	Description	Estimation approach	Comments
Control station parameters			
Command latency	Time between command input and platform response	Single numeric value	UMS with higher latency often have lower mission performance.
Portability	Is the ground station portable or not. Categories list: Yes/no	Single value from the list	Portability is an important for infantry operations.
Other parameters…			
Weather limits and environmental concerns			
Temperature	Min and max operation temperatures	Numeric values	
Wind	maximum wind speed in which the UMS can operate	Numeric values	Significant only for UAV and maritime assets
Optical visibility	Minimum operational visual range due to fog, clouds, rain, vegetation, etc.	Numeric values	Significant only for UAV and Maritime assets
Rain	Maximum rainfall in in which the UMS can operate	Numeric values	

Parameter	Description	Estimation approach	Comments
Wave height	Maximum wave height at which the UMS can operate	Numeric value	Significant only for maritime assets
Other parameters…			
Data links			
Range	max. range from control station	single numeric value	
Line of Sight	Does the UMS require LoS to operate?	Single value from the list	
Real-time configuration	does the control station allow real-time configuration of the UMS	Single value from the list	This parameter is currently qualitative and subjective.
Frequency	Transmission rate between the UMS and the control station	single numeric value	
Standards	Does the control station comply with any standards (i.e., JAUS)	Single value from the list	
Range	max. range from control station	single numeric value	
Other parameters…			

Parameter	Description	Estimation approach	Comments
Sensors			
Range (EO sensors)	Maximum range of the sensor	Single numeric value	In general, a LIDAR with a greater sensing range will provide a better overall UMS mission performance.
Resolution (EO sensors)	Maximum resolution (picture size for cameras, point spread for LIDAR, etc.)	Single numeric value	In general, a LIDAR or camera with a finer resolution range will provide a better overall UMS mission performance.
Field of view (EO sensors)	Angle of view (vertical and horizontal) for cameras and LIDAR	Numeric range	In general, a LIDAR or camera with a greater FOV will provide a better overall UMS mission performance.
Other parameters...			
Perception and intelligence			
Mapping type	Defines the map building approach used	Single value from the list	Currently this is a qualitative variable describing the general map- ping approach, i.e., SLAM, LIDAR segmentation, stereo-camera, etc.
Obstacle behaviour prediction	Can the UMS detect dynamic obstacles and predict their behaviours?	Single value from the list	Some UMS missions will require the UMS to interact with dynamic objects.

Parameter	Description	Estimation approach	Comments
Obstacle avoidance	Does the UMS react to obstacles to avoid them? Categories list: Yes/no	Single value from the list	
Path re-planning	Can the UMS re-plan its path due to changing mission parameters? Categories list: Yes/no	Single value from the list	
Other parameters (Large number)...			

Still, the main question is about the particular parameters to be estimated and how should they be combined to assess the MPP as close as possible to its true value – the actual performance. The current MPP approach is to define a set of fuzzy rules and aggregation methods for each mission or narrow enough mission class. During the practical experiments, the MPP provided by the framework and actual performance assessed by field experts on UAV showed that the MPP if properly defined is rather close (within the rage of 10%) to the actual performance. However, these are the very first experiments and the work is still ongoing.

CONCLUSIONS AND FUTURE EFFORTS

This article was to develop procedures for the assessment of system mission performance as a function of platform autonomy for unmanned land, sea, and air vehicles. To accomplish this task, a new performance assessment tool was developed to predict UMS performance for a given mission at a given autonomy level. The MPP was developed by first performing an in-depth review of many of the currently accepted metrics for UMS autonomy and performance.

The development of the MPP was necessary because the current methodologies used for autonomous performance assessment were insufficient, particularly in terms of defining a UMS' performance for its mission or range of missions. Many of the existing tools required extensive field testing to compute autonomy level or autonomous performance. Many of the existing tools also required well-defined metrics describing the UMS' environment and mission. Furthermore, while these tools measured autonomy level, they did not provide an answer for the impact of autonomy level on mission performance.

Using the fuzzy inferencing as a core mechanism the MPP combines data about UMS platform hardware, software, and intelligence, environment and mission. Through several steps of calculations, the MPP provides a single number describing the performance expectation for a given mission, environment and asset.

The key benefits of the MPP over other existing frameworks can be summarised as:

1. The MPP is predictive measure and does not depend on particular field tests. Thereby the MPP can be used off-line as a prior estimators of performance;
2. The MPP does not compute an autonomy level but rather fixes the UMS Autonomy Level (AL);
3. The MPP provides matter for comparative analysis of different systems providing a direct benefit for decision makers;
4. The MPP value is calculated using fuzzy logic, and the specific rules for the fuzzy aggregation of the MPP are defined using the mission description. This provides a possibility to use the existing field knowledge and incorporate it into the inference mechanisms. At the same time this is the main drawback because it requires an intensive use of experts, which is relatively slow;
5. The MPP allows cross-type comparisons between ground-, air-, and sea-based UMS since the mission description remains the same the other parts of the MPP framework might be combined in different ways for different platforms.

The current developments are focused on MPP application for other domains – ground and sea, which will be supported by the field experiments to validate the results and developed rule bases. Once the tool has been validated, it will serve as a key enabler for increased UMS use and increased UMS autonomy.

ENDNOTES

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