ACOUSTIC MODELLING KNOWLEDGE FOR DESIGN AND SPECIFICATION OF SITUATION-ADAPTIVE DISTRIBUTED NETWORKED SYSTEMS

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Abstract: *The design and specification of situation-adaptive distributed networked systems has to take the ability of the system to generate plans on the basis of its own assessments into account, i.e. considering the evaluation results from previous missions. Acoustic modelling should be the core of this planning and evaluation process. However, sophisticated detailed modelling is not computationally feasible at the level of design decision making because the optimization loops involved in adaptive planning and in the design and specification process are already demanding for the high-dimensionality of parameter sets found for realistic operational scenarios. On the other hand, just relying on fast modelling (e.g. insertion of the Sonar Equation) at the level of design decision making does not exploit the benefits of adaptability built into the system, hence might lead to wrong decisions regarding the selection of designs (resulting also in wrong decisions on plans and specifications). The aim of this paper is to generate a general recommendation on how to deal with acoustic modelling for design and specification of situation-adaptive distributed networked systems.*

Keywords: *Acoustic modelling, planning and evaluation, design and specification*

MOTIVATION

Underwater acoustic measurements are extremely important for the navigation and telemetry of autonomous underwater vehicles (AUVs). Underwater acoustic measurements are also a major element of distributed networked systems, e.g. as part of a surveillance systems looking for intruders. Combining networks with degrees of freedoms AUVs have or equipping AUVs with the sensors of distributed networks seems to be the natural follow-on research, given the demonstrated success of both concepts [1]. Such situation-adaptive distributed networked systems inherit the importance of underwater acoustic measurements from their parent systems, plus the ability of the system to generate plans on the basis of its own assessment. This ability has to be taken into account when designing and specifying situation-adaptive distributed networked systems: A clever plan might overcome limits of low quality sensor measurements, resulting in procurement costs efficiency and/or robustness of the system. Planning can be translated into mathematics as optimization regarding system degrees of freedom, assessment as optimization of model parameters regarding previous measurements. Hence, acoustic modelling is onboard the distributed networked system and the influence of its quality on the overall performance of the system has to be assessed when looking at designs and specifications for such systems. A very important aspect there is to take into account that only a few measurement samples might be available onboard an autonomous asset, hence model input errors and expected model output error have to be balanced. Furthermore, when a system reaches the level of an industrial product, verification and validation processes have to look into the details of acoustic modelling.

Simulations and analytical calculations are taking place in acoustic modelling, finite elements on one end of the scale (high-fidelity, processor power consuming), sonar equation calculation at the other end of the scale (general, fast). And in between there is a continuum of more exact (but slower) or more general (but faster) approaches. Certainly, for the verification and validation aim, the fastest solution seems appealing, since it has to be taken into account the simulation result onboard the network asset given its measurement in a simulated environment with a large number of situational (environmental) parameters. Unfortunately, details count: E.g. in Anti-Submarine Warfare (ASW) the “sonar range of the day” has been proven to be of limited use in a multistatic shallow water environment, or in Mine Countermeasures (MCM) the “look through the sensor” approach seems to be favorable when planning ahead missions.

In this paper, we are trying to compile a survey (in particular from the own, signal processing and data fusion driven, perspective) on acoustic modelling approaches in the realm of distributed sensor networks and AUVs. ASW and MCM are serving as example application areas. The aim is to generate a general recommendation on how to deal with acoustic modelling for design and specification of situation-adaptive distributed networked systems.

The remainder of this paper is organized as follows: In the next section, we explain how design and specification have to be linked. Then, we take a look at previous approaches in ASW and MCM dealing with estimating system performance facing the difficulty of environmental variability. Next, we formulate a concept called “Uncertainty Absorption” to discuss how situation-adaptive distributed networked systems can be characterized. Then, the predicted Bayesian effect of deeper modelling layers is suggested as core of an autonomous acoustic modelling. We conclude giving a final recommendation based on the discussions in the previous sections.

DESIGN AND SPECIFICATION

In [2], the ERE (Effectiveness, Robustness of evaluation, Efficiency) methodology has been developed. Fig. 1 is summarizing the approach. In its core, ERE is a reinforcement learning loop, aiming at operating at a given level of effectiveness while maximizing efficiency. In order to achieve this aim, a robust way of evaluating the effectiveness and efficiency is mandatory. Details of the system are captured in a realization of a NATO Architecture Framework, evaluations are made possible through a maintenance of independence between internal modules, and a Reasoner Module is making final decisions on activating or not specific behaviors.

Acoustic modelling is part of all modules listed in Fig. 1. For example, the “Estimator” has a sensor model with parameters to be set according to the conditions of sound transmission. Any action of the Independence Plan has to be evaluated according to its effect on the performance (e.g. diving deeper could lead to entering a favorable sound channel). All environmental details have to be stored in an organized manner, e.g. by an ontology fitting into the NATO Architecture Framework.

The overall system has to be verified and validated. Therefore, all parts have to be examined at their “atomic” level, where “atomic” means that a reasonable and understood physical model is available to analytically/stochastically justify all numerical parameter values set in the Verification and Validation step.

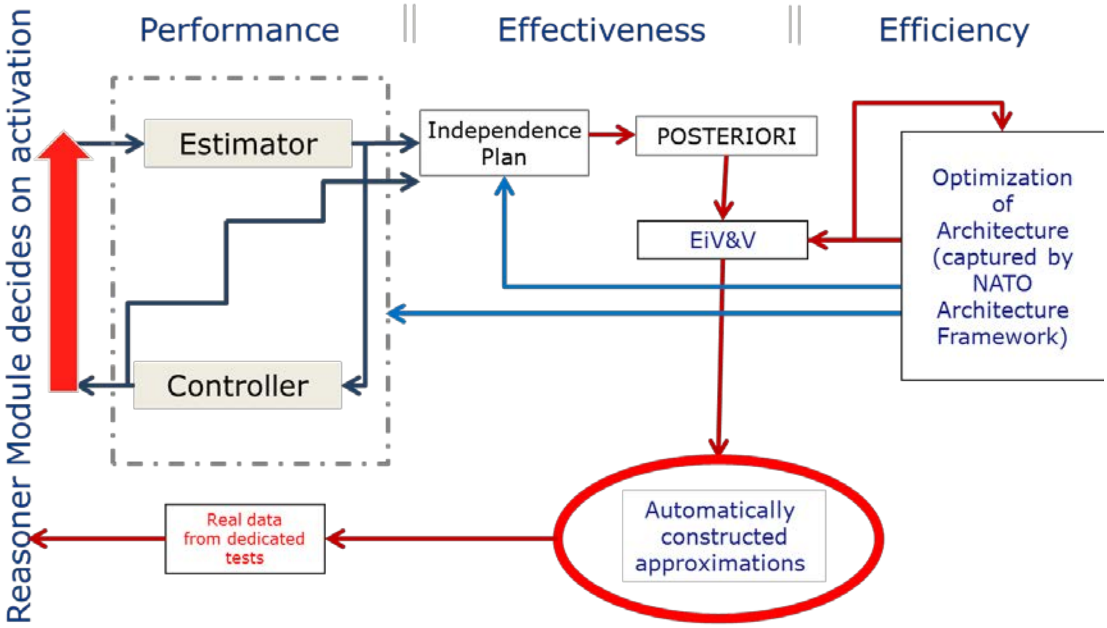

Fig. 1: Sensor employment solutions are evaluated under a variety of situations including the ability of sensors to adapt to changes. Adding Efficient independent Verification & Validation (EiV&V) to the standard learning scheme ensures solution effectiveness and allows for comparison of results leading to the best co-ordination method inside the networked system.

SURVEY

- Single system: The SONAR equation combines in logarithmic units (i. e., units of decibels relative to the standard reference of energy flux density of rms pressure of 1μPa integrated over a period of one second), the following terms:
    - SNRout = (S − TL1 − TL2) − (N − AG) + TS which define signal excess where:
        - S: source energy flux density at a range of 1 m from the source;
        - TL: propagation loss for the range separating the source and the target (TL1) and the target and the receiver (TL2);
        - N: noise energy flux density at the receiving array;
        - AG: array gain that provides a quantitative measure of the coherence of the signal of interest with respect to the coherence of the noise across the receiving array;
        - TS: target strength whose value strongly depends on the aspect of the target to the source receiver pair [3].
    - The SONAR equation can be treated as "atomic" level if all assumptions for its application are valid. Resolution of sonar systems has to be taken into account, in higher frequencies (without resonance effects of the object structure) facet models of objects can be established.

- Environmentally adaptive systems: The maritime environment affects the acoustic measurements. Detailed models exist in many cases, e.g. matched-filter loss from time-varying rough-surface reflections [4] or the effect of internal waves in MCM [5], just to name two. Looking through the sensor is a technique that extracts environmental information from the sonar data. However, the effect of the feedback of these estimated parameters into the system has to be taken into account. Does matched-filter loss affect a specific ASW mission? Do internal waves affect a specific MCM mission?

- Distributed systems: The fusion of multistatic homogeneous or heterogeneous ASW systems has been studied e.g. in [3]. Its performance has been evaluated by a list of values [6], but not based on the actual effect on the given ASW mission goals. In fact, depending on the behavior of the sensors e.g. track length might be very important (in case of a reachability based hunting behavior) or less important (in case of a percolation based hunting behavior). In other words, performance measures are linked to behaviors (called Independent Plans in Fig.1).

  Also in MCM SAS multi-pass applications can be translated into the PHD data fusion and tracking domain [7], e.g. via the reconstruction/simulation proposed in [8].
  The use of Compressive Sensing in [7] is one path towards distributed networked systems with real-time fusion under communication constraints. Of course,

information theoretic approaches are needed to decide whether or not measurement information from one location is needed at another location.

- Situation-adaptive distributed networked systems: The focus is set on decision making in terms of sensor management and platform movements regarding the operational objective. Defining autonomous systems as systems capable to make decisions beyond the foresight of developers, programmers and operators, situation-adaptive distributed networked systems could be seen as located in both, the sensor management realm (with foreseen actions of the system) and those autonomous systems that have "assured autonomy" (meaning here, that they cannot harm the overall operational objective by following some strict rules in their state space).

For ASW, two different approaches have been tried to implement a design decision making:
A) tracking performance with simulated targets included in evaluating multistatic sonar systems with high-fidelity modelling, but non-sophisticated tracking [9], and
B) an information theoretical approach simple sensor model, but actually executing target tracking with Particle Filters in the simulation [10]. Combining both approaches is computationally too challenging when following a straight-forward approach.

For MCM, a fine-scale simulation/reconstruction is proposed in [8], another approach by inserting artificial mines in real data and using operational ATR [11] Is there a similar implementation gap as for ASW when straight-forward combination of both approach is tried? Probably, yes, because performing simulations for all possible fine-scale variations of the MCM-environment is too challenging.

Summarizing the finding in this survey: Well-understood physics (linked to many environmental and system-internal details) on the one side has to be connected to operational specifications on the other side, whereby the linkage cannot generally be implemented in a straight-forward manner.
In the next section, we propose the concept of "Uncertainty Absorption" as a tool to characterize approaches to implementing this details-to-specification connectivity.

UNCERTAINTY ABSORPTION

Referring to Fig. 1, the ERE methodology can be interpreted as a system design process where effectiveness is preserved by uncertainty absorption. There are several tools that can be used (as templates) within the design process, some of them are listed here as examples. The idea behind these uncertainty absorption templates is that their parameters span the workings space for the design process (instead of the actual state space of the assets of the distributed system), i.e. by such transformation "invariant" (or independent) variables can be exploited in order to generate new "atomic" elements for which analytical calculations/simulations are available (for these new atomic elements the Bayes effect of more detailed acoustic modelling can be used as decision criterion on whether or not such more detailed acoustic modelling should be started or not).
Imagine a surveillance area with a grid of small grid size. For ASW, the area has to be scanned simultaneously everywhere, for MCM, there is also the choice for a sequential search (because mines do not move). The simplest, but very inefficient system design is

positioning a sensor in each grid cell. Saving sensors, one might use active sound with higher stand-off ranges.

- Matched Filters are absorbing noise regarding the echoes of the active sound and uncertainty regarding the resolution.

In the surveillance, ASW targets or MCM echo highlights on larger objects are moving and need to be concatenated.

- The tracking approach has Cramer Rao lower bounds which can be used to construct decision making algorithms of how good the estimation is depending on the geometrical situation, i.e. the tracking algorithm is an uncertainty absorber.

For the localisation on the global surveillance grid, source-receiver localisation is necessary.

- Source receiver localisation: SAS, SLAT [12], and SLAM algorithms absorb the uncertainty of own localisation.

For track-and-trail (ASW) or re-localisation (MCM) a reachability of the object tracked has to be ensured.

- Reachability analysis absorbs all uncertainty of target movement (given observability of the target)

Since sensor performance might be degraded, non-concatenated tracks (in ASW) or multiple passes (in MCM) might be necessary to be handled.

- Percolation analysis absorbs uncertainty regarding the effectiveness of the surveillance mission.

Each of these templates contains acoustic modelling (e.g. waves affect the Matched Filter performance, internal waves affect the SAS processing). Acoustic modelling results contain the uncertainty of its input data. Hence, the question arises how this uncertainty can be absorbed.

Look-through-the-sensor and the platforms autonomy to act according to this sensor information gathering seems to be one reasonable approach for this uncertainty absorption. This means that the AUV has to decide on the level of uncertainty of the look-through-the-sensor and modelling information, i.e. the AUV has to answer the question when the overall performance starts to degrade due to improper estimates and improper modelling.

THE PREDICTED EFFECT OF DEEPER MODELLING LAYERS AS CORE OF AN AUTONOMOUS ACOUSTIC MODELLING

As concluded in the previous section, a (Bayes) decision making on whether to go into deeper layers of modelling/more look-through-the-sensor or not has to be performed on board the AUV. The ERE concept of Uncertainty Absorption provides “atomic” modules with known statistics that link the potential decisions to the system-wide effectiveness. However, actual data sets (or high-fidelity simulations) can only be produced in a very limited amount. This situation is comparable to medical investigations comparing studies of treatment with studies of no treatment.

Meta-analyses of clinical trials targeting rare events face particular challenges when the data lack adequate numbers of events for all treatment arms. Especially when the number of studies is low, standard meta-analysis methods can lead to serious distortions because of such data sparsity. To overcome this, [13] suggests the use of weakly informative priors (WIP) for the treatment effect parameter of a Bayesian meta-analysis model.

In the implemented execution phase, a correct modelling/look-through-the-sensor level can be examined by the AUV via checking (with given statistical guidelines) the effect of the current level compared with a next higher level.

In the design-specification phase the execution is to be modelled, hence correct levels are not yet known, and the effect has to be studied. Operational scenarios are the equivalent of medical studies (with and without treatment). An example is given in [14, p. 124]. If the same design should be able to handle various scenarios (which might lead to overall efficiency), hierarchical models can be used to combine the outcome of dedicated tests at sea or of high-fidelity simulations. To perform this mathematical operation, the basic statistics to generate the appropriate re-sampling statistics have to be known, i.e. Indendence Plans (as in Fig. 1) have to be available. Obviously, a fix-point algorithm is entered here, where approximated solutions are re-entered into the system to produce better solutions. The solution of this algorithm determines finally the level of autonomy (in terms of how wide or specific the rule sets are) a system has to have to reach its operational goal.

Stated differently, the effect of better acoustic modelling has been based on a low number of samples, hence “automatically constructed approximations” (as in Fig. 1) have to be used to base the decision on. These “automatically constructed approximations” stem from the Uncertainty Absorbing templates which already reduce the parameter space the decision depends on.

This discussion leads back to the survey section, in particular to the statement on situation-adaptive distributed networked systems: Do these systems need to store (and take with them) the complete knowledge of the entire operation? Certainly, for a fully autonomous operation the calculations have to check for effects within their entire (unconstraint) action space. On the other hand, such fully autonomous systems are then free of any programming bounds. Verification and validation seems to be impossible with the numerical tools we have available today. Instead, when following the ERE methodology, the autonomy plus the need for the autonomous systems to being able to make decisions given their limited amount of data and modelling capability, results in a set of rules for the autonomous system which makes possible its verification and validation and takes away the autonomy to perform actions that have never been foreseen by developers, programmers or operators.

RECOMMENDATIONS

The maritime environment is highly variable in space and time. Pure modelling with historical data can introduce huge errors into planning processes. Therefore, the autonomy via the look-through-the-sensor concept is pushed forward to the executing sensor platform. This autonomy is absorbing the uncertainty given by the environment.

However, this autonomy comes with a price: either access on each asset to the entire system plus (unrealistic) computational processing needs on each asset, or an extensive concatenation phase of design and specification where the autonomy is then finally bound by a rule set (“assured autonomy”).

This second option (“assured autonomy”) seems to be a viable way ahead. However, the concatenation phase has to deliver (like a mathematical proof) a complete chain of arguments, any hole in this chain will make the verification and validation process become invalid. Acoustic modelling is an inherent part of this chain and is used in the sensor models, in the target models, and in the look-through-the-sensor estimations. Furthermore, consistency is needed: The concatenation phase has to take the optimal choices of the autonomous systems and they have to be able to make these optimal choices in the real implementation.

For some systems, the core (or atomic) elements of the models are relatively easy (like reflection of high frequency sound on a facet), for other systems the acoustic modelling is very challenging (like low frequency coupling of sediment and multi-component partially buried mine-like object). As depicted in Fig. 1, “real data from dedicated tests” is needed to step forward and make core (or atomic) models available for these difficult acoustic problems.

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