Intelligent Operator Support Concepts for Shore Control Centres

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Abstract. This paper introduces three intelligent operator support functions to allow multiple operators to effectively and efficiently supervise multiple autonomous operations. The many-to-many concept assumes a stage in human-automation collaboration design where supervision of maritime autonomous surface ships is not permanently required anymore. Only in extreme and very rare situations the human may need to intervene. One of the challenges is balancing the task assignments and support functions over the operators to ensure the cognitive task load matches the operator's mental capacity. For this purpose we introduce and described a dynamic task allocation algorithm. Also, human attention is limited and operators therefore must constantly shift attention resulting in moment-to-moment fluctuations in situation awareness. To overcome these reductions in situation awareness, operators must reassess the environment to recover situation awareness. We introduce the concept of continuous risk assessment to initiate the process of situation awareness recovery. Furthermore, the many-to-many ratio between supervising operators and autonomous ships implies that operators will not be able to supervise all ships in parallel. This makes current supervisory control interfaces less suitable. Instead we opt to apply the idea of progressive disclosure in the operator's interface and interactions. The work described in this paper is directed towards developing an intelligent operator support system with which the operator support functions will be demonstrated as part of a Robotic Container Handling System, an innovation of the European MOSES research project.

1. Introduction

It is expected that in the maritime domain, automation will advance to levels where supervision of maritime autonomous surface ships is not permanently required anymore, as systems are able to work fully autonomously in almost every condition. Only in extreme and very rare situations the human may need to intervene. This implies that the human operator will be out-of-the-loop by definition and will not have the skills to take measures in these, probably, difficult conditions. This has led to different opinions and strategies on how to deal with remote operator support in the transition to fully autonomous systems.

Van den Broek et. al [1], distinguish three different stages for highly automated human-automation collaboration that require different operator support designs (see figure 1). In the supervision stage, the first distinguished phase, the human operator monitors the system 100 percent of his time and is not involved in other tasks. Supervision of dynamic positioning systems by onboard operators is an example of this (e.g., [2], [3]). Such one-to-one supervision duties require continuous high vigilance levels and are prone to loss of situation awareness (SA), out-of-the-loop problems [4], and complacency [5].

Stage	Support functions	References
1. Supervision stage. The human operator is 100% of his time supervising the system(s) and is not involved in other tasks	Common (SCADA) interface support	[2], [3]
2. Partial supervision/autonomy stage. Self-directness is higher. The human operator spends part of his or her time conducting secondary tasks.	Supervisory displays; SA recovery support after returning to the main task; Increase the reaction window by detecting early signals; Situation awareness recovery.	[6], [8], [9], [10], [13]
3. Intervener/full autonomy stage. Both self- sufficiency and self-directedness are high. The system is working autonomously almost 100%	Dynamic task allocation; Continuous Risk Assessment; Progressive Disclosure Interface Design.	This paper, [17], [21]

Figure 1. Overview of three different stages for highly automated human-automation collaboration that require different operator support designs.

SA is defined as the conscious knowledge of the immediate operational environment and the events that are occurring in it. It involves the perception of elements in the environment, comprehension of what they mean and how they relate, and projection of their future state. It refers to the operator's awareness of the current operational status and the anticipated future status of a system, necessary to intervene in an effective and timely manner.

To address these operator related issues (i.e., human factors issues), a new operator support concept has been developed and demonstrated in previous research by TNO to enable partial supervision [6]. In the partial supervision/autonomy stage, the second distinguished human-automation collaboration stage, the system self-directness is higher. This allows the human operator to spend time performing secondary tasks and thereby leave the control station on the bridge. In case a critical situation is building, the operator gets informed, via a smart watch and tablet computer. It is the operator's decision whether or not it is necessary to return to the bridge and to intervene. The main challenge for stage two is to keep the operator posted of the status of critical tasks and to enable him or her to resume control effectively when required. Both the human operator and the automation develop SA relevant for the primary task [7].

The operator support for the partial supervision/autonomy stage consists of the following functions [8]:

1. Support the upkeep of operator SA using supervisory displays [9] to help the operator decide whether involvement in the primary task is required;
2. Provide SA recovery support after returning to the main task;
3. Increase the reaction window by detecting early signals and providing on-time alerts for the primary task;
4. Situation awareness recovery [10]: provide, change detection and option awareness support for quick decision making when a critical event has occurred at the primary task.

However, it is expected that future shore control centres will be staffed in such a way to allow for the supervision of multiple operations in parallel, because it will be more cost efficient compared to the one-to-one set-up (a single human supervises a single operation) described above. Supervisory control by a single operator over multiple operations could match the efficiency requirement. When a human supervises a set of multiple operations (one-to-many) care must be taken to ensure that the operator has the capacity to give adequate attention to each operation [11]. Neerincx [12] developed a cognitive load model, distinguishing three load factors that have a substantial effect on task performance and mental effort: percentage time occupied, level of information processing, and task-set switching. The combination of the three load factors determines the cognitive task load. The challenge is to balance the task load in such a way that it matches the operator's mental capacity in a certain task setting. In addition, unexpected situations can arise in which autonomous systems require human assistance. It can be assumed that these will be safety-critical and difficult situations that will require full attention. As a result, the operator span of facilitation will be limited to one system, with the result that other operations under the responsibility of the operator are forced to left unattended [13], providing a potential risk. For reasons of operational safety, therefore, a transfer of supervision responsibility to another operator is necessary under these circumstances. So, for reasons of cognitive load balancing and for guaranteeing the overall span of facilitation, it is necessary to have some sort of task allocation over multiple operators. For this reason, we propose a many-to-many remote control centre concept, in which several operators supervising a set of multiple operation (several one-to-many instantiations) allowing for dynamic task allocation over operators.

For a many-to-many shore operation concept to work requires that both self-sufficiency and self-directedness of the autonomous systems are high and the systems are working autonomously nearly 100 percent of the time. This allows the operator to work on other tasks, i.e., to work on other operations. But even fully autonomous systems fail sometimes, for different reasons, and in these exceptional cases the operator needs to intervene. This third and highest level of human-automation collaboration is the so-called intervener/full autonomy stage.

In line with the above, this paper advocates the necessity of additional operator support concepts to enable this high level human-automation collaboration.

The additional operator support concepts that will be discussed in this paper are:

1. *Dynamic task allocation.*
   Assign ships (operations) to operators based on user and task profile.
2. *Continuous Risk Assessment.*
   Assess in real-time potential risks and warn, inform, explain and help solve them.
3. *Progressive Disclosure Interface Design.*
   Show information and offer control on different abstraction levels.

The research outlined in this paper is carried out as part of the European MOSES[1] research project. As a system demonstration is part of the MOSES scope, the concepts will be integrated into a single AI-based Intelligent Operator Support System (IOSS).

The use-case within MOSES is to enable multiple operators to oversee and track multiple loading and offloading operations, executed by robotic container handling systems mounted on autonomous feeder vessels, and to take action and intervene when necessary. The MOSES research scope and the robotic container handling systems innovation will be described in the next section.

The three additional operator support concepts are described in the following paragraphs. The article ends with a conclusion section.

2. The MOSES research context

The European MOSES research project [14] is one of three research and innovation projects within the Horizon 2020 program that contributes to more automation and autonomy in Europe's short sea logistics. The other two projects are AUTOSHIP and AEGIS. The main focus of AUTOSHIP is on vessel technology. The AEGIS consortium, on the other hand will design Europe's next generation sustainable and highly competitive waterborne logistics system comprising more autonomous ships and automated cargo handling.

The innovations within the MOSES project, aim to significantly enhance the Short Sea Shipping (SSS) component of the European container supply chain by implementing a constellation of innovations including innovative vessels and the optimization of logistics operations.

The work described in this paper is directed towards developing and demonstrating a Robotic Container Handling System (RCHS) that, when mounted upon a hybrid electric and autonomous feeder

[1] AutoMated Vessels and Supply Chain Optimization for Sustainable Short SEa Shipping.

vessel, will stimulate and support the use of short sea container services for small ports that have limited or no (un)loading infrastructure.

Normally, a crane operator controls the crane based on his/her eye-hand coordination, e.g. knowing which container to pick-up, he/she looks for the position of the container, estimates the distance between spreader and container, reduces speed if needed, locks, etc. Furthermore, the safety of the operation is guaranteed with a relatively high degree of oversight from other people as well as the creation of a secured and sealed-off area. The RCHS research challenge[2] is to bridge the large gap between the current way of working and the envisioned concept where the RCHS can perform all these tasks on its own, i.e. autonomously.

The RCHS is approached as a systems-of-systems. In fact, the RCHS consists of five major components, each consisting of multiple subcomponents.

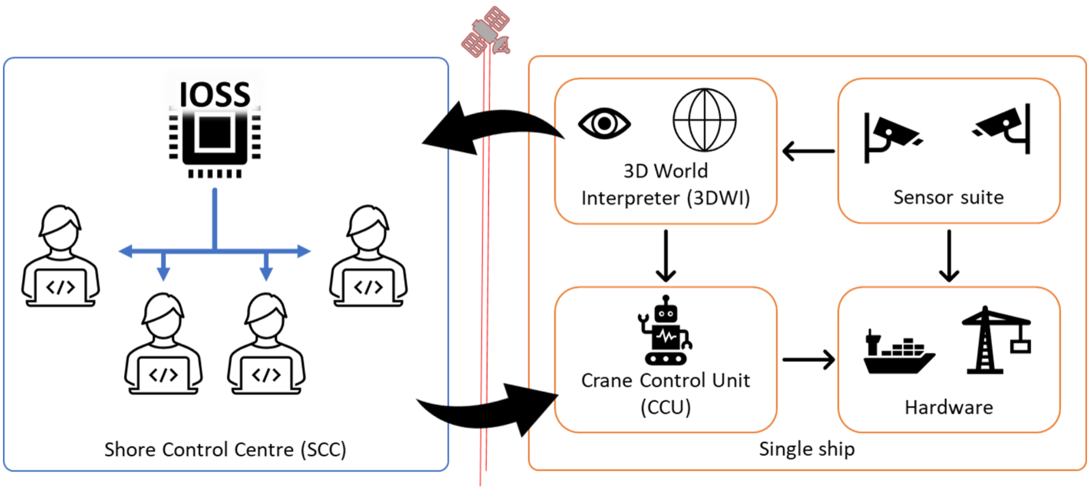

Figure 2. As a systems-of-systems, the robotic container handling system consists of five major components.

1. The crane, spreader, and automatic swivel control system.
2. The Crane Control Unit (CCU), responsible for both the control and high-level decision-making needed to load and unload containers safely in a public area at a small port. The control functionality of CCU is responsible to drive the crane and all of its sub-components. The decision-making function is responsible to decide which container to load or unload when and where.
3. The 3D World Interpreter (3DWI), is responsible for the perception (detection) of elements in the environment, comprehension of what they mean (identification) and how they relate. This SA is required by the CCU for controlling the crane and high-level decision-making. Likewise, it provides the local information needed both for operator SA as for the functions the operators support. Combined, the CCU and the 3DWI is the core of a self-sufficient autonomously operating crane system.
4. Sensor suite, a combination of (stereo) cameras and lidars to provide the 3DWI with images of the operational area.
5. The Intelligent Operator Support System (IOSS) is responsible for safely managing a large amount of autonomous container handling operations occurring in parallel and their supervision from a remote shore control centre. This system ensures that every ongoing operation is performed effectively and safely. It does so by providing support to enable only a few operators

[2] Within the RCHS research and development TNO closely collaborate with MacGregor Finland Oy, the company that provides the physical crane system and crane control software.

to supervise many operations. Examples are the allocation of operations, SA support, risk assessment, control suggestions and more.

3. Dynamic task allocation

As indicated, within the concept it is envisioned that several remote operators within the Shore Control Centre will be responsible for several loading and unloading operations at the same time.

To deal with workload fluctuations in a dynamic way, the dynamic task allocation algorithm connects to the voyage and operational stage planning on fleet level and estimates the operator workload level associated with the number of ships under supervision and their voyage stage [13]. When workload thresholds threaten to be exceeded, the span of control, i.e. the number of ships under control, can be enlarged or reduced through task reallocation.

The algorithm takes five stages into account: sea passage (transit), port departure/approach, leaving/approaching berth, and container handling. For each stage the autonomy mode changes for which the workload demands can be planned in advance with exception of the stage in which exceptional circumstances occur.

We face two challenges when allocating ships to operators based on expected workload per stage. From a human factors perspective we face the challenge of modelling workload. Second, this model needs to be incorporated into a feasible optimization algorithm to compute an responsible allocation.

To model workload we opted to define a cost function. This function takes a given ship-to-operator allocation and returns how costly it is in terms of workload. Workload is defined as a percentage of an operator's total capacity (e.g., 100%). This abstraction allows us to circumvent the issue of formally defining the cognitive processes that determine workload. For instance, a task with an expected load of 10% implies that the operator can handle ten of such tasks in parallel given a capacity of 100%.

Given a ship and a certain loading/offloading at a port, we assign such a workload to each of the stages. For instances, for a particular combination of a ship, port and containers the sea passage might require 5%, the port approach 10%, and the container handling stage 15%. These percentages can vary given the complexity of the tasks. For instance, autonomously berthing to a crowded port might be more difficult and thus potentially require more supervision. To determine these relative percentages an approach such as by Wilson et. al [15] can be used that utilizes physiological measurements to assess the cognitive strain a task has on people. Such an approach should typically be performed in the design phase of the shore control centre and can be repeated when necessary.

We also account for the fact that these workloads per stage depend on an operator's expertise. As such, we increase these expected workloads as operator expertise decreases. For instance, in the example above, the stages might require double the workload for a junior operator resulting in an actual workload of 10%, 20% and 30% respectively. Operator expertise can be simply defined by their years of experience with a fixed factor affecting the workload of various tasks. However, it is more optimal to perform a more in-depth task analysis on what expertise each task and difficulty in an operation requires combined with assessments how skilled an operator is in such an expertise. Although this remains an open challenge, works such as by Allais et. al [16] illustrate how this can be done in other domains.

This provides us with a basic model of workload that is feasible to work with. Next we define the cost function. The purpose of this function is to compute how "bad" any given allocation of ships to operators is. The higher the cost, the worse the allocation in terms of workload distribution. We define this function as a simple linear additive function, where several components model an aspect of human factors knowledge.

The components we defined are as follows:

1) The average and variance of workload over time and all operators. Minimizing this ensures that the workload is equally distributed over all operators.
2) The average time in a critical workload for all operators. A critical workload is defined as either too high of a workload (e.g., above 80%) or too low of a workload (e.g., below 20%). Minimizing this ensures that operators are not cognitive over- or underloaded.

3) The average time operators still have work after a certain amount of time. This models the requirement to take breaks. For instance, every four hours operators should have time with no workload. Minimizing this ensures operators have sufficient breaks.

These components are each weighted in linear fashion. The selection of weights should be considered in the design phase of a shore control centre as it is dependent on the models of workload, operator expertise, and tasks as well as the desired working environment within the centre. The summation of the weighted components result in single combined cost. For instance, an allocation with a cost of 0.5 is a worse fit given these than one with a cost of 0.25. See figure 3 for an illustration how workload is modelled over time for three operators and six operations. For a more detailed overview and evaluation of this cost function we refer to Brug et. al [17].

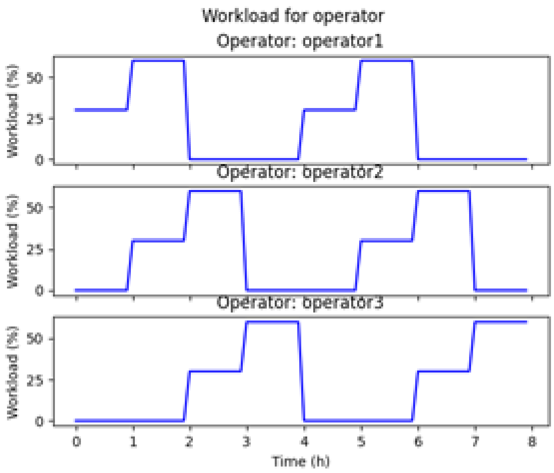

Figure 3. Three graphs depicting how we model workload for three operators given the allocated ships for him/her to supervise. The x-axis depicts workload capacity and the y-axis the time.

Given this cost function we can know apply common optimization strategies to find the best possible allocation of ships to operators based on our workload model. We opted for the Iterative Deepening Depth First Search (IDDFS) [18]. This is not necessarily the only available algorithm as we defined the challenge of dynamic task allocation as a straightforward optimisation problem. The IDDFS algorithm however is a relatively straightforward approach that is reasonably efficient and performant, and it lends itself to reallocate tasks by reusing previous computations. Which is a beneficial property to dynamically reallocate tasks based on events (i.e., a new operation becomes known or the difficulty of an operation changes suddenly). Alternative approaches could include classical approaches such as A* [19] and derivatives, or more recent algorithms based on linear programming [20]. The only additional requirement is that the selected algorithm can efficiently handle the reallocation of already assigned operations. Otherwise, the algorithm will be uncapable of handling the dynamic reallocation of operations effectively when a new operation is introduced.

The IDDFS algorithm functions by iteratively selecting an unallocated ship and assigns it to each operator. It computes the cost of each potential allocation and selects the best fit. Then it continues with the next unallocated ship, until all are allocated. Since the order of ships matters, several samples must be taken to improve the allocations. This is repeated for a number of times with the operations being allocated in different orders to ensure enough of the search space is covered. If all orders are addressed, the optimal allocation will be found. This is still more time and memory efficient (both linear) then a brute force search (exponential) since computations can be reused and only a fraction of all potential allocations are actually computed. For a more detailed discussion of this we refer to Brug et al. [17].See figure 4 for an overview how this algorithm functions in one iteration given three operators and three ships to allocate.

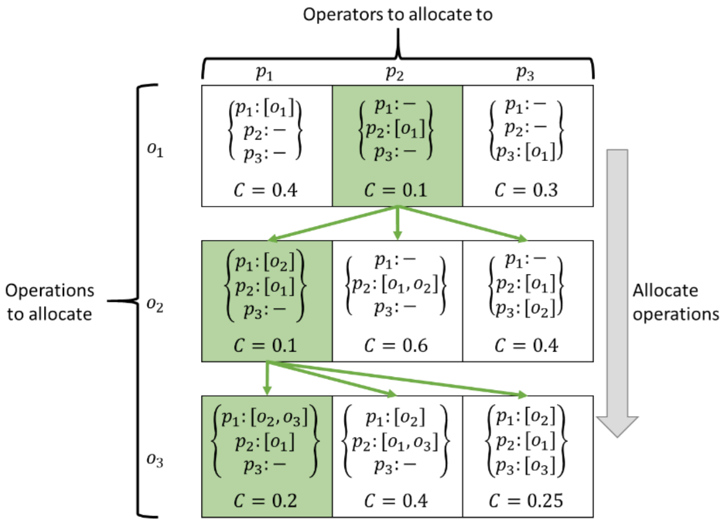

Figure 4. An illustration of the IDDFS algorithm used to allocate three autonomous ship operations (rows; o1, o2 and o3) to three operators (columns; p1, p2 and p3). At each allocation iteration the cost of allocating a ship to any operator is assessed (depicted as C), and the best one is selected (green highlight) until all ships are allocated. Such a search tree is repeated with the operations in various orders to ensure convergence to the optimal allocation.

This approach fulfils three major requirements;

1) It models workload in an abstract sense that is easily extendable with more notions from the human factors literature.
2) It is guaranteed to find the optimal allocation given sufficient time, which increases only linear given the number of operators and ships.
3) The allocation is dynamic.

Especially the latter is a major advantage. As this approach allows for the introduction of new ships requiring supervision as well as operators to flag ships they do not feel they are suited to supervise. In both cases a new allocation needs to be found. This can be done by allocating that ship to the operator with the lowest workload at the time of the operation. However, there might be a better allocation if additional ships are reallocated. For instance, in cases when the new operation's difficulty requires a more experienced operator then is available.

With the IDDFS algorithms we can efficiently reallocate operators by reverting several steps of the computation. Each reverted step signifies an operation that might potentially be reallocated. For instance, we could undo the last five allocated operations. This would give the IDDFS algorithm more freedom to allocate the new operation to a suitable operator without having to reallocate all operations. To determine how many operations should be reallocated we introduce a fourth component in the cost function that penalizes each operation that is being reallocated (e.g., reallocating five operations might introduce an additional cost of 0.1 whereas three operation an additional cost of 0.06). This allows us to incorporate the decision how many operations should be reallocated into the optimisation process itself. In other words, the IDDFS algorithm can revert steps incrementally and reallocate those operations until the gain in reallocating operations balances the cost of doing so. See for more details on this the work by Brug et. al [17] that describes this process in more detail and demonstrates it on several simulated cases.

Since we provide operators to flag operations they feel should not be allocated to them for some reason, it might occur that a single operator does not accept a necessary reallocation. In this case the IDDFS can fall back to a less optimal allocation. However, if operators are reluctant and flag operations too often, we put the computed plans up for review for a team leader to allocate operations manually by presenting the expected cost and workload over time.

To conclude, this dynamic task allocation method allows for the efficient allocation of supervisory tasks to operators under changing conditions while accounting for human factors knowledge on the ideal workload for operators.

4. Continues risk assessment

Because human attention is limited, operators in this dynamic environment must constantly shift attention between different autonomous ships and operations. These shifts in attention result in moment-to-moment fluctuations in situation awareness (SA). For example, when one ship needs assistance, the operator's attention is mainly focused on a single ship and the operator cannot know or forgets about other ships, situations and critical information. Such reductions in SA are a constant, given the fact that attention has to be divided over several operations. To overcome these reductions in SA, a skilled operator must reassess the environment to recover SA; Gartenberg et al. [10], call this process situation awareness recovery (SAR).

It is vital to the SAR process that operators are informed in a timely manner about a critical situation or receive information about a situation that could develop into one. The IOSS has therefore been given the functionality to continuously assess risks for each ship and to adequately bring a risk to the attention of the operator. This raises the question of what is 'adequate' and what this means for the assessment of such risks.

In the case of our operators, every intervention requires SAR. Risk assessment can provide the means for IOSS to evaluate whether an intervention is, or will be, required. For instance, if the weather worsens the risk of an unsuccessful autonomous berthing might increase and thus offer a trigger for IOSS to bring this to the attention of the allocated operator.

This raises the question however, what needs to be communicated to provide this awareness. A risk can be defined by its expected impact, which is a combination of its likelihood of occurring and severity of its consequences if it occurs. While this seems to be an adequate definition, it lacks real world complexity, and in particular the complexity seen in maritime industry. It is common for errors, malfunctions, calamities and other events to be interrelated, resulting in a potential long list of risks with various likelihood and severity. Such a long list does not improve an operator’s SAR process.

Instead we opt to also include the connectivity and velocity of risks in its expected impact. A highly connected risk, is a risk that – if it occurs – affects the likelihood of many other risks. The velocity of a risk dictates how much more likely it makes those other risks it is connected with. This makes the expected impact of a risk much richer as it also includes the relations between risks. For instance, a malfunctioning sensor and a busy port might not be that severe on their own, but combined make the risk of human injury much more likely.

Without modelling the connections between risks, operators might not be involved in a sufficiently timely manner. In addition, modelling such relations allows for a straightforward root cause analysis – and even tracing causes and effects – by analysing the network of risks and their effects on each other given a situation. This kind of information can be visualized and communicated to an operator to facilitate a quick grasp of the situation and how to effectively intervene.

The challenge is to find a way to model these risks. We opted for the use of graphs, where a single node represents a certain risk. Within that node is a computational model of its likelihood given a current situation. This can be as straightforward as a slowly increasing likelihood of a sensor malfunctioning as time progresses, or include a much more sophisticated predictive maintenance model using AI methods. See figure 5 for an example of such a graph.

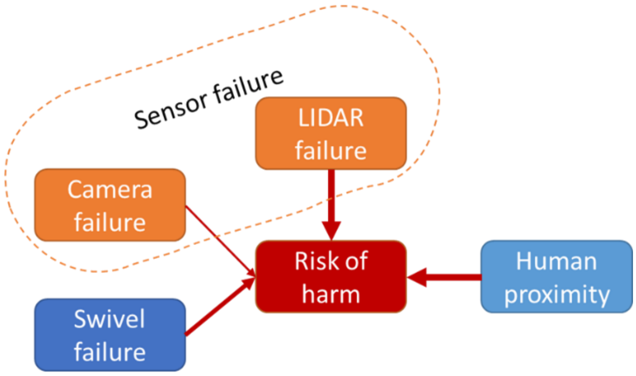

Figure 5. An example on how we propose to model risks and their relation through the use of graphs. It illustrates four risks (rectangles) and their causal connections (red arrows, strength depicted by thickness). A single high-level risk category is depicted for sensor failures. This small toy example shows how the risk of harm is significantly more likely if the LIDAR fails and people are detected nearby.

Also contained in that node is a similar model of its severity. Again, this can be as straightforward as a relative number dictating that a risk such as a busy port is of medium severity. Instead, it might again be a much more complex model where the severity depends on the situation as well. For instance, that a port busy with commercial traffic is less severe than a port with much recreational boating.

The edges between the nodes dictate the relations between the risks. On each edge there might be a simple weight to model its connectivity; the larger the weight, the more it impacts the likelihood of a connected risk. Again, it might also be much more complex where connectivity depends on the situation. For instance, the sensor failure and busy port can be both connected to the risk of human injury. However, if the sensor has another as backup, then its velocity – its weight on the edge between itself and the risk of human injury – might be much lower.

The impact of each risk can then be computed using so-called “spreading activation algorithms”. These algorithms propagate the effects, a node’s “activation”, of risk to its connected risks. This “activation” of a node is equal its likelihood, which in turn is affected by the likelihood of the nodes connected to this it. Ideally, such graphs are acyclic, meaning that risks are not connected to themselves through other risks. As this would introduce a feedback-loop, resulting in a cascade of spreading activations that end with all risks being entirely likely to occur. If, for some reason, the graph needs to be acyclic this effect can be easily prevented by introducing a diminishing effect of one risk on another based on how many risks are between them.

As stated, this approach allows for a straightforward approach to root cause analysis, which can be used to explain to an operator why a certain risk has such a high likelihood. What is needed is only to trace back how much each linked risk affected that risk’s likelihood. This can also be visualized in various ways. The most interestingly is presenting the graph itself as an overview of all current risks. If such a graph contains many nodes, a (hierarchical) classification of risks can be defined. For instance, a class “malfunctions” can be made that in turn can contain a class “sensor failures” which contains a singular risk such as “camera #1 failure”. Not only can such a classification be used to visualize a comprehensible graph, it can also offer a way to organize risks. For instance, a risk of “malfunctions” can be defined which is simply the highest likelihood of one of the risks contained in this class.

To conclude, a graph-based risk assessment approach enables the use of state of the art risk models to provide an operator with timely notification of a potential risk occurring and a relevant causal analysis to support his/her SAR process.

5. Progressive disclosure interaction design

With IOSS we aim to achieve this many-to-many ratio between supervising operators and autonomous ships. By definition this implies that operators will not be able to supervise all ships in parallel under their responsibility. This makes current supervisory control interfaces less suitable. Instead we opt to apply the idea of progressive disclosure in the operator’s interface and interactions.

Progressive disclosure is an interaction design pattern that provides a user with increasingly more and detailed interactions about a topic [21]. The pattern entails the idea that interactions (or control signals) should start simple, and progressively become more complex and intricate based on previous interactions and the situation. The reason to do so is to prevent overload, reduce the risk of human-error, and prevent micro-management.

The idea of progressive disclosure for operators is not novel [22]. We argue however that this idea should be much pervasively present to enable a many-to-many ratio. Furthermore, progressively disclosing interaction designs tend to be entirely user-driven where the user determines the pace and next steps. With IOSS functions as dynamic task allocation and continuous risk assessment this does not necessarily need to be the case.

We developed for IOSS a three-layer interface that progressively discloses more information about the operations an operator supervises and enables increasingly more complex and involved control actions. These three layers are; 1) a global view providing an overview of the entire fleet an operator is responsible of, 2) a localized view providing an overview of the status of a single ship, and 3) a situational view providing an entirely immersive view using virtual reality on a single situational perspective of a ship. See figure 6 for an overview of each level.

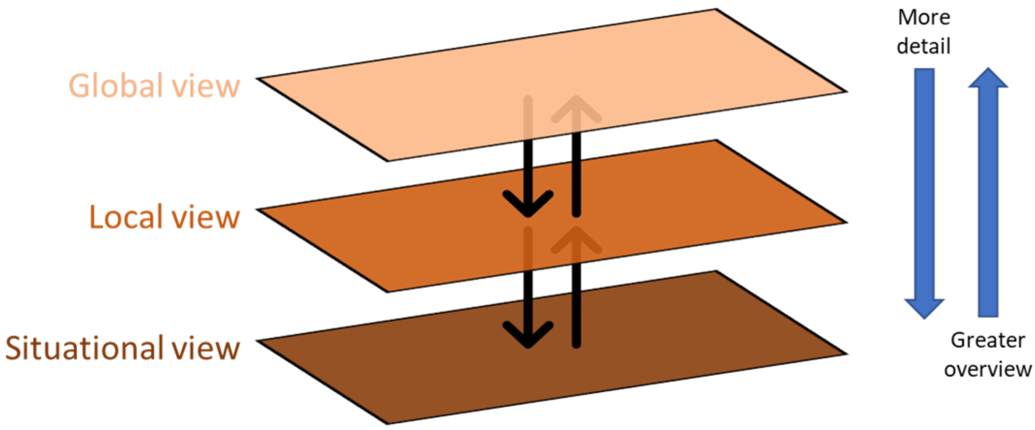

Figure 6. An overview of the three interface layers for the operator. This follows the design pattern of progressively disclosing more information and allowing more complex control actions.

The global view lists all ships that were allocated and accepted by an operator. For each ship it provides general information, such as tasks (e.g., berthing checklist), operation phase (e.g., ship approaching port), and issues (e.g., low risk level). In addition we opted to illustrated the expected workload over time of the operator, as well as give an indication of the workload of his/her close colleagues. Control actions are limited here to accepting responsibility of newly allocated ships or flagging a ship to allocate to a different operator, potentially accounting for his/her own workload compared to that of any colleagues. From here the operator can decide to move towards a localized view of a single ship, or IOSS can proactively suggest this based on an upcoming activity for the operator or a risk that is increasing. See figure 7 for an initial interface design of this global view.

Figure 7. Our concept for the global view of an operator's interface. It lists all ships the operator is currently responsible for and detailed information such as open tasks, ship phases, and the expected workload of him-/herself and direct colleagues.

The local view shows the detailed status of a single ship. Here the operator can review the voyage plan and -stages as well as various tabs with detailed information, such as assessed risks, open tasks, operation progression, cargo status and manifest, and the ship's history (e.g., sensor malfunctions, ports visited, etc.). Typical control actions are here to complete open tasks, understand the assessed risks and act upon them. Acting on such risks, whether current or expected, is done through contacting relevant parties (e.g., terminal operator or cargo owner). This is done through a message-based interaction if low priority. Where – on the operator's or IOSS' initiative – a conversation can be started. Given the topic, IOSS will automate any information transfer. For example, if a sensor is malfunctioning and needs to be checked in the next port, the terminal operator can receive the details from IOSS on the sensor's make, location and malfunctioning without involvement from the operator. See figure 8 for an initial interface design of this local view.

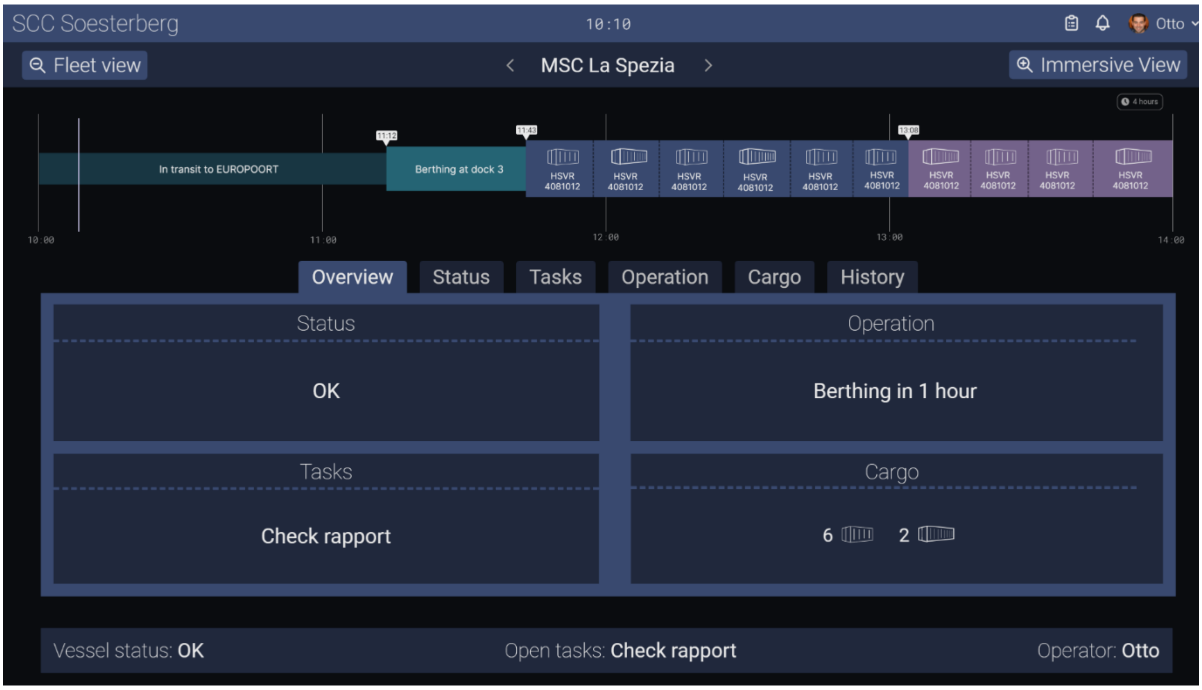

Figure 8. Our concept for the local view of an operator's interface. It presents a single ship's voyage plan as well as various tabs with detailed information. Typical control actions are contacting relevant people on risks and completing verification tasks.

The situational view aims to immerse the operator entirely in the ship's current situation. Here we rely on the real-time reconstruction of a ship's situation into a digital twin. This digital twin is used as a virtual reality environment in which the operator can freely explore the sensor data the ship acquires. Outside the ship's sensor range either a default ocean view is presented when the ship is in transit or a 3D reconstruction of a port is rendered based on predefined models. The role of IOSS is to retrieve the high-level sensor data and create this digital twin (e.g., position and classification of objects), and where needed or requested provide the actual raw data (e.g., a camera feed). This ensure this immerse view can be maintained with a regular 4G connection. Control actions in this view may vary depending on the level of autonomy of the ship. For instance, control can be restricted to a (safe) stop signal and informing relevant parties or might support an IOSS assisted tele-operator. We opted for the former, as we assume a high degree of autonomy. The situational view is currently in development, see figure 9 for an impression.

Figure 9. An indication how the situational view could look like. It is a real-time digital twin rendered by IOSS to enable an operator to view an autonomous ship's current situation through virtual reality.

Note that the idea of progressive disclosure can and should be implemented throughout. For instance, the local view presents a tab of assessed risks, which can also first present only the high level and summarized risks and through interaction or necessity further details can be presented.

6. Conclusions

The work described in this paper is directed towards developing an intelligent operator support system (IOSS) with which the operator support functions will be demonstrated as part of a robotic container handling system, an innovation of the European MOSES research project. For this purpose, we introduced three intelligent operator support functions to allow multiple operators to effectively and efficiently supervise multiple autonomous operations.

Despite the fact that we have developed IOSS to fit in the operational context of the robotic container handling system, we believe that the operator support functions introduced and described above should be considered as generic and necessary support functions for many-to-many remote control centre concepts, in which several operators supervising a set of multiple operation.

1) Due to the dynamics in the task environment, the many dependencies in the overall planning and the unpredictability of system failures and unsafe situations, the cognitive task load will not be completely predictable and will fluctuate as a result. To mitigate these fluctuation and to balance cognitive workload distributions a dynamic task allocation mechanism should be in place. One can argue whether it should be an AI algorithm or human supervisor to execute the load balancing is yet another discussion.

2) Human attention is limited and operators therefore must constantly shift attention resulting in moment-to-moment fluctuations in situation awareness. Such reductions in SA are a constant, given the fact that attention has to be divided over several automated operations. The more reliable and robust that automation is, the less likely that operators overseeing the automation will be aware of critical information and are able to take action when needed [23]. The concept of continuous risk assessment support the process of situation awareness recovery by presenting operators information over critical situation or development that could develop into a critical situation.

3) The many-to-many ratio between supervising operators and autonomous ships implies also that operators will not be able to supervise all ships in parallel nor in full detail. Because operators want to

have on overview of all the operation (the broader picture) but also want to be able to zoom in to a higher level of detail, a three-layer interface that progressively discloses more information about the operations an operator supervises and enables increasingly more complex and involved control actions is eminent.

Although generic in nature, to be able to deploy the support functions for effective and efficient human automation collaboration in other contexts, adaptation is necessary. It is the domain, i.e., task context in which IOSS is applied that determines what critical information is, which risks can arise and how the layers of a progressive disclosure interface should be designed.

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