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# Maintaining Situation Awareness Over Time

## — A Survey on the Evolution Support of Situation Awareness Systems

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***Abstract*—Situation awareness (SAW) denotes a human's adequate interpretation of the observed environment, which is of prime relevance for human operators in control center applications (e.g., road and air traffic control). Since humans may lose their SAW due to information overload and time criticality, a series of intelligent systems have been proposed that should support human operators in *gaining* and *maintaining* SAW, whereby existing approaches focus more on the *gaining* aspect so far. However, a comparative evaluation of the distinct approaches has not been the focus up to now, as has been recently acknowledged. Therefore, the present work attempts at filling this gap by providing a comparative evaluation of approaches for gaining and maintaining SAW, thereby focusing on the less studied aspect of support for maintaining SAW. Thus, this survey highlights open issues and directions of further research.**

## I. Introduction

**Situation Awareness.** Situation awareness (SAW) denotes a human's adequate interpretation of the observed environment. SAW is thus especially relevant in control center applications, where a human operator needs to stay fully aware of the state of the monitored environment, and anticipate critical situations emerging in that environment in order to undertake the appropriate (counter)actions. However, a human's correct situation assessment (SA), i.e., the process to obtain SAW, is severely affected by *information overload* and *time criticality*, which induce the risk of a partial loss of SAW, or in the worst case even a complete misinterpretation of the current situational state [1], which may entail fatal consequences.

**Systems Supporting SAW.** Therefore, intelligent systems have been proposed that should support human operators in *gaining* and *maintaining* SAW of today's increasingly complex environments. Such SAW systems are capable of autonomously deriving the situational state, or critical situations, of the observed environment by fusing, analyzing and interpreting the sensed data, i.e., performing high-level information fusion (HLIF) [2]. By communicating this already interpreted picture to the operator, the operator is supported in *gaining* SAW, as the cognitive load on the operator is reduced. However, as a user study in [3] revealed that time is a key factor, to further support the operator in *maintaining* SAW over time in a rapidly evolving environment, the SAW system needs to account for evolution in order to retain its usefulness: (i) by tracking the evolution of the underlying environment, especially w.r.t. inferred situations, (ii) by allowing the system to evolve over time to keep up to this changing environment, and (iii) by evolving to the needs of its users, i.e., incorporate and adapt to operator feedback.

**Contributions.** Whereas the necessity to provide support for these evolution aspects has been acknowledged recently (e.g., in [4], [5]), a comparative study of current SAW systems especially regarding these issues has not been the focus so far, as also recognized in [6]. Therefore, the aim of the present paper is to take a first step towards filling this gap for that: We propose a criteria catalog allowing to study how SAW systems can support an operator in *gaining* and *maintaining* SAW. Based on these criteria, we perform a comparative evaluation of SAW systems, and identify directions for further research.

**Structure of the Paper.** In the next section, we discuss existing work aiming at giving an overview and explaining how they relate to our survey. In section III, we outline and justify the criteria forming the basis for our evaluation of the selected approaches. Section IV continues with a discussion of the systems selected for our survey. Section V then presents the results of the evaluation, and concludes with the lessons learned. Section VI ends with a summary and an indication on future work.

## II. Related Work

A series of work aiming at providing an overview on existing and challenges on prospective SAW systems is found in the overall area of HLIF: A recent, extensive survey on current HLIF systems, i.e., SAW systems, is presented in [6], focusing on describing the different functional models for HLIF, and systems implemented in various application domains. However, no comparative evaluation of the discussed approaches is provided, which therein is suggested as necessary future work.

In [7], a literature survey of sixteen publications on frameworks and framework issues for HLIF applications has been conducted, where Llinas focuses on outlining different HLIF procedures, but neither contrasts the approaches w.r.t. SAW maintenance aspects.

A review of the state of the art in HLIF has traditionally also been conducted in the course of the International Conference on Information Fusion, based on panel discussions

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or retrospectives identifying the challenges and trends in this subject (e.g., [8],[9]). [10] also represents the insightful conclusions from a panel discussion involving leading experts of the HLIF community, which summarizes the issues and challenges regarding HLIF. The publications resulting from these discussions address the state of the art in HLIF from a methodological perspective, i.e., no explicit comparison and evaluation of concrete fusion system implementations is provided. These extensive methodological discussions serve as a valuable basis for our criteria catalog.

Therefore, despite valuable preparatory work, there is still a need for a comparative survey as aimed at in this paper, based on a catalog of criteria, methodologically adhering to our previous surveys like [11].

## III. Criteria

In this section, we present our catalog of criteria based on the core components of SAW systems (cf. Fig. 1), which we employ for our comparative survey. Since prior to maintaining SAW, SAW first needs to be established or *gained*, thus comprising a prerequisite for the *maintenance* of SAW, our criteria catalog is structured into two subsections. The first focuses on aspects related to *gaining* SAW, whereas the second studies which concepts are provided to *maintain* this SAW, and thus the usefulness of the SAW system over time.

### A. Gaining SAW

The following criteria discuss the abilities of the SAW system necessary to support the operators in *gaining SAW*. Thereby, dedicated criteria investigate the representation of the observed environment and the core functional capabilities of the SAW system for supporting the control center operators.

**Input Data.** Whereas some approaches use a rather homogeneous, clearly specified set of input data (e.g., [12], [13]), other systems employ a variety of heterogeneous data types (e.g., [14]). The heterogeneity of input data types supported provides an indication on the potential application domains of these SAW systems, i.e., whether they are better suited for homogeneous domains (comprising few different types of input data) or highly heterogeneous domains (comprising a variety of different entity types).

**Domain Model.** Many SAW systems utilize ontological representations of the environment of interest, which allows to encode a priori knowledge of the specific application domain (e.g., [14], [15], [16]). However, SA techniques exist that do not utilize an *explicit* domain model, and thus are of interest if prior knowledge is not available. Purely data-driven machine learning methods, for instance, may only operate on the observed data, without specifically relating it to a dedicated model of the underlying domain (e.g., [13]).

**Situation Assessment.** Rule-based expert system implementations (e.g., [14], [16]) require an a priori specification of the domain knowledge and situation types of interest, thus conform to a template-based, top-down approach, as classified in [13]. Situations are explicitly modeled as situation types of interest, which need to be specified by the domain experts. Therefore, their successful application depends on a profound knowledge of the underlying domain, and may be hampered by the *knowledge acquisition bottle neck* [3]. Whereas they are perfectly suited to monitor recurring events, they fail to detect novel, unexpected behavior, which, however, is often of interest, especially in surveillance monitoring applications. Thus, over the last years SA techniques based on bottom-up, i.e., data-driven, anomaly detection approaches became popular in such domains (e.g., [13], [12], [17], [18]). These methods aim at detecting anomalies from the normal environmental picture, which are reported as potential situations of interest to the operator. Whereas this approach provides more flexibility, as not everything about potentially interesting situations needs to be known in advance, it is limited to detecting "abnormal" situations. Typical behavior of interest cannot be specified. Furthermore, most of these methods depend on a sufficiently large training data set. Regarding the degree of required a priori knowledge, Graphical Models, such as Bayesian Networks and Hidden Markov Models (e.g., [19], [20]) represent an intermediate form. Their structure, which describes the sought-after situation types, can be either explicitly defined a priori, or may be autonomously learned from available data, although techniques for the latter are currently still in an early stage.

**Action Support.** As motivated in [4], SAW ultimately provides the basis for decision support, and forms a key constituent in Boyd's OODA loop [21]. Advanced SAW systems could thus go one step further by linking the derived situations to actions suitable in that situation, which should be suggested to the human operator.

**Application Domain.** This criterion states the domain the system has been applied to, or evaluated on. In case where no online, real-world evaluation has been performed, it is detailed whether an analysis of recorded real-world data had been performed, or only tests on synthetic data had been conducted.

### B. Maintaining SAW

Whereas criteria for evaluating the SAW systems' abilities of gaining SAW comprised the previous part of the catalog, the present subsection studies how the systems support *maintaining* this SAW, in order to retain their usefulness. Thereby, from a systemic point of view, we need to consider (i) the evolution of the observed environment, (ii) the evolution of the SAW system, and (iii) the evolving needs of the operators interacting with the system.

***i) Environment Evolution***

**Capturing and Tracking Evolving Situations.** As identified in [3], the *evolution* of a specific situation is essential to judge the current situational state, and the effect of time on SA severely goes beyond the typical definition of SAW in the HLIF community. The need for SA concepts better capable of capturing evolving situations has also been recognized in [4]. Thus, we specifically assess whether and how currently available SAW systems are capable of *capturing* and *tracking* the *evolution* of the inferred situations. Capturing evolution might be supported by explicit evolution models, for instance

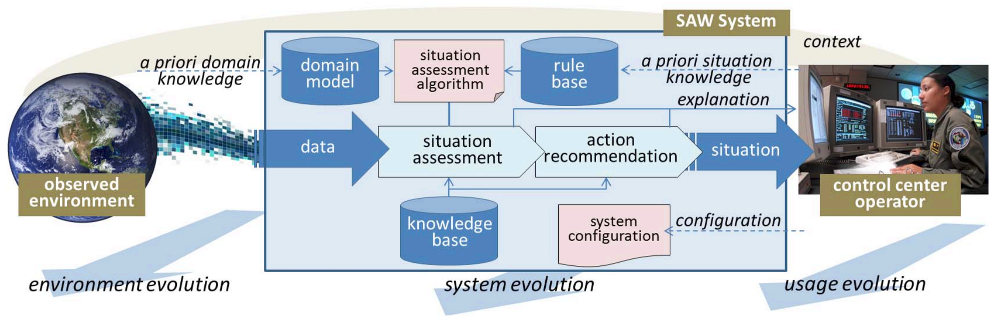


Figure 1. A systemic viewpoint of automated SAW systems.

in form of evolution templates (as e.g., suggested in [20], [22]), preconditions, or evolution patterns. For tracking aspects, estimating the probable evolution paths (e.g., as in [20]) and criticality escalation (as has been recognized in [23]) are relevant. Further relevant aspects could address the following questions: Can the operator specify the evolution of situation types, i.e., templates, of relevance? Is the operator supported therein, for instance the system could suggest preconditions to a critical situation, which have been observed in the data? Is the operator enabled of specifying possible situation evolution patterns of interest? Can the operator specify different criticality levels and alerts along the evolution path?

**Projection.** However, not only the past evolution of a specific situation is of relevance: *Projection*, i.e., the correct anticipation of the current situation's future development, represents the most difficult to achieve level in Endsley's human mental model of SAW [1]. Estimating the future development represents the grounding for taking the suitable actions in a given situation in order to achieve the desired goals, which is termed *impact assessment* in the HLIF terminology. This criterion therefore assesses whether a SAW system provides such *projection* support, and how these predictions are formed and communicated to the user.

**Incorporation of Contextual Knowledge.** As could be shown in a user study on operators in a maritime surveillance center [3], operators assess the provided information differently dependent on certain contextual information (e.g., a sudden increase in the number of boats departing from Germany towards Sweden would normally correspond to an unusual situation, but not at the start of the main holiday season). Thus, such contextual information (e.g., the time of the day or the time of the year), albeit not part of the situation definition itself, severely affects the interpretation of a certain situation. Therefore, we assess whether currently available SAW systems provide dedicated means to incorporate contextual knowledge.

**Incompleteness and Inconsistency.** SAW systems likely deal with only partially observable environments and additionally are limited by technical parameters. Thus, they need to expect to encounter incompleteness and inconsistency in the data [19]. These issues, of course also present in *gaining* SAW, are leveraged however through the evolution in the environment, since additional environmental information may emphasize but also contradict existing knowledge and introduce new inconsistencies or allow to resolve existing ones. This is also interlinked with adjusting the trustworthiness of the situational information as the situations evolve, making the proper detection of the situation even more complex. Therefore, this criterion investigates how the SAW system deals with incompleteness and inconsistencies over time.

### *ii) System Evolution*

**SA Adaptation.** The user study in [3] motivated the need for SAW systems that can be adapted towards the activities of the operators, like routine tasks as well as special occasions, due to the changing roles of the operators, and the changing underlying environments. This necessitates the functionality to adapt the SA methods accordingly. Operators of maritime surveillance centers, for instance, are routinely provided with lists of suspicious vessels which need to be tracked. This requires that some rules need to be added "on the fly", which may also only be valid during a limited time period, whereas others remain more stable.

However, the system should also be capable of updating itself without explicit user intervention, i.e., it should detect if the previously learned models have become outdated over time (i.e., detect concept drift), or if situation type definitions may have become inaccurate over time. This criterion therefore identifies the ability to either *fine grained* evolution, by e.g. updating existing or adding new rules, or *coarse grained* evolution, by allowing to incorporate different SA algorithms and strategies. Additionally, it is highlighted whether this adaptation is conducted automatically, e.g. incorporating new rules for identified outliers, or allows for *manual* SA adaptation.

**System Tuning.** The workload put onto a SAW system may heavily depend on various factors like the state of the environment, available extent of (sensor) information, identified situations, complexity of the SA algorithm etc., which are subject to changes over time. Despite these influencing factors, such systems are required to respond in a timely manner, calling for an appropriate reaction of the system through, for instance, allocation of additional resources or the adjustment of optimization strategies. Therefore, this criterion evaluates whether the system allows for a runtime tuning of the system to maintain SAW with respect to, for example, performance and response time.

**Knowledge Base.** Analogously to a human operator who gets more and more experienced during this career, an intelligent system should become better in its assessment capabilities over its lifetime. Incorporating a dedicated knowledge base allows for storing available domain knowledge, as well as persisting historic data, which could be employed to aid the interpretation of ongoing situations. An intelligent SAW system could for instance refine its predictions regarding the *Projection* of situations based on similar situations experienced in the past. Conversely, *Action Support* could be refined based on analyzing which actions that have been performed in the past in similar situations have yielded the desired output.

Therefore, we analyze whether the surveyed approaches make use of a knowledge base, and how this knowledge base is used within the SA process, in order to learn from past experiences.

***iii) Usage Evolution***

**Incorporating Human Intelligence.** [8] has emphasized the need to directly incorporate the role of human intelligence into SAW systems. A successful SAW system should combine machine computing power with human cognition and intuition. Therefore, this criterion studies how operators can transfer their knowledge to these SAW systems (e.g., by guiding the system learning, as in [24]).

**Personalization.** As highlighted in [3], different operators exhibit different roles and preferences, for instance some individuals prefer many, others fewer or different types of alerts of different levels of criticality (e.g., as realized in [24]). Different working procedures also demand for a *configuration* thereof. Furthermore, tracking, persisting and analyzing the preferences and working routines of different operators corresponds to user refinement, and would allow to match the users preferred working routines. Therefore, this criterion investigates the provided personalization through explicit *configuration* support as well as *self-learned adaptivity* of the system.

**Explanation and Exploration.** Trust and understanding is a critical aspect for the acceptance of a SAW system through operators [3]. To increase that, a SAW system needs to be capable of providing an explanation of the conducted processing of the situational information in terms of data and workflow provenance [25] over time and allow for an exploration of that by the operator. Therefore, this criterion discusses the explanation and exploration capabilities of the system.

## IV. SAW Systems

In the following section, we evaluate and compare a selection of currently available SAW solutions on basis of our criteria catalog. Our selection of approaches is targeted towards providing a broad overview of distinct SA techniques, whereby we aimed at choosing recent as well as influential approaches. We shortly sketch each approach, and highlight distinctive and interesting features. The systematic evaluation w.r.t. our criteria catalog is summarized in Fig. 2.

The Situation Awareness Assistant (SAWA) described by Matheus et al. [15], [26] represents a flexible tool suite for creating SAW applications as rule-based expert systems (*Situation Assessment*). These are based on an explicit *Domain Model* comprising of formal ontologies, which the user must specify by extending the encompassed SAW Core Ontology using the provided Knowledge Management suite. In principle, thus a variety of *Input Data* is supported, which may be of heterogeneous nature. SAWA-based systems can only detect a priori specified situations, and SAWA does not support uncertainty reasoning (*Incompleteness and Inconsistency*), however provides *Projection* support in the form of *what-if* queries. Therefore, SAWA's successful application massively depends on the user's profound domain knowledge, requiring the user to exactly know all aspects of interest. No facilities are provided to validate that domain knowledge (e.g., by incorporating and checking with available data). SAWA has been evaluated on a simulated, manually constructed scenario from the application domain of supply logistics (*Application Domain*).

Edlund et al. [16] describe a SAW system for sea-surveillance (*Application Domain*) similar to SAWA, which also bases upon an ontology (*Domain Model*) and a rule-based reasoning engine (*Situation Assessment*). It is especially emphasized that this system is suited to reason about situations that develop over time (*Capturing and Tracking Evolution*), which are modeled by connecting the sets of interrelated objects with time connectors (e.g., corresponding to *later*, *contemporary*, *synchronic*, *prestart*). However, these situation evolutions thus can only be specified in a sequential manner using a dedicated rule editor. Alternative evolution cannot be specified within a single situation type (e.g., a given situation might either evolve one way or the other). Furthermore, situations can be only detected *after* they have occurred. Therefore, Edlund et al. state the need to extend their system to allow for situation warning, as operators should be warned of possible situations *while* they are occurring, not just *after* they have happened. The system has been evaluated in a user study involving maritime surveillance operators [3], who especially appreciated the support for detecting and tracking evolving situations. As this SAW system is realized as an agent system, Edlund et al. emphasize it would allow for *System Tuning*. Regarding load balancing purposes, agents could be moved to faster systems if their loads were continually high, or currently unnecessary reasoning modules could be discarded easily. However, when tested with real-world maritime surveillance data quantities, the employed agent framework was not capable of handling the amount of data.

BeAware! [14] represents another framework for ontology-driven, rule-based SAW systems (*Situation Assessment*). However, it specifically targets SAW applications in control center environments, therefore spatio-temporal primitive relations (*Domain Model*) are introduced, which facilitate the configuration and reusability of this framework for these real-world monitoring applications. Baumgartner et al. have demonstrated the applicability of their framework in a real-world road traffic monitoring setting (*Application Domain*). BeAware! provides concepts for *Projection*, as the likely evolution of a situation can be predicted on the basis of these qualitative spatio-temporal relations. Baumgartner et al. conclude with ideas to extend their SAW ontology with an action awareness core ontology, to provide support for modeling *Actions* suitable in a given situation, which can be suggested to the operator.

Salerno suggests the integration of knowledge discovery tools, such as data mining components, into SAW frameworks [27], which aid analysts in the discovery or learning of domain models and patterns relevant in this domain (*Incorporating Human Intelligence*). Previously discovered or learned models can drive situation assessment, therefore Salerno proposes to store learned models in a model library for later use (*SA Adaption*). He also underlines the value of historic data, such as the knowledge of similar situations that occurred in the past, which should be persisted in the *evidence database* (*Knowledge Base*).

Approaches that employ anomaly detection techniques (*Situation Assessment*) for maritime vessel monitoring (*Application Domain*) include [13], [17], [28], [29], [30], whereby we will discuss the first representatively, where Laxhammar performs unsupervised clustering (*Situation Assessment*) of normal vessel traffic patterns [13]. The learned cluster models can be used for anomaly detection in sea traffic (*Application Domain*), and have been trained and evaluated on real recorded sea traffic. Laxhammar notes the developed technique would be applicable to other domains involving surveillance of moving objects. The momentary location, speed and course of the tracked vessels are used for creating the patterns, corresponding to a homogeneous set of *Input Data* expressed by defined feature vectors. However, Laxhammar notes that complex anomalies involving multiple vessels and/or behavior that develops over time (*Capturing and Tracking Evolving Situations*) would necessitate a more sophisticated pattern model, which remains future work.

Johansson and Falkman used Bayesian networks (*Situation Assessment*) to detect anomalies in vessel monitoring (*Application Domain*) [31], which however has only been evaluated on a synthetic test data set. They advocate for Bayesian networks due to their explanatory power (*Explanation*) and their ability of handling incomplete data (*Incompleteness and Inconsistency*). Furthermore, they especially highlight the possibility of easily including domain experts' knowledge during the creation and for the validation of the models generated by data (*Incorporating Human Intelligence*), which is in their approach however restricted to the configuration phase of the system, thus does not aid the maintenance of the SAW system at runtime.

In [24], Rhodes et al. extend their previous work and present a highly sophisticated approach by combining a rule-based pattern recognizer with an anomaly detection model based on the automatically learned behavior normalcy models suggested in [12] (*Situation Assessment*). Thus, both anticipated, routine behavior, as well as novel, unanticipated behavior can be detected. Their system, which has been implemented as a prototype for the US Coast Guard port surveillance system (*Application Domain*), provides elaborate strategies for operator-guided learning: Operators can refine the performance of the learning system by confirming alerts, or indicating examples of false alarms. Furthermore, they can optionally guide learning by providing the system with examples and counter-examples of activities of interest (*Incorporating Human Intelligence*). Regarding the incorporation of *Contextual Information*, normalcy models can be learned for different contexts (e.g., based on season, day-of-week, or for different vessel classes).

Gariel et al. use clustering for anomaly detection (*Situation Assessment*) for airspace monitoring [18], in order to detect non-standard aircraft landings. As an interesting idea regarding the *Explanation* to human operators, they suggest a complexity measure computed from all currently observed outliers, which is based on Shannon's entropy measure. This measure represents an indication of the "disorder" of the current environmental state in comparison to its typical state, which increases with the proportion of outliers detected, and thus serves as valuable information for managerial purposes (i.e., the higher the disorder of the monitored environment, the more operators are needed for controlling, and the higher the workload on the operators).

Meyer-Delius et al. model spatio-temporal situations as a combination of Hidden Markov Models and Bayesian Networks (*Situation Assessment*) [20]. These situation models describe how the system evolves over time (*Capturing and Tracking Evolving Situations*), and allow to track the current state of an evolving situation. Furthermore, these models allow for predicting the situation's future state (*Projection*). They evaluated their approach on simulated and real data on vehicle passing maneuvers, as would be obtained from a driving assistance system (*Application Domain*).

Krishnaswamy et al. propose an Advanced Driving Assistance System (ADAS), which monitors and classifies driver behavior in real-time and suggests appropriate countermeasures (*Action Support*), such as issuing alerts to fatigued drivers [32]. On-board vehicle data streams are mined, related to contextual information (*Incorporation of Contextual Knowledge*) and compared to a *Knowledge Base* comprising historical data on crashes. This *Knowledge Base* is constantly populated with new data gathered from the proposed vehicle on-board system. The employed predictive models (*Situation Assessment*) are thus incrementally updated and refined based on this new data (*SA Adaption*).

Mirmoeini and Krishnamurthy suggest an algorithm for adaptive *Situation Assessment* employing reconfigurable Bayesian networks [33], [34] , which should account for dynamic battlespace situation changes (*Application Domain*). Bayesian networks have been chosen for the ability to handle the dependencies among uncertain and incomplete information (*Incompleteness and Inconsistency*). By learning the parameters of small batches of data, the Bayesian network's parameters are adapted to slow changes in the battlespace situation (*SA Adaption*). Furthermore, their proposed architecture feeds the results from SA to a decision making system, where the derived hypotheses are mapped to a set of actions. Since the actions' potential effects are also modeled, their effects on the battlespace can be examined (*Projection*) The taken actions' effects in turn are reflected in the next SA step, thereby this approach implements a stochastic feedback algorithm.

## V. Lessons Learned

Fig. 2 represents a condensed summary of our evaluation, serving as a quick overview of the capabilities of current SAW systems in comparison. Based on this evaluation, we draw the following conclusions regarding the state of the art in research on systems supporting SAW, and directions for future research:

**Indication that certain application domains favor certain SA methods.** The encountered application domains of the surveyed approaches range from road and air traffic monitoring, maritime traffic surveillance, military applications, supply logistics to driving assistance systems. It is interesting to note that the distinct application areas expose trends to certain SA techniques, implying that the domains exhibit crucial characteristics that favor one technique over another. In the course of this survey ontology-based systems have been applied to road traffic monitoring, supply logistics and a maritime surveillance application. The approaches in the maritime surveillance domain rather expose a strong trend towards anomaly detection techniques whereas in the military domain, Graphical Models have been very popular. However, this indication would need to be verified by a dedicated survey, and does not necessarily exclude the approaches from being applied in different domains.

**Domain characteristics.** The choice of a SA technique suitable to the problem domain at hand vastly depends on the heterogeneity of the input data and the available a priori knowledge about the domain and the situation types of interest: If detailed a priori knowledge about the domain is available, the input data comprises heterogeneous entities, and the situation types of interest can be determined in advance and are not subject to frequent changes, template-based SAW systems basing on ontologies and rules occur to be preferrable [3]. However, if the observed domain frequently changes, comprises rather homogeneous objects, and the situation types cannot be specified in advance, but correspond to abnormal events and behavior, machine-learning based anomaly detection techniques represent the favorable choice. Examples of methodologies for anomaly detection that include human expert knowledge are rare. Furthermore, models generated by these techniques are generally more difficult to understand than human-readable rules.

**Hybrid systems.** Only recently, hybrid approaches are emerging, which comprise a combination of expert-defined rules with anomaly detection based data mining techniques (e.g., [24], [35]), thus aiming at combining the advantages of both approaches. However, this raises the interesting issue of how these distinct approaches can be interlinked. A highly promising way towards this direction has been suggested in [35], where Riveiro et al. studied interactive ways of visualizing both expert-coded rules as well as the normal behavioral models built from data of a hybrid SAW system: Joint visualizations of normal behavioral models and the corresponding rules allow to depict the whole system knowledge space, thus revealing how the expert-defined rules fit with the normalcy models built from the data, which highlights areas the system has not knowledge about. However, this visualization approach mainly targets at *Explanation and Exploration*, but thus not allow to interlink these concepts further based on the derived conclusions. Future research could investigate whether the two approaches, which currently are used in an independent fashion, could be integrated more tightly. An operator might for instance decide to create a rule for a certain anomaly, in which case the system could provide support by automatically suggesting potential rules (e.g., by deriving the spatio-temporal relations of the current anomalous case).

**Action support scarcely available.** Supporting the operator by suggesting suitable actions in a given situation is scarcely supported by current SAW systems. Of those rare systems like [34], a dynamic evolution of the suggested actions on basis of, either user feedback or through dynamically learning applied actions from a knowledge base, is not provided. This also entails that the implications of taken actions on the long-term evolution of the situations at hand cannot be appropriately analyzed within the SAW system.

**Learning from the past is mostly not supported.** Previously observed data is rarely reused to refine the predictions of evolving situations, or suggest actions that should be undertaken in a given situation, which could be considered squandered potential in the light of ever-growing amounts of sensed data, and decreasing prizes for data storage devices.

**Explanations of not a priori defined situations problematic.** A priori specified, rule-based situation types are considered to be more or less "self-explaining" to a human reader, likewise for the visually descriptive Graphical Models. Contrastingly, the results of machine-learning based techniques, allowing for the detection of situations that are not a priori known, are often more difficult to interpret, especially if they incorporate feature vectors of multiple dimensions, which cannot be jointly visualized. Consequently, this hampers the trust of operators in the systems. However, interesting concepts have been proposed aiming to address these issues (e.g., [17]).

**Maintaining SAW evolution not yet matured.** As can be inferred from the evaluation, concepts for maintaining SAW have been emerging just recently. Maintaining SAW is supported only by some recent approaches like [24], whereas older approaches disregard SAW maintenance completely. If maintenance is supported, it is however not supported to a full extent, leaving space for further improvements.

**Evolution models rare.** Whereas the capability of tracking evolving situations, as well as predicting their likely evolution, is stated as a relevant issue in numerous publications, situation models explicitly accounting for this are rarely found.

| Criteria / Approach | Gaining SAW | | | | | Maintaining SAW | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Environment Evolution | | | | System Evolution | | | Usage Evolution | | |
| | Input Data | Domain Model | Situation Assessment | Action Support | Application Domain | Capturing & Tracking Evolution | Projection | Contextual Information | Incompleteness & Inconsistency | SA Adaptation | System Tuning | Knowledge Base | Incorporating Human Intelligence | Personalization | Explanation & Exploration |
| Baumgartner et al., 2010 | heterogeneous | ✓ | ontology + rules | x | road traffic | ~ | ✓ | x | x | x | x | ✓ | x | x | ✓ |
| Edlund et al., 2006 | heterogeneous | ✓ | ontology + rules | x | maritime surveillance | ~ | x | x | x | x | ~ | ✓ | x | x | ✓ |
| Gariel et al., 2011 | homogeneous | x | anomaly detecion | x | airspace monitoring | x | x | x | x | x | x | x | x | x | ~ |
| Johansson and Falkman, 2007 | homogeneous | x | Bayesian Networks | x | maritime surveillance | x | x | x | ✓ | x | x | x | x | x | ✓ |
| Krishnaswamy et al., 2005 | homogeneous | x | predictive models & clustering | ✓ | driver-assistance | x | x | ✓ | x | ✓ | x | ✓ | ~ | x | x |
| Laxhammar, 2008 | homogeneous | x | clustering for anomaly det. (GMMs) | x | maritime surveillance | x | x | x | x | x | x | x | x | x | x |
| Matheus et al., 2005 | heterogeneous | ✓ | ontology + rules | x | supply logistics | ~ | ~ | x | x | x | x | ✓ | x | x | ✓ |
| Meyer-Delius et al., 2009 | homogeneous | ✓ | Bayesian Networks & HMMs | x | driver-assistance | ✓ | ✓ | x | ✓ | x | x | x | x | x | ✓ |
| Mirmoeini and Krishnamurthy, 2006 | heterogeneous | ✓ | Bayesian Networks | ✓ | military | ~ | ~ | x | ✓ | ✓ | x | x | x | x | ✓ |
| Rhodes et al., 2007 | homogeneous | ✓ | normalcy models (outlier detection) + rules | x | port security | x | x | ✓ | x | x | x | ✓ | ✓ | ✓ | ✓ |
| Salerno et al., 2004 | heterogeneous | ✓ | acyclic graphs | x | military | x | x | x | ~ | ✓ | x | ✓ | ✓ | x | ~ |

**Legend:**
✓ is supported
~ is partially supported
x is not supported

Figure 2. An evaluation of the SAW systems depicted in section IV w.r.t. our criteria catalog.

## VI. Conclusion

In the present survey, we analyzed a range of recent SAW systems w.r.t. their abilities for supporting human operators in *gaining* and *maintaining SAW*, which requires that these systems are capable of tracking the evolution of the monitored environment and adapt themselves to environmental changes and user needs. Based on a set of criteria allowing to study these issues, we performed a comparative survey, which revealed that especially the aspects needed for *maintaining* SAW are not fully supported by current SAW systems, thus indicating needs for further research in this direction.

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