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Simulation and Evaluation of Mixed-Mode Environments: Towards Higher Quality of Simulations

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Abstract. For rescue and surveillance scenarios, the Mixed-Mode Environments (MMEs) for data acquisition, processing, and dissemination have been proposed. Evaluation of the algorithms and protocols developed for such environments before deployment is vital. However, there is a lack of realistic testbeds for MMEs due to reasons such as high costs for their setup and maintenance. Hence, simulation platforms are usually the tool of choice when testing algorithms and protocols for MMEs. However, existing simulators are not able to fully support detailed evaluation of complex scenarios in MMEs. This is usually due to lack of highly accurate models for the simulated entities and environments. This affects the results which are obtained by using such simulators. In this paper, we highlight the need to consider the Quality of Simulations (QoSim), in particular aspects such as accuracy, validity, certainty, and acceptability. The focus of this paper is to understand the gap between real-world experiments and simulations for MMEs. The paper presents key QoSim concepts and characteristics for MMEs simulations, describing the aspects of contents of simulation, processing of simulation, and simulation outputs. Eventually, a road map for improving existing simulation environments is proposed.

1 Introduction

Mixed Mode Environments (MMEs) describe the wide range of scenarios that are heterogeneous with respect to the physical environment (which can be static and structured or highly dynamic and unstructured), and the involved agents (mobile robots with heterogeneous motion, sensing and communication capabilities, heterogeneous static sensors, and humans-in-the-loop). Possible scenarios in this context are monitoring and surveillance tasks using heterogeneous sensors, but also the coordination of multiple autonomous vehicles in a search and

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rescue scenario. In the considered applications, robots equipped with heterogeneous sensors and networking capabilities play an essential role (see Sec. 2 for more examples of MMEs).

Testing of the algorithms and protocols developed for such MMEs before their real-world deployment is vital. However, due to cost and safety issues, real-world tests are often replaced by simulations [1]. Simulators are essential tools that permit thorough testing in the considered multi-sensor-actor systems in MMEs. Evaluation based on simulation is one of the keys to efficient development of dependable algorithms for these systems, ensuring that they perform as expected in the target environment [2].

As already proposed with "MM-ulator" [3], the specific benefits of using simulators in a common platform open the door to systematical studies, evaluations, and development. However, the complexity of the addressed scenarios results in very complex simulators, which are usually a combination of other simulators specific for different research disciplines. With these growing combined simulation and evaluation platforms, the importance of systematically ensuring specific levels of accuracy arises.

The Quality of Simulations (QoSim) needs to be evaluated in order to characterize the consistency of the simulation results with respect to the real world. QoSim is meant to encompass the degree of quality characteristics, focusing on i) accuracy, ii) validity, iii) certainty, and iv) acceptability. The terminology of QoSim is new. However, the inspiration of QoSim derives from the concepts of Quality of Information (QoI), which is typically used in areas such as database management, management studies and Wireless Sensor Networks (WSNs) [4–8].

Unfortunately, existing simulators are not always satisfactory in terms of the simulation characteristics i)–iv) for MMEs. Hence, this leads us to bring the concepts of QoSim to simulators in robotics, WSNs, autonomous vehicles, and distributed systems in general in MMEs.

Simulators are based on models that abstract the reality. The abstraction often is intentional for simplification. However, a question that arises is: "How confident are the results of simulators for transferring them into the real world?" Often, the goal of a simulation is to test accurately only one part of the system, loosing constraints for the rest of the components and skipping their validation process. This equals to ignoring some simulation parameter; sometimes by intention to avoid unnecessary "input noise", or due to lack of support in the simulator. Hence, it is unclear whether such approximate models still provide the desired level of QoSim accuracy in the real world. To this end, we must know the validity of the model to be acceptable in the real world.

Bringing simulated results close to real environments such as MMEs and satisfying their requirements will be further improved by considering QoSim. Some of the real benefits of existing simulators [9–16] are discussed in surveys, e.g., [17–19]. It comes down to advantages such as reduced cost, higher level of details and safety. However, there are disadvantages as well, such as results not respecting all real-world requirements due to simplified models [20], or the lack of parameters. Moreover, one of the core objectives is to satisfy the set of user requirements, and to assess the usefulness of the simulated results for a real environment. Consequently, the concept of QoSim reflects an extension to the concept of "MM-ulator" [3].

Instead of simple validation of simulation results, QoSim has a broader meaning with respect to the relation to real-world experiments – namely the aspects i)–iv). Hence, we discuss this set of simulation requirements to show that they are significantly important. QoSim is rarely taken into account in the design of simulators. Thus, we classify the simulations with respect to: (1) the model view, (2) the application view, and (3) the user view. This helps us to map the simulation characteristics with the provided classification to understand why the aspect of QoSim is important for simulations.

Besides providing the QoSim definition, characteristics, and classification, we also suggest the use of QoSim for simulations based on the following aspects: (1) the simulation content, which takes into account the different models and parameters provided by simulators, (2) the process of simulation, based on the duration of simulations, models used, and (3) the simulation results, which provide the level of abstraction to the developer.

In particular, the scientific contributions are: (a) a systematic analysis of QoSim for MMEs, (b) providing simulation characteristics, (c) the classification of simulations and their mapping to QoSim characteristics, and (d) the conceptualization of QoSim.

The paper is organized as follows. After characterizing specific requirements and features of MMEs simulations in Section 2, and after a definition of QoSim in Section 3, in Section 4 simulation characteristics are discussed. In Section 5 the classification of simulations is presented and mapped to the simulation characteristics. In Section 6, we conceptualize QoSim and in Section 7 the road map for future research directions is depicted.

2 Simulation and Evaluation in Mixed-Mode Environments

In MMEs, the application scenarios vary from search and rescue, to exploration of hostile terrain, to planetary exploration, etc. In [3], requirements of inter-disciplinary simulation were already discussed, benefits of using multi-disciplinary knowledge were presented, and road-maps for a common evaluation platform were proposed.

Still there is no implemented solution satisfying the whole spectrum of needs in MMEs-scenarios. These needs contain different time-scales and abstraction levels (cf. Fig. 1), various interfaces, possibly to be combined with real-world experiments (including the known elements of software- and hardware-in-the-loop tests), physical details like dynamic temperature distribution, interaction and manipulation of robots in their environment, etc. The basic corresponding modular architecture consists of components for simulating node properties, and components for simulation and interaction with the physical environment.

Thereby, the idea of using a network of sensing platforms, i.e., combining low-end monitoring equipment with high-end data gathering functionality, has to be reflected into the architecture of each simulated node and its interfaces.

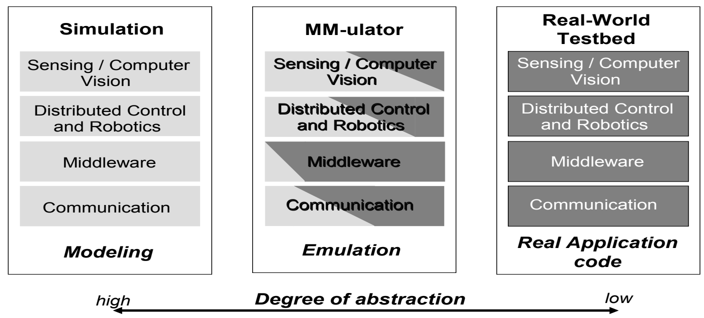

Fig. 1. Simulators from different research disciplines are using a common validation platform "MM-ulator" for emulation.

For illustration, we are mentioning a disaster scenario after an earthquake, where multiple distributed sensors and mobile robots are assisting humans in mapping and monitoring the environment, and in detection of victims. The scenarios ask for communication among nodes (for coordination and sharing data), for applying principles of distributed sensing and feature detection, for dependable middleware in the multi-agent system, and for elaborated locomotion and cooperative control of robots. Evaluating the collaboration of these components requires a detailed simulation on different levels of abstraction. For example, the physical model of the robot can either be a bounding box around the whole robot, with just a point mass, or a more detailed model with bounding boxes around the body parts that are connected with joints, or a detailed physical model based on the CAD data, with exact masses and inertial tensors. Since robots are equipped with sensors, also their readings are simulated on an adjustable accuracy. The simulation of a laser scanner, for example, can either return ground truth distances, or can add noise, or consider different reflectance properties from different materials or effects occurring at fast motions.

State-of-the-art simulators in robotics like [12, 13] provide functionalities to simulate robotic environments. Evaluation in the whole spectrum of MMEs lies beyond these capabilities, and requires information from additional models as implemented, e.g., in WSNs simulators like TOSSIM [9]. Combined simulations environments for sensors and robots with detailed models for wireless communication, enable to study effects in controlling network topology by positioning of robots as well as cooperative data aggregation and feature detection.

As a consequence, the availability of a holistic evaluation platform based on simulations allows for more flexible and multi-disciplinary performance metrics, and problems can be seen from new perspectives. For instance, by migrating wireless network constraints into robot control, new metrics like coordination stability are emerging.

All these aspects give a further motivation in the current phase of building and connecting more and more complex simulation and emulation environments for a more systematical consideration of QoSim concepts, and it draws out that QoSim is one of the key points to apply these complex evaluation platforms for substantiated answers to new difficult scientific questions.

3 Quality of Simulations: Forms and Definitions

We are introducing the concepts of simulations to formalize the definition of QoSim from the basics of QoI. With the set of characteristics associated with QoSim, different levels of abstraction can be obtained, which helps the developer in evaluating cost, safety, duration, and results of the simulation.

Developing robots, particularly cooperative multi-robot systems, strongly relies on simulations to test hardware and integrated software. In particular, many algorithmic tests must be done within a controlled simulated environment to detect failures and misbehaviors without cost and safety concerns, therefore simulations must consider detailed physical 3D properties, like obstacles or gravity.

Sensor nodes in WSNs or robots equipped with sensor nodes also have a set of specific requirements. There are a few simulators, such as TOSSIM [9], where the evaluated code can be directly brought into the real world. However, the simulated results vary in real environments due to perturbations and environmental conditions, leading to a lack of quality. Moreover, using existing simulators for MMEs sometimes does not satisfy the requirements of the applications.

The core objectives of a MME-simulator is to satisfy complex requirements needed by the user, and assess how close the simulated results are to a real environment. Our main focus is on quality aspects of simulations, and since we are motivated by QoI [7][8][4], let us brief through some of QoI definitions in WSNs. We choose these definitions of QoI in WSNs because of their relevance of quality aspects in MMEs. QoI definition in regard to monitoring environments [5] is defined as "the difference between the data that the output of the WSNs produces concerning some environment that is being monitored, and the actual events in that environment which one wishes to observe or track". The multidimensional concept [6] of QoI on application view is "the collective effect of the available knowledge regarding sensor derived information that determines the degree of accuracy and confidence by which those aspects of the real world (that are of interest to the user of the information) can be represented by this information".

In this paper, from the inspiration of QoI we define QoSim in regard to its attributes in MMEs. We therefore propose the following definition:

Definition 1. Quality of Simulations *(QoSim) represents the discrepancy between the simulation results and those expected by the user.*

This definition is meant to encompass the degree of quality characteristics accuracy, validity, certainty, and acceptability.

4 Abstracting the Features of Quality of Simulations

After defining the QoSim with a set of characteristics, we now detail these characteristics and also brief their importance. In literature, several quality characteristics exist, such as stability, robustness, and consistency. Although we acknowledge their importance, we did not address them in this paper because they go beyond our scope. They depend mostly on the application to simulate rather than the simulator. We assume simulator developers to be more experienced programmers than common users, therefore already considering such important aspects which have been thoroughly addressed in several areas. We considered instead accuracy, validity, certainty, and acceptability (cf. Table 1). The main reason for this choice is the relevance in simulations and for the developer.

Accuracy is the characteristic of simulations in which results are similar to real-world values. Therefore, it is most relevant to consider accuracy of models and of simulation output. The developer would accept the results of simulation only if achieving the same level of accuracy of real-world experiments.

Validity is based on the models used for simulation. The validity of the model reflects the consistency to the real world. If the selected model in the simulator is not satisfying the developer's requirements or if a specific model developed by the user is not satisfying the real-world conditions, then the model lacks validity for certain simulations. However, the level of validity strongly depends on the application; if the application is requiring only a small set of parameters, then the simulation can be simple enough to be proved for its validity.

Certainty is the characteristic of simulations on which the developer can place a certain level of belief about the model and simulation itself. Certainty is closely related to accuracy and validity of model and simulation. After simulating an application, and if the results are comparable to real-world experiments, then it fulfills the aspect of certainty. In robotics, during some simulation, the results are good enough to validate the model, but to prove the same model in real world, it could get less belief, or sometimes the real-world results completely deviate from the simulated results. In this case, one can accept the model with lower level of certainty.

Acceptability is the degree of satisfaction in terms of factors such as cost, safety, time and results of simulation. The selected model and the simulations can be accepted by the developer based on these factors. The most important are cost and safety, which can be reliably accepted. However, sometimes computational complexity and simplification in the model used make the results insufficient, and they can be barely accepted by the developer.

5 Simulation Classifications

This section gives a QoSim-based classification of simulations, not implemented so far to the authors' knowledge. This is relevant to achieve accuracy levels and helps to understand different perspectives of simulations as well as it shows how existing simulators can be improved by adopting the classification from low to

Characterizing feature	Definition
Accuracy	The accuracy of simulation results compared to the real-world results
Validity	The prediction of the model consistency from simulation to real world
Certainty	The belief and level of abstraction of the developer on the model and simulations
Acceptability	The acceptance of simulations based on cost, safety, time and results

Table 1. Summary of main QoSim characteristics

high level of abstraction. We classify the simulations into three classes, the model view, the application view, and the user view. Fig. 2 illustrates the mapping of different characteristics to them.

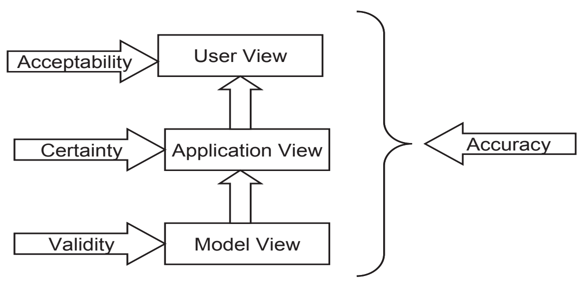

Fig. 2. Simulation Classifications and requirements of corresponding characteristics.

Model view This view is solely dependent on the combination of selected model and the simulation environment. The model view can be directly mapped with the *validity* characteristic. The model hast to satisfy all the user's requirements. This view strongly affects the next two classes. If the chosen model is not satisfactory in providing all the parametrization required by the application, it will be hard to bring the same model into real-world applications. Therefore, the model must be accurate enough to provide results comparable to real-world experiments.

Application view Sometimes, in MMEs, application scenarios get complex by exploding the amount of requirements that comes up with a simultaneous use of robots and WSNs. In this case, the simulation results depend on the simulator which can simulate both robotics and WSNs models together. Sometimes this creates a hard situation for the developer searching for the right simulator to satisfy the requirements of the application. On the other hand, the model view of the simulations plays an essential role and affects the application view of the simulations. This class is mapped with the *certainty* characteristic. Since the certainty gives the level of abstraction, if the simulator is capable of fulfilling all the required parameters for the environments (consisting of robots and WSNs), then the developer can have a strong belief on his application and simulation results.

User view This class of simulations is about performing experiments using simulations and how they can be applied in real world. Usually, when the user is working on real-world experiments and has simulated the model in advance, the developer needs to understand how well these results match the accuracy level of real-world experiments. This can be achieved only with a good model and it is specific to the application; hence, the above two classes affect this class. Moreover, this class also depends on the aspects of cost, safety, time, and results. Therefore, it is mapped with the *acceptability* characteristic. This class provides the acceptance rate of the simulation results to work with the same prerequisites in real world.

6 Conceptualizing Quality of Simulations

After presenting the QoSim characteristics and its mapping with different classes of simulations, we now conceptualize QoSim.

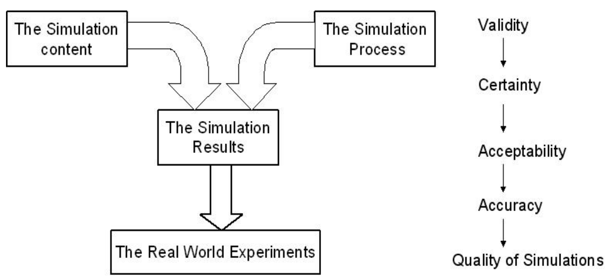

Fig. 3. Conceptualizing Quality of Simulations: related aspects and characteristics

The first and foremost aspect is the *simulation content*. One of the main objectives of simulations is to understand and validate the model in order to bring the same to real world. Here, simulation content represents the available models, parameters and level of details of the simulation environment. Moreover, the simulation content is based solely on the chosen simulator. Generic simulators such as ns-2 [10] and OMNeT++ [11] provide most of the models and parameters, but lack support for WSN platforms. Thus, the simulation content is not satisfying the complex requirements of MMEs. Simulators such as COOJA [21] and MSPSim [22] simulate WSNs but do not provide all required models. Hence, it is essential that simulation content in MMEs is verified with the QoSim characteristics.

The second aspect we consider is the *simulation process*, which depends mainly on the developer and the usage of the simulator itself. If a simulator meets all the necessary requirements to satisfy the application, then the QoSim depends on how well the developer uses its characteristics in order to obtain simulated results comparable to real-world experiments. The simulator chosen, the duration of simulation, and how well the algorithm was simulated – including different models – are the main factors during the entire simulation process. However, in MMEs, with increased complexity of the requirements, the developer must be thoroughly aware of the abstraction level achievable by using QoSim characteristics. If the developer *validates* the model in an efficient way and has a *certain* belief on the simulation process, then the results can be carefully checked for the aspects of *acceptability*.

The third aspect is the *simulation results*, based on the usage of results and their acceptability. The developer can predict the use of simulations results in real cases. As shown in Fig. 3, the simulation results are based on the simulation content and simulation process, which lead to real-world experiments. Once the chosen simulator and its content is satisfying the QoSim aspects in terms of validity, the developer has to perform simulations in such a way that the aspect of certainty is fulfilled. Later, achieving the simulated results, the developer can know the level of acceptability.

7 Discussion and Future Directions

QoSim is highlighted as a vital factor to be considered in simulations for MMEs. Since to the authors' knowledge there is no such simulator which simulates applications with all the characteristics presented, the gap to fill is to develop new simulators or improve the existing ones to achieve reasonable results that can be brought into real-world experiments.

While replacing real-world experiments with simulations, a realistic simulation also has to contain effects like disturbance, noise, chaotic behavior of non-controllable agents. These factors help in bridging the gap between real world and simulation. This research focus helps in building up a new simulation environment and hence leading to an efficient simulator satisfying environmental requirements.

In this paper, QoSim is simplified. Considering the provided classification, one of the improvements that can be applied to existing simulators is adapting the different views mapped with QoSim characteristics. This provides levels of abstraction for adopting the simulations to real-world experiments.

Though some existing simulation environment like ns-2 and OMNeT++ is generic and provides a few models, it is difficult to use them in MMEs including robots, WSNs, and possibly humans-in-the-loop. Hence, a necessary step is to draw attention towards developing a simulator satisfying the MMEs requirements while taking into account the aspects of QoSim.

8 Conclusion

The complexity of requirements in MMEs evolves depending on many factors such as environmental and operational conditions. Using simulators to evaluate approaches for multi-disciplinary research, for the benefit of cost, safety, scalability, repeatability, etc., is well-accepted and often the only possible way to evaluate new methods in early stages of development. However, taking simulated models, algorithms, and results to the real world degrades QoSim characteristics. Sometimes, these characteristics are not even considered. The focus of this paper was to identify the gap and provide a road map to apply QoSim concepts in holistic evaluation and simulation platforms. We discussed that considering QoSim is necessary in order to achieve comparability to real-world experiments. We also provided sufficient QoSim characteristics and conceptualized them. However, this paper does not give a specific solution to the mentioned problem, but details the gap existing between real-world environments and simulations. Thus, for very complex MMEs, we highlight the importance of systematically applying QoSim concepts for the goal of studying new fundamental multi-disciplinary research questions in a significantly more reliable way.

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