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ORIGINAL RESEARCH

Fuzzy logic for situation awareness: a systematic review

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Abstract

Situation awareness is the cognitive capability of human and artificial agents to perceive, understand and predict the status of the situation in an environment. Situation awareness systems aim at supporting the situation awareness of human and artificial agents using computational techniques, models, and approaches for supporting the assessment, tracking, and prediction of critical situations. Fuzzy logic formalisms have been extensively used in situation awareness systems thanks to their capability of dealing with uncertainties while providing agents with easily understandable models of situations and decisions. This paper proposes a systematic, unbiased, and updated review of the literature on fuzzy logic for situation awareness from 2010 to 2021, conducted using the PRISMA methodology, analyzing 139 articles. An in-depth discussion of the main open challenges and future research directions is provided.

Keywords Situation awareness · Fuzzy logic · Situation-aware systems · Cognitive situation management · Fuzzy inference system · Fuzzy cognitive map

1 Introduction

Situation awareness (SA) is the capability of smart agents (both human and artificial) to understand what is happening in the surrounding environment with respect to the specific goal the agents are pursuing. SA has been studied in many highly dynamic environments including aviation, healthcare, military, industrial process, command and control rooms, transportation, cybersecurity, etc. Several studies have claimed that the root cause of many human errors is the lack of SA, and therefore SA is important for safety and for achieving good human performance in dynamic environments.

Unfortunately, obtaining and maintaining adequate levels of SA is difficult and critical for many operational tasks performed by human and artificial agents. To solve this issue, researchers proposed a variety of different techniques ranging from expert-based approaches such as formal logic, ontologies, situation theory, and evidence theory, to learning-based approaches such as Bayesian network, Hidden Markov models, neural networks, data mining, etc, and hybrid techniques combining these two categories.

Fuzzy logic and its several formalisms have been extensively used to realize SA systems. The primary motivation for using fuzzy logic lies in the ability to address the inherent uncertainty of the SA assessment process. The sources of uncertainties and vagueness in SA systems are many and heterogeneous. The information collected by the sensors or coming from knowledge bases is affected by faulty data, noises, interferences, and redundancies. Furthermore, the process of understanding situations is not deterministic and crisp. The prediction of situations and the decision-making processes are intrinsically characterized by uncertainties that can be represented and processed by fuzzy formalisms. In addition, fuzzy models are human-understandable, especially when they use fuzzy linguistic sets. This aspect is crucial for SA since providing users with an explanation of what is happening in the system is of paramount importance for contributing to the formation of adequate mental models.

Given the importance that fuzzy formalisms have in the SA system design, this paper proposes a systematic review of fuzzy formalisms for situation awareness.

The main contributions of this work are:

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1. A systematic literature review of fuzzy logic for situation awareness conducted according to the PRISMA methodology for systematic review (Moher et al. 2009);
2. The identification of open research challenges;
3. The proposal of future research directions.

The motivations for this study are:

1. To identify, summarize, categorize, interpret and discuss the extensive literature on fuzzy logic for SA from 2010 to 2021;
2. The definition of a sound background for new studies that can leverage the provided analysis and categorization to propose novel fuzzy-based approaches for SA;
3. The identification of research challenges in the current literature, suggesting new directions for future research.

To the best of our knowledge, this is the first systematic literature review on the topic of fuzzy logic for situation awareness. In fact, other systematic reviews on situation awareness are not focused on fuzzy logic. The only related works that have been found are systematic reviews regarding the broad topic of SA or the techniques used in a particular domain. For instance, a review of clustering techniques for SA is proposed in (Mitsch et al. 2013). Agrawal et al. (Agrawal et al. 2014) propose a review of multispectral image fusion for situation awareness. Yang et al. (Yang et al. 2022) propose a survey of the fusion methods for battlefield situation awareness. Regarding the domain-specific reviews, there are reviews and surveys for emergency management (Pavkovic et al. 2014), network security (Xuan 2014), sports (Huffman et al. 2022), connected cars (Golestan et al. 2016), industrial systems (Li et al. 2017), road transportation systems (Salmon et al. 2012), wearable systems (D'Aniello et al. 2022), and smart grids (Dong et al. 2017).

The rest of the paper is organized as follows. Section 2 briefly describes the fundamental concepts of Situation Awareness and Fuzzy Logic. Section 3 describes the search methodology according to the PRISMA systematic review methodology. Section 4 offers a description of the works included in the review, classified into 10 different fuzzy formalism categories. Section 5 analyzes and discusses the main findings of the review, highlighting the open challenges and providing future research directions. Finally, Sect. 6 ends the paper with the main conclusions.

2 Background

2.1 Situation awareness

Situation awareness (SA) has been defined by Endsley (Endsley 1995) as:

> the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.

In this definition, we can identify three levels that concur with the formation of the SA:

1. Perception: the perception of the status of the elements in the environment.
2. Comprehension: understanding what the data perceived at level 1 means in relation to the goals of the human operator. Therefore, a goal-related meaning is associated with each piece of data and the relations between them. This level requires a good mental modal and adequate prior knowledge.
3. Projection: at level 3, it should be assessed how the comprehended situation is likely to evolve in the near future. A proper understanding of the dynamics of the system is necessary to project the current situation and identify the potential future states of the system and of the related situation.

Along with this definition, Endsley defined a cognitive model of SA that takes into account both the cognitive individual factors and the system factors influencing the SA.

Another important definition is the difference between human and computer SA, as defined by Kokar et al. (2009): i) Human situation awareness (HSA) is the process made by a human operator to achieve SA, described in detail in Endsley's model of SA; ii) Computer Situation Awareness (CSA) is the capability of autonomous agents and machines to be aware of the current situation. In this survey, we will consider systems and techniques both supporting human or computer SA.

2.2 A reference architecture for situation awareness support systems

Fig. 1 depicts a functional view of an SA system, in terms of its core components and functionalities, based on the Endsley model. This reference architecture identifies the following main functionalities of a SA system:

- Sensing: acquisition of the physical signals and measurements from sensors and other data sources. It manages the sensors' life-cycle, data cleaning, representation, and storage of the measurements.
- Data processing and fusion: processing of the data gathered in the sensing phase and performing data pre-processing, data segmentation, feature extraction, observation generation, and low-level event detection. Low-level events are simple events that can be detected by

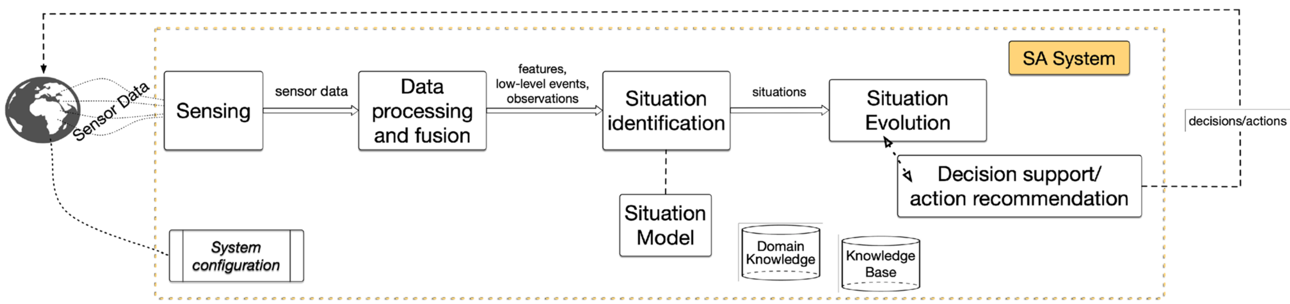

Fig. 1 A reference architecture for situation awareness systems

processing each signal or measurement. A specific issue to be addressed in this phase is the incompleteness and inconsistency of data, which may lead to an erroneous comprehension of the situation in the next phase.

– Situation identification: the features, observations, and events detected in the previous phase are further processed according to a situation identification technique in order to assess the current situation. Usually, a formal and explicit model of the situation is adopted.
– Situation model: a model of the situation is needed in order to provide concrete support to SA, as well as to support the other capabilities of the system. The support to decision making, the interface update, the adaptation of the system, and the notification of alarms and events depend on the identified situation.
– Situation evolution: this phase should support the agent in evaluating the possible evolution of the situations in the near future. This step is critical for SA and decision-making, as understanding the best action to take according to the situation is required to anticipate how the situation could potentially evolve.
– Decision-making and action support: the role of situation awareness is essential to support decision-making and the consequent performance of actions.

2.3 Fuzzy logic

Fuzzy Logic and Fuzzy Set Theory were introduced by Zadeh in 1965 (Zadeh 1965) as an extension of traditional crisp logic. The fuzzy set theory provides natural ways to model ambiguous and vague events that occur in human-like reasoning (Fogel and Keller 2016). A fuzzy set allows the representation of vague knowledge by defining a membership function that maps objects in a domain of concern to the membership value in the set (Kaya et al. 2019). While in a crisp set C, an element x may belong to C ($x \in C$) or not belong to C ($x \notin C$), in a fuzzy set F, an object x may belong to this set with a varying membership degree in the range [0,1]. A fuzzy set F is described by its membership function $\mu_F : (X) \rightarrow [0, 1]$. The most used membership functions are the gaussian, trapezoidal, triangular, and singleton functions. A thorough introduction to fuzzy logic, to the main properties and operations, can be found in (Tomasiello et al. 2022; Jezewski et al. 2017).

Numerous extensions and techniques have been proposed to the traditional fuzzy set theory, such as type-2 fuzzy sets, hesitant fuzzy sets, intuitionistic fuzzy sets, and Pythagorean fuzzy sets. Moreover, hybrid approaches of fuzzy logic integrated with other computational intelligence techniques have been also proposed. Relevant is the hybridization of neural networks with fuzzy logic, as in neuro-fuzzy, ANFIS, and fuzzy support vector machines. Fuzzy logic has also been adopted to model knowledge and expertise, like in rule-based fuzzy inference systems (FISs), fuzzy cognitive maps (FCM), and fuzzy ontology.

3 Research methodology

A review of scientific articles on fuzzy logic and situation awareness spanning 12 years (from January 2010 to December 2021) was conducted in accordance with the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher et al. 2009). The PRISMA methodology is adopted in order to realize an unbiased and reproducible review of the literature on fuzzy logic for situation awareness. After the records screening and the reports selection processing, conducted as described in the following subsection, a total of 139 works are included in the review.

3.1 Search strategy

Figure 2 depicts the adopted methodological approach. According to the PRISMA guidelines, an exhaustive search of the articles regarding fuzzy logic and situation awareness was performed on the following scientific digital indexes and databases: Scopus; Web of Science Core Collection; ScienceDirect; PubMed.

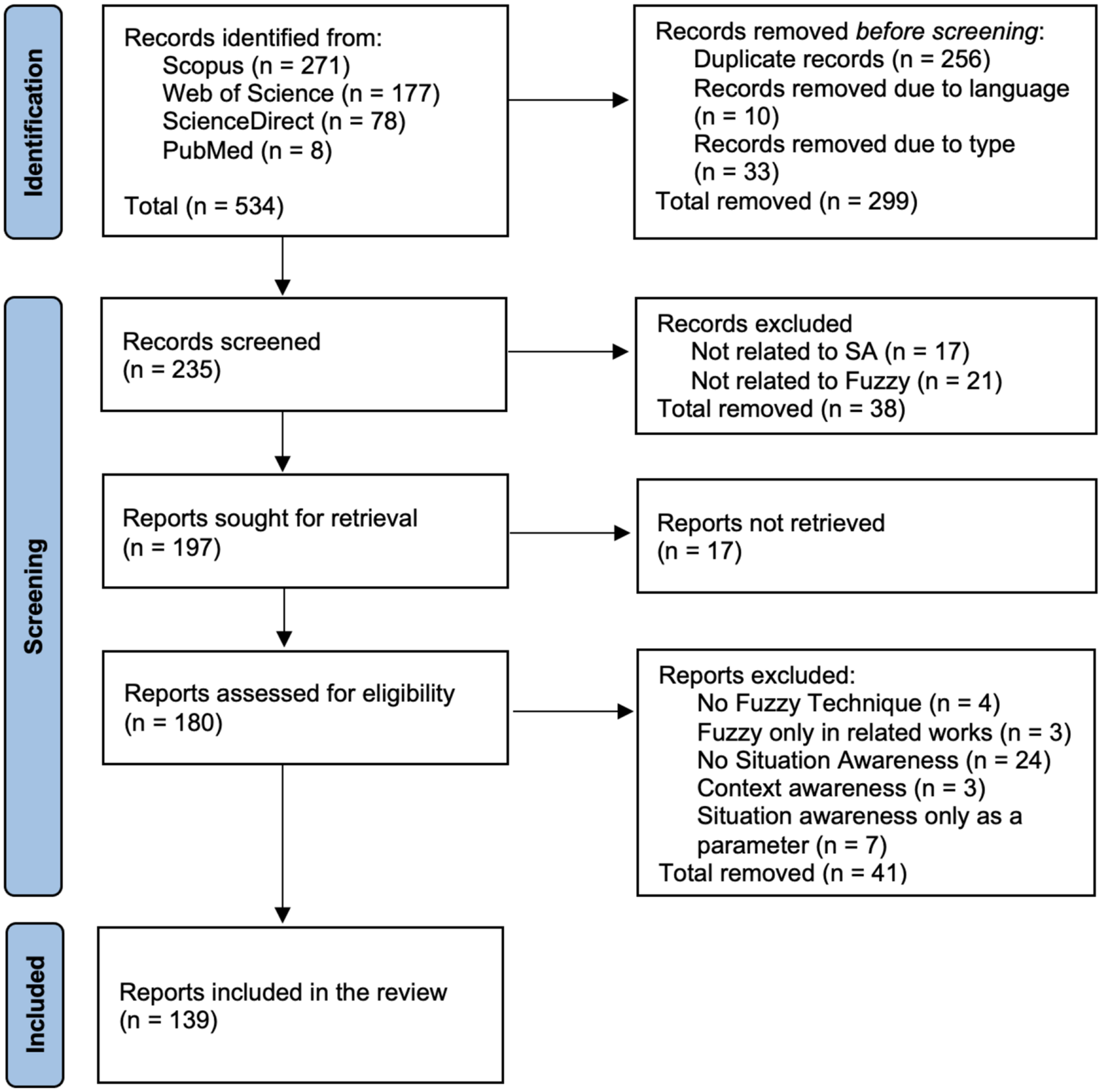

Fig. 2 Literature review selection process according to the PRISMA guidelines

The search focused on retrieving relevant scientific publications proposing any kind of solutions (i.e., studies, models, techniques, methodologies, approaches, systems, methods, applications) regarding fuzzy logic and situation awareness, published from 2010 to 2021. In particular, a publication is included in the review if the fuzzy logic, in any of its formalisms, is used to support human or computer SA (Kokar et al. 2009; D'Aniello et al. 2022), or to realize one or more functionalities of the SA architecture described in Section II (i.e., sensing, data processing and fusion, situation identification, situation evolution, decision support) or to represent situations (e.g., fuzzy-based situation models). Moreover, approaches wherein fuzzy logic is used to evaluate the level of SA of the human operators performing operational tasks are also included in the review. The review considers only those works in which both the fuzzy logic and the situation awareness paradigm are the main elements of the work. To find such works, the following keyword search string has been defined:

`fuzzy AND ( ”situation awareness”`
OR ”situational awareness”
OR ”situation-aware”)

The use of quotation marks surrounding some of the keywords performs an exact search of the contained strings.

This search string has been defined according to these criteria:

– The keyword “fuzzy ”allows for searching any kind of fuzzy variants or formalisms, both theoretical and practical

- The word “situation ”and the word “awareness ”are both very common words. The search for the string `situation awareness` (without quotation marks) would have retrieved also work containing only the word situation or the word awareness. Considering that these words are very common and frequent, this would have retrieved a high number of irrelevant works.
- In the SA research field, there are two main factions: those who refer to SA as situation awareness (as the author) and those who refer to it as situational awareness. Both terms are included in the search string.

The search has been performed in the fields: title, abstract, and keywords. The reviewed works are from January 2010 to December 2021.

3.2 Study selection

As depicted in Fig. 2, during the identification phase of the PRISMA methodology, the search in the four scientific indexes and databases using the search string, retrieved a total of 534 records (271 from SCOPUS, 177 from Web of Sciences, 78 from ScienceDirect, 8 from PubMed). After removing 256 duplicates, a total of 278 records were obtained. From these, 10 records have been removed as these were not written in English but in Chinese, Japanese, Korean or Portuguese.

Since the review aims at analyzing full research articles, 33 works have been removed from the 268 records as belonging to the following typologies:

- Rditorial
- Proceedings cover or message
- Abstract
- Position paper (1 or 2 pages)

At the end of the identification phase, a total of 235 records were identified. In the screening phase, for each record, the title, abstract, and author/index keywords have been read. The records for which the SA and the fuzzy logic are not the main topics have been eliminated. Specifically, 17 records have been removed because not related to SA and 21 not related to fuzzy logic. For the remaining 197 records, the full papers (indicated as reports in the PRISMA methodology) were sought. Unfortunately, the full manuscript has not been found or was not accessible for 17 records that have been removed. The remaining 180 reports were assessed for eligibility. A report has been excluded if it matches at least one of the following exclusion criteria:

- No fuzzy technique: the report does not propose, use or refer to any fuzzy technique
- Fuzzy only in related work: the report refers to fuzzy logic only in the analysis of related works or in the references
- No situation awareness: the report does not propose, use or refer to situation awareness. If the term is only in the related works or used as a buzzword, or it is not the main focus of the work, the report is excluded.
- Context awareness: although the report refers to SA, it only considers context awareness
- Situation awareness as a parameter: the SA is not one of the main topics of the report, but only one parameter among many others considered in the work. Usually, this happens in studies where the effect of the SA is considered in the context of a wider approach, especially as a part of human subjects evaluation.

41 reports have been removed according to these criteria, and therefore 139 reports were included in the final review.

Figure 3 depicts the evolution of the number of papers concerning fuzzy logic and situation awareness published from 2010 to 2021 and included in the final review. The figure shows that fuzzy logic always attracted attention in the field of research of SA, with a slight increase from 2016 onwards.

4 Fuzzy logic for situation awareness

Table 1 reports the 10 categories of fuzzy techniques and formalisms for situation awareness identified in the review. The fuzzy rule-based approach (including fuzzy logic and fuzzy inference systems) is the most employed approach appearing in 48.2% of the analyzed papers.

Fuzzy Cognitive Maps (FCM) is also very popular in SA (13.67% of papers) for their capacity of modeling cognitive relations among concepts and supporting situation

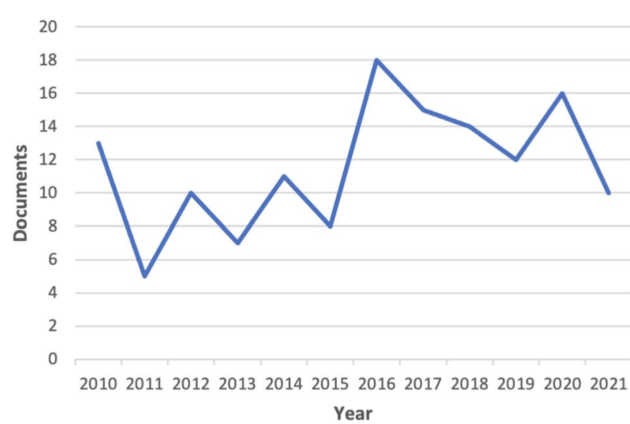

Fig. 3 Number of documents published in each year from 2010 to 2021

Table 1 Fuzzy techniques employed in Situation Awareness from 2010 to 2021

Rank	Technique	N. papers	Percentage
1	Fuzzy rule-based	67	48.20%
2	Fuzzy Cognitive Map	19	13.67%
3	Fuzzy decision making and Fuzzy AHP	15	10.79%
4	Neuro-fuzzy	14	10.07%
5	Fuzzy number, measure, integral	6	4.32%
5	Fuzzy ontology	6	4.32%
7	Fuzzy clustering	5	3.60%
8	Fuzzy Bayesian network	3	2.16%
9	Fuzzy FCA	2	1.44%
9	Fuzzy optimization	2	1.44%

identification and reasoning. The integration of neural networks and fuzzy systems (Neuro-fuzzy systems like adaptive neuro-fuzzy inference system - ANFIS) has been used in the perception and comprehension phase to identify observations and situations. Fuzzy decision-making techniques and Fuzzy Analytic Hierarchy Process (AHP) have been used to support situation-aware decision-making and to evaluate and measure human situation awareness in the 10.79% of works. Due to the limited adoption of approaches based on fuzzy numbers, fuzzy measures (such as fuzzy entropy), and fuzzy integrals (such as Sugeno integral), these approaches have been merged into a single category, as they are essentially based on the definition of fuzzy sets and measures. Such approaches are adopted in 4.32% of the papers. Ontologies have represented one of the first and most used formal models to represent situations. Fuzzy ontologies have been proposed to combine the formal logic of the ontological models with the capability of dealing with uncertainty and imprecise knowledge of the fuzzy logic (4.32%). Fuzzy clustering (like fuzzy c-means) is investigated in 3.6% of the papers. Few approaches combine Fuzzy logic with Bayesian networks (2.16% of the papers). Fuzzy Formal Concept Analysis and fuzzy optimization techniques are used in 2 papers each. The following sections discuss the works classified in each category, according to the ranking of Table 1 (Li et al. 2019a).

4.1 Fuzzy rule-based models

Rule-based models allow describing prior knowledge and decision functions using linguistic if-then rules. This is the basis of traditional crisp expert systems which define rules for manipulating numeric confidences or probabilities. Fuzzy logic extends this rule-based approach by modeling linguistic propositions, rules, and the inference procedure with fuzzy sets (Keller et al. 2016).

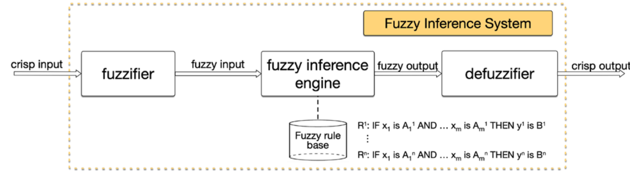

Fig. 4 Mamdani-type Fuzzy Inference System

According to the Mamdani model of inference, both the input and the output of the FIS are represented by fuzzy linguistic terms (Zgurovsky and Zaychenko 2017). Expert knowledge is represented with a set of fuzzy rules of the predicate form:

$$R^i = \text{if } x \text{ is } A^i, \text{ then } y \text{ is } B^i \quad (1)$$

with $x^i \in X$ is an input variable, $y^i \in Y$ is an output variable, A^i and B^i are the linguistic terms represented by membership functions defined on the sets X and Y. Figure 4 shows a Madani-type FIS. The crisp inputs are transformed into fuzzy sets in the fuzzification phase. Then, all the rules contained in the rule base are evaluated and applied. The fuzzy output is finally transformed into crisp output using a defuzzification technique.

Sugeno models (Zgurovsky and Zaychenko 2017) differ from Mamdani in that the consequent of each rule is a real-valued function of the inputs.

In the sensing and in data processing phases of SA systems, fuzzy rule-based approaches are used to support data fusion and data preprocessing tasks. In (Lili et al. 2012), a FIS is employed to identify low-level events which are then processed by a bayesian network to identify the situations. (D'Aniello et al. 2016b, 2015) proposed an approach based on the Fuzzy Consensus model to preprocess sensor data and avoid sensor data mismatch to support situation-aware systems. A Type-2 Fuzzy Inference System is used in (Castañón-Puga. et al. 2015) to identify user indoor location using WiFi RSSI to support situation-aware applications.

The main task for which FIS is widely used is to identify situations through rules that represent expert knowledge (Ciaramella et al. 2010a, c, b; Naderpour and Lu 2012; Rolim et al. 2015b; Shin et al. 2020; Rolim et al. 2015a; Dridi et al. 2016; Wu et al. 2021a), also with hybrid approaches combining FIS and machine learning (Pavlik et al. 2010; Khayut et al. 2017), SOM (Van Pham and Moore 2019), and Deep Learning (Juuso 2018). In input to the FIS, there are the linguistic representations of sensor data, observations, low-level events, and activities, which will be combined according to if-then rules to identify situations, which are represented by the fuzzy sets of the output variables. Some works combined multi-agent architectures with FIS to identify situations (Castellano et al. 2013; D'Aniello et al. 2015) or to support agent behavior with information regarding situations.

Gerken et al. (2010) proposed a Fuzzy Complex Event Processing approach to identify situations defined as a course of action for military operations. (Haghighi et al. 2010) proposed a situation-aware visualization tool for sensor data visualization and analysis in which a FIS is used to identify situations. Some approaches combine probabilistic models such as Bayesian networks and Markov models with fuzzy inference systems to model and identify situations. (Gerken et al. 2010; Naderpour et al. 2014a, 2015, 2014b) propose a bayesian network to model situations and a FIS to evaluate the risk of such situations. A combination of Hidden Markov Models (HMM) to identify the severity level of suspicious activities and a FIS to identify situations is proposed in (Du et al. 2015) in the context of cyber insider attack detection and in (Psarros 2018) for maritime safety navigation. Van and Liam (Nguyen and Mellor 2020) proposed a Fuzzy Markov Logic Network for activity recognition and situation identification in the situation awareness framework RUSH.

Other works have a simplified model of situations, in which instead of defining a formal model of the possible situations, a situation is defined as a risk index or a dangerousness index. This is the case, for instance, of the approach in (Xiao and Chen 2011) which proposes the identification of a risk level of the cybersecurity of a network using a fuzzy reasoning approach, or the one in (Falcon et al. 2017) for the safety risk during maritime navigation. (Gao et al. 2020) proposed a FIS combined with semantic analysis to assess the level of security of UAV in terms of link jamming and intrusion situation. Arunagirinathan and Venayagamoorthy (2020) use a FIS to evaluate the situations in terms of the performance of power management in power grids to respond to system disturbances. Furthermore, Wu et al. (2021b) proposed an approach to evaluate situations in terms of security problems in power systems by combining the hierarchical cellular rule-based fuzzy system and cellular computation network. In (Chandra et al. 2020), a cybersecurity risk maturity model, based on the Endsley model, is implemented using a FIS.

Other approaches combine fuzzy inference with ontologies or semantic models to support situation identification and situation comprehension. De Maio et al. (2012) combine situation theory with a FIS to identify situations taking into account data uncertainty. Anagnostopoulos and Hadjiefthymiades (2010) combine FIS with semantic relations (mereology, specialization, compatibility) to classify situations by taking into account imperfections in the perceived contexts. Description logic (Puls and Wörn 2013) and ontologies have been combined with Fuzzy Logic have been combined to model and identify situations (Cimino et al. 2012; Loia et al. 2012).

FISs have been also used to measure and evaluate the level of human operators SA performing tasks and operations or making decisions. An agent-based system equipped with a FIS to measure the level of SA of aviation pilots by means of linguistic rules that take into account the attention level, focus, and risk related to the situation is proposed in (Di Nuovo et al. 2011). Similar approaches have been proposed for the SA of surveillance operators (Agrawal and Karar 2019), and for vehicle drivers (Bylykbashi et al. 2020; Acarman 2012), also to evaluate the SA of drivers performing secondary tasks in autonomous vehicles (Aksjonov et al. 2017) and to predict the pedestrian movements in the context of autonomous vehicles (Hwang et al. 2021).

Situation Awareness plays a major role in human–machine collaboration and teaming. Some works studied the effect of SA on human–machine collaboration by modeling the interactions using fuzzy rule-based approaches, as in (Mitchell and Cohen 2012; Cook et al. 2013; Mitchell et al. 2014; Hanratty et al. 2017).

Lastly, fuzzy rule-based models represent the grounding of many situation-aware systems aiming at supporting human operators' SA, their performances, and their decision-making capabilities, like in expert systems, command and control centers, and decision support systems. Kaneshiro et al. (2014) propose a fuzzy rule-based situation-aware system to control and optimize energy consumption in buildings; Evesti and Frantti (2015); Sivils et al. (2017) propose similar approaches for industrial control systems. Such kinds of approaches have been proposed also in healthcare (Yamamoto et al. 2010), in particular for mental healthcare (Teles et al. 2016; Zhang and Kaber 2016; Soares Teles et al. 2017). FISs have been used also in Geographical Information Systems (GIS) to create situation-aware maps and to support operators SA, as in (Stanley and Kirschbaum 2017). Many fuzzy rule-based situation-aware systems have been defined for network security and cyber security, in particular, to support network operators in identifying security risks and responding quickly, as proposed in (Allison Newcomb et al. 2016; Graf et al. 2016; Liu and Feng 2019), also for VANET security (Thanuja and Umamakeswari 2018). Military, intelligence, and airforce operations always received great attention from the SA research community (Miao and Tang 2017; Hammell and Hanratty 2017; Fellah and Guiatni 2019; Gaeta et al. 2021). For air traffic control operations, due to the high cognitive workload required by such tasks, different fuzzy rule-based situation-aware systems have been proposed, such as in (Skorupski and Ferduła 2018; Ferduła and Skorupski 2018).

4.2 Fuzzy cognitive map

A Fuzzy Cognitive Map (FCM) is a model that can be used to represent the behavior of complex systems at a macro-level (Mourhir 2021). It is a common technique used in SA as it tries to operate in a similar way to the reasoning and decision-making of humans (Amirkhani et al. 2017). Therefore, it can be used to model the processes of SA assessment and decision-making in several complex human–machine systems.

A FCM, introduced by Kosko (Kosko 1986), is a signed direct graph that represents a set of concepts (the nodes of the graph) and the causal relationships between these concepts, using fuzzy causal weights, as shown in Fig. 5. In this way, a FCM can capture the functional and causal interactions between the system and the social factors of complex systems, representing explicit expert knowledge, belief, and understanding regarding the system. The FCM inference (Mourhir 2021) is based on the weights associated with each concept, according to Eq. 2:

$$C_i^{k+1} = S\left(\sum_{j=0}^{n} C_j^k * w_{ki}\right) \tag{2}$$

where C_i^{k+1} is the activation value of concept C_i at the iteration $k+1$, C_i^k is the value of causal concept C_j at iteration k, w_{ji} is the weight of the cause-effect link between C_j and C_i. $S(\cdot)$ is a nonlinear activation function, like a sigmoid function, to transform the results in a nonlinear way, as occurs in neural networks.

FCMs are rarely used to support low-level event identification and perception level of SA systems, as they are more useful to support cognitive processes and decision making. One of the few examples of FCMs to identify low-level events is proposed in (Loia et al. 2016). FCMs have been used in SA in particular to support situation modeling, identification, reasoning, and decision making. In particular, FCMs were used to represent causal relations between goals and situation information requirements, identified with cognitive task analysis approaches (Parisi and Lüdtke 2016) like Goal-directed Task Analysis (GDTA) (Kokar and Endsley 2012; Jones et al. 2010, 2011; Xue et al. 2014). The FCMs are then used to support situation identification and decision making. Recently, a similar approach has been used to model and identify situations regarding students of e-learning systems, mainly in terms of their motivation and engagement (D'Aniello et al. 2020b, a; D'Aniello and Gaeta 2021). In these cases, the FCM is useful to model the expert knowledge of the teachers, to understand how they evaluate the motivation of students and how they react to these situations, and to model the uncertainty in the identification of the level of motivation and engagement of students.

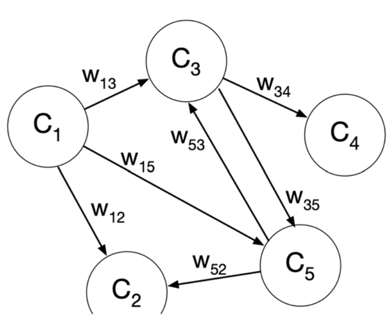

Fig. 5 Fuzzy cognitive map

FCMs have been used often for the control and interaction with Unmanned Vehicles (UVs). Cavaliere et al. in (Cavaliere and Senatore 2018; Cavaliere et al. 2018, 2019) proposed a multiagent system where the FCM is combined with ontologies to perform data fusion and situation identification and support scene understanding in remote sensing using grounded and aerial UVs. In (Schwerd and Schulte 2021), a system to support human-UAV cooperation is proposed. In this case, the FCM is adopted to support situation comprehension and projection by combining information from different sources, based on the goals and information requirements analyzed and identified with the GDTA. In the military domain, situation-driven FCMs have been used to support fast decision-making for the cooperation of humans with Unmanned Combat Aerial Vehicle (UCAV) (Zhao and Niu 2017), and to support threat assessment in modern air combat scenarios (Chen et al. 2018).

Cyber security is another domain in which FCMs have been employed, in particular, to identify intrusions (Aparicio-Navarro et al. 2016) and attacks, or to support what-if analysis to identify vulnerabilities (Fan et al. 2018), also for the monitoring of utilities like smart grids (Mohagheghi 2014).

FCMs have been combined with other approaches to defining hybrid techniques, such as in (Nguyen et al. 2010) where Bayesian networks are used for data fusion, while FCM and Case-based reasoning are used to support situation reasoning. De Maio et al. have combined FCM with Fuzzy Formal Concept Analysis to identify situations in sensor data streams (De Maio et al. 2017).

4.3 Fuzzy AHP and fuzzy decision making

Multiple criteria decision-making (MCDM) methods are used to solve decision-making problems with multiple and conflicting criteria (Kubler et al. 2016).

In (Ouahli and Cherkaoui 2018), an intuitionistic fuzzy MCDM technique is used for analyzing the relationships between critical factors of complex systems (e.g., personal factors, skills, activity features) and level of situation awareness of the operators of a network security system.

Analytic Hierarchy Process (AHP) introduced by Saaty (Saaty 1988) is one of the most used MCDM techniques thanks to its ability to reduce biases, allowing for comparing dissimilar alternatives and leading to impartial and logical conclusions. Fuzzy logic has been combined with AHP in Fuzzy AHP approaches to deal with fuzziness and uncertainty in decisions and criteria. The Fuzzy AHP method involves the following steps:

- Define the problem and the quality criteria
- Create a fuzzy pairwise comparison matrix A to compare the items according to the criteria. The matrix is defined as $A_{nxn} = (a_{ij})_{nxn}$ where a_{ij} is a fuzzy set reflecting the relative importance of criterion i over the criterion j
- Calculate the fuzzy weights of the criteria, by aggregating multiple fuzzy sets in the matrix into a single fuzzy set
- Defuzzification of the fuzzy weights
- Ranking and selection of decisions

Fuzzy AHP has not been used in the sensing and data processing phases of SA systems. There are few works in which the technique has been used to support the situation identification task, particularly for network security as in (Sun et al. 2015) and in (Bian et al. 2013) where Fuzzy AHP is used to fuse multiple indicators about the status of the network. It was also used to implement a situation awareness-based cloud resource management approach wherein Fuzzy AHP is used to identify the current situation (in terms of resource consumption) and a neural network to predict future situations (Wang et al. 2020). A similar approach is proposed in (Zhang et al. 2021) where Fuzzy AHP is used to evaluate the current situation regarding the status of high voltage switchgear in a power distribution network while an LSTM-attention mechanism is used to predict the future state of the system safety. In (Zhang et al. 2020a) a model of SA, based on Endsley's model and JDL data fusion model, is proposed for the security of the Internet of Vehicles (IoV). In this model, fuzzy AHP is used to identify the security situation of the IoV regarding a single vehicle or multiple vehicles in a region, and a Markov Chain is used to predict the evolution of the situation.

One of the main uses of Fuzzy AHP in SA is the evaluation of the SA of human operators. In (Li et al. 2019b, c), fuzzy AHP is employed to assess the level of SA reliability of operators in the control rooms of nuclear power plants. In (Im et al. 2021), it is used to find the variables affecting SA and aviation safety for training pilots. In (Liu et al. 2012), fuzzy AHP is used to analyze the relationship between SA and the short-term memory of air traffic controllers. Lastly, (Ouahli and Cherkaoui 2019) propose a team performance model based on the concepts of SA and human reliability for team working in safety-critical systems; fuzzy AHP is adopted to support decision-making for team selection based on the proposed model.

Another well-known fuzzy-based MCDM approach is the fuzzy decision-making trial and evaluation laboratory method (fuzzy DEMATEL). DEMATEL is an effective method for the identification of cause-effect chain relationships of complex systems. It was used to identify the relationships between the main variables influencing situation awareness and the safety performance of human operators according to the opinions of human experts (Mahdinia et al. 2021) and to investigate the relationships between individual, situational and organizational variables affecting situation awareness in industrial workspaces (Mohammadfam et al. 2019).

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is another MCDM method based on the principle that the alternatives selected must have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. In Fuzzy TOPSIS, the weights in the decision matrix are fuzzy linguistic terms. It was used in (Sodhi and Sharieff 2015) to identify the main factors (like network state, voltage, tie-line oscillations, availability of communication network, etc.) that influence the situation awareness of the operators of the control system of a power distribution network.

Lastly, (Teixeira et al. 2019) proposed a situation-aware multi-objective decision-making method based on *mathcalL*–fuzzy set in Ambient Intelligence settings to ensure thermal comfort and energy efficiency in homes.

4.4 Neuro-fuzzy

Neuro-fuzzy systems are defined by the fusion of artificial neural networks (ANNs) with fuzzy logic systems. This approach aims to merge the benefits of the two techniques and reduce the weaknesses of the individual approaches.

Neuro-fuzzy systems are used for implementing situation identification approaches. In particular, the most used technique is the Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS uses a Sugeno-type FIS in a five-layered neural network structure, depicted in Fig. 6. The

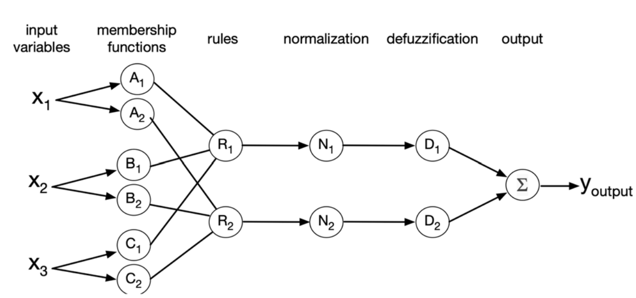

Fig. 6 Adaptive Neuro-Fuzzy Inference System (ANFIS)

networks find fuzzy if-then rules between antecedent and consequent parameters.

An ANFIS approach is used in (Vijay Rao and Balas-Timar 2014) to model the behavior of an artificial pilot agent used in warfare simulations, taking into account the human pilot's cognitive factors and situation assessment. Castellano et al. (Castellano et al. 2014) propose a multi-agent architecture for collaborative situation awareness, using an ANFIS to exploit positioning information of people from mobile devices to identify situations related to social events. ANFIS has been used in Intelligent Transportation Systems (ITS) and in particular in connected cars to identify situations related to the behaviors of preceding cars and aid drivers to avoid collisions (Balakrishnan et al. 2018).

Fuzzy Neural Network (FNN) has been used in networks to identify network security situations and support cybersecurity (Li and Li 2017). In (Mendis et al. 2019), an ANFIS is used to assess the level of cybersecurity of an aircraft energy management system, together with a Deep Learning architecture to detect cyber attacks. A 4-layer FNN with a new backpropagation algorithm is proposed in (Liu et al. 2017) to assess the computer network operating situation. In several works, FNN is combined with evolutionary algorithms, like Particle Swarm Optimization (PSO) (Fu and Li 2018), in the backpropagation algorithm to find the optimal link weights of the ANN. Similarly, in (Liu and Zeng 2020), FNN is combined with the chaos particle swarm algorithm and wavelet packet to identify security situations in IoT networks for smart cities.

In (Shouming et al. 2021) a FNN is used to identify fire scene situations. ANFIS was also used in infrastructure management. In (Zhang et al. 2020b), ANFIS was used to identify dangerous situations related to the inflow and infiltration of the sanitary sewer system through supervisory control and data acquisition (SCADA). The ANFIS had an overall higher performance than ANN. Lastly, in (D'Aniello et al. 2016a), an ANFIS is used to identify situations regarding customers and their shopping behavior in shopping malls to support marketing strategies.

A particular kind of fuzzy neural network is Fuzzy Associative Memory (FAM). An associative memory is a type of memory that stores the mappings of specific input representations to specific output representations. The addressing of the memory is not based on the data location, but on the input content. When the associative mapping between input and output is learned with an ANN, the memory is called neural associative memory. In a FAM, the associative mapping is performed by a one-layer fuzzy neural network, and therefore the input–output patterns are defined by fuzzy sets. The advantage of FAM is that it is robust to perturbations and noises in the inputs. FAM is used in (Drayer and Howard 2012) to support the perception phase by combining and transforming sensor information into operational conditions that facilitate the recognition of situations and the development of control strategies of a bio-regenerative life support system. FAM has been used also in the military domain to identify the most valuable information for making decisions based on the current situation (Newcomb and Hammell 2013; Hanratty et al. 2013).

4.5 Fuzzy number, measure and integral

A fuzzy number is a generalization of a real number, expressed as a fuzzy set defining a fuzzy interval in the real number domain $\mathbb{R}$. Fuzzy numbers are used in (Huang et al. 2016) to support communication in a team regarding cyber security, to avoid inconsistencies, and to reach a consensus on the decision, by supporting the team's cyber situation awareness.

Fuzzy measures have been introduced by Sugeno as the generalization of classical measures. A fuzzy measure on X is defined (Grabisch 2015) as the set function:

$$\mu : 2^X \rightarrow \mathbb{R} : \mu(\emptyset) = 0 \tag{3}$$

and μ is monotonic:

$$A \subseteq B \subseteq X \implies \mu(A) \leq \mu(B) \tag{4}$$

A fuzzy measure and the Choquet fuzzy integral have been used in (Zhang et al. 2020c) to assess the risk situation of power information and communication network in a cyber-physical system and specifically in power grids. In this work, a fuzzy density measure is calculated for each risk indicator connected with the power information network; then, all the indexes are aggregated using the Choquet fuzzy integral.

In (Mills et al. 2020), a deep-growing self-organizing map (deep GSOM) is used to generate a representation of situations in IoT data streams in order to manage the scale, velocity, and magnitude of the data. The GSOM uses a fuzzy integral as a metric to profile the density of the network congestion. Gross et al. in (Gross et al. 2014) propose a complex fuzzy graph-matching approach to handle huge amounts of uncertain data to identify situations in intelligence analysis. The approach is based on fuzzy numbers and fuzzy similarity relations.

Fuzzy measures have been also used in human SA evaluation. The work in (Kim et al. 2016) defines fuzzy indices and coefficients to take into account the effects of metacognition on SA of pilots, measured via a retrospective confidence judgment probe; a fuzzy linear regression technique is used to estimate the relations among these indices. Fuzzy entropy is used in (Zhao et al. 2016) to describe the human cognitive process under uncertainty in the context of a SA-centered cognition architecture.

4.6 Fuzzy ontology

An ontology is a formal conceptualization of a domain of interest shared among agents. It consists of entities, attributes, relationships, and axioms to provide a common understanding of a real-world domain (Gruber 1993). In a fuzzy ontology, concepts and relationships are fuzzy. In particular, a fuzzy ontology has been defined by Calegari and Ciucci (Calegari and Ciucci 2007) as the quintuple:

$$\mathbf{O_F} = \{\mathbf{I}, \mathbf{C}, \mathbf{R}, \mathbf{F}, \mathbf{A}\} \tag{5}$$

where

- **I** is the set of individuals
- **C** is the set of concepts, where each concept $c \in \mathbf{C}$ is a fuzzy set on the domain of instances $c : I \rightarrow [0, 1]$
- **R** is the set of relations where each $r \in \mathbf{R}$ is a n-ary fuzzy relation $r : E^n \rightarrow [0, 1]$
- **F** is the set of the fuzzy relations on the set of entities E and a specific domain like integer, string, etc.
- **A** is the set of axioms expressed in a logical language.

Fuzzy ontologies have been used in SA to model situations and to support situation identification via ontology reasoning, using the fuzzy description logic language (Liu et al. 2010a; Souabni et al. 2016; Cavaliere et al. 2020), the F-OWL language (Liu et al. 2010b) or with a fuzzy version of the Situation Theory Ontology (Furno et al. 2010, 2011).

4.7 Fuzzy clustering

Clustering is an unsupervised learning tool for knowledge discovery and data analysis aiming at finding homogeneous groups (clusters) from finite, unlabeled, multivariate data. In fuzzy clustering, an element belongs to a cluster with a membership degree $\in [0, 1]$ represented by a fuzzy set.

Wang et al. (Wang et al. 2012) proposed a data fusion algorithm that combines Bayes estimation and fuzzy clustering to support the perception phase in a network security situation awareness system. In (Bao and Ding 2020), Fuzzy C-Means is used to cluster the features of network data to support a network security analysis approach. Considering the huge amount of data generated by modern computer networks, the fuzzy C-means is used to reduce the complexity of data. On such data, a network security situation awareness model is proposed, based on an artificial neural network. In (He et al. 2017), Fuzzy C-Means is adopted to recognize radar targets in a maritime situation awareness system.

Fuzzy clustering is also combined with supervised learning approaches to support situation awareness. In (Yi et al. 2016), Fuzzy C-Means is used to categorize the drivers' behaviors in different clusters, and then a fuzzy supervised learning technique, namely the Fuzzy K-NN, is applied to classify situations. Finally, a Kalman filter is used to predict the future states of the vehicle. In (Wu et al. 2018), fuzzy clustering is combined with game theory and reinforcement learning to define a security situation awareness approach for a smart grid, quickly identifying and anticipating threats that could have a huge impact on of smart grid operations.

4.8 Fuzzy Bayesian network

A Bayesian Network (BN) is a pair $N = \{(V, E), P\}$ where V and E are the nodes and the edges of a directed acyclic graph, and P is a probability distribution over V. $V = \{X_1, X_2, ..., X_n\}$ are discrete random variables assigned to the nodes in V. The edges E represent the causal probabilistic relationship among the nodes (Ren et al. 2009b). The extension of the classic BN to the Fuzzy Bayesian Network (FBN) uses fuzzy numbers and fuzzy probability measures. In particular, fuzzy probability inference is executed on the following Fuzzy Bayesian rule is defined as:

$$P_f(X = x_i | Y : y_j) \cong \frac{P_f(X = x_i)P_f(Y = y_j | X = x_i)}{P_f(Y = y_j))} \tag{6}$$

where P_f is a fuzzy probability measure. A comprehensive description of FBN and fuzzy probability inference process can be found in (Ren et al. 2009a; Pan and Liu 2000).

FBN has been used to model and identifies hazardous situations, inferred from the sensor observations, in the context of cyber-physical systems and in particular for a chemical plant control system (Naderpour et al. 2013) and in railway physical protection system (Flammini et al. 2016). Xing-Zhu in (Xing-Zhu 2016) demonstrated that a FBN has better performance than a classic BN in the identification of dynamic changing situations in the context of battlefield network security.

4.9 Fuzzy formal concept analysis

Formal Concept Analysis (FCA) is a data analysis technique that takes data in the form of binary object-attribute values and groups objects together when they share attributes, obtaining a lattice view of formal concepts, as shown in Fig. 7. The fuzzy extension (FFCA) allows to model vague binary attributes. FFCA is used in (Benincasa et al. 2015) to model the relationships between objects of the environment and their attributes to formally model a situation. Specifically, a given situation is described by the fuzzy context attributes of the FFCA lattice. A reasoning algorithm on the obtained lattice allows for identifying the dynamic situations starting from the properties (attributes) of the objects in the analyzed environment. Martin and Azvine in (Martin

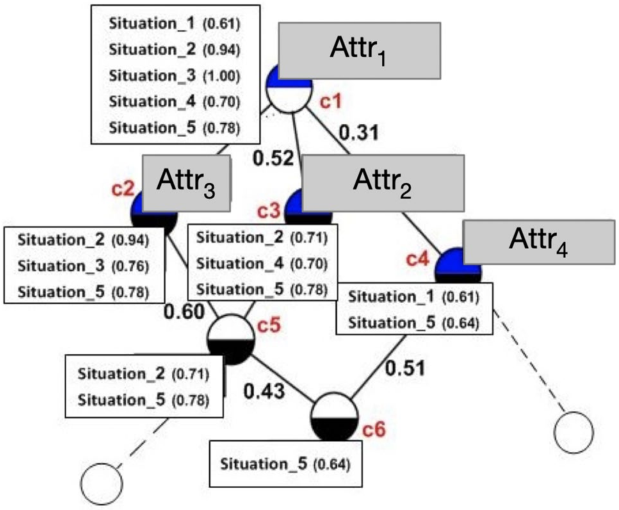

Fig. 7 Fuzzy Formal Concept Analysis (FFCA) (Benincasa et al. 2015)

and Azvine 2017) propose an approach that combines x-mu fuzzy sets with FCA to support the information representation and exchange between humans and machines to support human SA in collaborative intelligence analysis.

4.10 Fuzzy optimization

Fuzzy optimization methods aim at solving optimization problems that can not be formulated by crispy specific objective functions in order to take into account real-world situations wherein various types of uncertainties and vagueness are present.

In general, a fuzzy optimization problem can be defined as follows. Let universe $X = \{x\}$ be a set of alternatives, X_1 a subset or a fuzzy subset of X. The objective/utility function is a mapping $f : X_1 \rightarrow L(R)$, where $L(R)$ is a subset or a class of fuzzy subsets of real value set R, the feasible domain is described by a subset or a fuzzy set $C \subset X$, with a membership function $\mu_C(x) \in [0, 1]$, which denotes the degree of feasibility of x. In this case, a fuzzy optimization problem may be generally expressed as $f(x, r) \rightarrow \max_{x \in C}$, where r is either a crisp constant or a fuzzy coefficient (Jiafu et al. 2004).

In (Zhu et al. 2017), fuzzy optimization is used to find a tradeoff between surveillance mission and connectivity maintenance of multiple UAVs during cooperative surveillance, trying to optimize the limited communication capabilities and the need to obtain a real-time high-quality surveillance information transmission. System hierarchy fuzzy optimization is used to evaluate the network security situation awareness level in terms of target system security status by analyzing potential cyber threats (Hongbin Zhang 2018).

5 Discussion

The analysis of the literature showed that fuzzy logic has been employed in all the phases of a SA system: sensing; data processing and fusion; situation identification; situation evolution; decision support (see Fig. 1). In particular, only a few works focus on techniques for the sensing and data processing phases. This is justified by the fact that these phases require activities such as data segmentation, feature extraction, data fusion, low-level events detection, activities where learning-based and statistical approaches work better and are often used in SA systems, such as Markov models, neural networks, clustering, mining, etc. Some of the analyzed works adopt Fuzzy Cognitive Maps (Loia et al. 2016), fuzzy rule-based techniques (Lili et al. 2012; D'Aniello et al. 2016b), and Neuro-fuzzy (Drayer and Howard 2012), to support the data processing and fusion phase. However, many of the analyzed works adopt fuzzy formalisms to describe and represent the output of the sensing and data processing phases, by modeling low-level events, activities, actions, and observations using fuzzy sets, fuzzy numbers, fuzzy integrals, to model uncertainty and vagueness of data and events. These are then used as the fuzzy input of the subsequent phase to identify situations.

Situation identification is the phase in which a greater number of works, with different fuzzy techniques, have been proposed. Expert-based approaches, including rule-based (Wu et al. 2021a), FCM (D'Aniello et al. 2020b), Fuzzy AHP (Wang et al. 2020), and Fuzzy ontologies techniques (Cavaliere et al. 2020), to represent situations with formal and visible models of situation. This provides human operators with an understandable representation of situations, which could also explain why a given situation is occurring, helping to build better human mental models and leading to higher levels of SA. For their nature, such expert-based approaches are time-consuming and require a huge effort to be adopted, especially in formal models such as ontologies. This reduces the number of different situations that can be explicitly modeled. For these reasons, very often the systems based on this kind of model are able to represent only the most common and frequent situations. Although this can be considered reasonable, there is a major drawback to this approach. Unforeseen but dangerous situations that are not modeled with such approaches cannot be recognized by the system. However, unforeseen situations are those situations in which human operators most need support from the system to maintain a high level of SA for dealing with the situations. Of the specification-based approaches, fuzzy rule-based systems are the most frequently adopted. A possible explanation for this popularity can be found in the relative ease of their application. Providing that there is expert knowledge to model the situations in terms of if-then rules, the implementation of the fuzzy inference system is straightforward and supported by a variety of tools and libraries. However, as above mentioned, the process of acquiring and formalizing expert knowledge may be costly and time-consuming.

Another drawback of rule-based systems, and in general of the other specification-based approaches, is the difficulty in modeling complex situations characterized by complex dynamics and relations among the elements of the environment. If-then rules or ontology reasoning can support the definition of relatively simple situations, in which essentially the situation is identified by verifying the existence of some properties or relations between objects and elements. It is much more difficult to represent complex temporal dynamics, sequential patterns, and multi-user situations. Many rule-based approaches analyzed in the review are able to model situations as instantaneous snapshots of what is happening. They struggle with modeling the complex temporal dynamics of the environment. The challenge is therefore to model and represent evolving situations, by means of sequential pattern mining and identifying the most important temporal features. It is also very complex to identify when a specific situation is changing and how to represent this change for the user.

The learning-based techniques including neuro-fuzzy (Mendis et al. 2019), fuzzy clustering (Wu et al. 2018), and fuzzy Bayesian network (Naderpour et al. 2013), are frequently used to identify situations. The great advantage of such techniques is that they do not require expert knowledge modeling, reducing time and effort for their applications. Moreover, in some cases, the analyzed works showed higher performance when compared with traditional non-fuzzy techniques like ANN and clustering. This demonstrates the usefulness of fuzzy modeling in dealing with uncertainty and vague information in real-world applications. Learning-based approaches are effective in modeling and identifying complex situations, taking into account the temporal effects providing that adequate datasets are available for the training phase. Indeed, the big drawback of learning-based approaches is the availability of training data which greatly influences the performances of the approaches. It should also be considered that it is quite difficult to find sufficient data regarding dangerous and unexpected situations, as these rarely occur. This limits the capability of such techniques to identify and model unexpected situations. Hybrid approaches combining expert knowledge and learning-based techniques can be a valid solution to this problem.

The analysis showed limited support for the projection phase. This phase is the most critical but important for SA. Since SA is a prerequisite for decision-making, the ability to anticipate and understand the evolution of the situations based on the possible decisions that can be made is essential. Unfortunately, supporting situation projection is not easy and also requires correct and complete modeling of the system dynamics, which is not always feasible. Many of the analyzed works give limited support to the projection phase, by essentially providing the user with information on the risk or danger of the situation. In such cases, the most used techniques include FCM (Fan et al. 2018) which has the ability to analyze the effects of causal relationships; fuzzy rule-based (Hwang et al. 2021) in which the knowledge of the experts could also include rules on the evolutions of the situations, and neuro-fuzzy (Mendis et al. 2019) in cases where the dataset contains information on the future states of situations.

Many works proposed the use of fuzzy techniques to support the decision-making phase. Fuzzy logic has a long tradition in decision-making techniques, thanks to its ability to model the inherent uncertainties of any decision problem. Fuzzy decision-making techniques (Wang et al. 2020; Zhang et al. 2020a) such as AHP, fuzzy DEMATEL, and Fuzzy TOPSIS are used to support situation-aware decisions. Again, fuzzy rule-based are adopted to map the current state of the situations (in the antecedent of the rules) with the decision (in the consequent). Such rule-based approaches are mostly used in autonomous agents.

In addition to the implementation of the situation awareness phases, fuzzy logic is used also to evaluate and measure human SA. In particular, fuzzy sets are used to model the relationships between some cognitive and system factors and the level of SA gained by the human operators, as well as between the SA and the human performances in terms of decision-making tasks. Fuzzy measures and integrals, fuzzy decision-making techniques, and Fuzzy Cognitive Maps are the main approaches used to evaluate human SA.

5.1 Research directions

The increasing complexity of systems and environments, the advent of new sensors, devices, and technologies, as well as the new domains in which the SA is gaining momentum, such as IoT, wearable computing systems (D'Aniello et al. 2022), self-aware systems (Cámara et al. 2017), demands novel approaches capable of handling such complexity, where fuzzy logic can play a fundamental role in addressing uncertainty, vagueness, and imprecision.

Hybrid techniques combining expert-based (like FIS) and learning based (like neural networks) may represent a valid solution that should be investigated more in future works. However, considering that the success of the rule-based approaches can be found in the ease of use of such a technique, it is necessary that new approaches possess this characteristic. Designers of real-world SA systems need effective situation models and identification techniques to realize new systems, but they also need these approaches to be easily usable, integrable, and implementable in their solutions. Researchers and practitioners in SA should consider this requirement to make a real contribution to human–machine systems and cyber-physical-social systems. Design methodologies, standards, tools, and software libraries based on fuzzy logic are needed to support and disseminate the adoption of SA principles in real-world systems. Otherwise, computational fuzzy-based SA approaches risk remaining research-level with no real-world fallout.

The temporal dimension is another aspect of modern SA systems that should be considered in future research efforts. A greater emphasis on monitoring and forecasting the evolution of situations is required. This demands explicit support for the projection phase which is lacking in many of the analyzed works. To cope with time-varying situations, it is necessary to process streams of data from heterogeneous sources, and therefore to consider and process streams of evolving situations. Fuzzy formalisms can greatly contribute to dealing with the uncertainty and noises that characterize data streams if coupled with streaming computing approaches and architectures.

Another future research direction is the definition of a methodological and technological framework grounded on fuzzy logic to support the definition of SA systems. In such a sense, a very promising research direction is the advent of the Granular Computing (GrC) paradigm (Bargiela and Pedrycz 2008). GrC is an information processing paradigm focused on representing and processing basic chunks of information, namely information granules. Information granules are collections of entities that are aggregated together on the basis of similarity, functional adjacency, indistinguishability, and functionality. The process of forming granules from raw data is called granulation. Granulation is an efficient way to modularize problems into a series of well-defined subproblems to reduce the complexity and the computing effort. Specifically, it is possible to have multiple levels of granules at different levels of abstraction, from finer granules to coarser ones. This allows problems to be abstracted and solved at different levels of detail. At different granularity levels, different relationships and insights into the structure of the information may be discovered. From a computational viewpoint, the granules must be described and represented. Several formalisms can be used based on the specific type of granulation and the characteristics of the problem, such as interval sets, rough sets, and fuzzy sets.

The reason why GrC seems to be a valid foundation paradigm for novel SA techniques is that it shares many principles with human SA. Indeed, GrC is not only an information processing paradigm, but it can be analyzed from three perspectives (Yao 2006): (i) a general method of problem solving; ii) a paradigm for information processing; (iii) a way of structured thinking. Therefore it can be used for: (i) analyzing SA problems from a human-oriented perspective; (ii) to identify computationally efficient techniques to process data supporting SA systems; (iii) to support the definition of SA systems considering the cognitive mechanisms underlying the structured thinking approaches. More details on the commonalities between GrC and SA systems can be found in (Loia et al. 2016). Some early approaches of GrC for SA have been successfully proposed in the literature, such as in (Loia et al. 2016; D'Aniello et al. 2017; Gaeta et al. 2021; Fujita et al. 2019).

6 Conclusion

Situation awareness systems support human operators in achieving and maintaining good levels of SA. Fuzzy logic has been extensively used to realize the main functionalities of SA systems. A first systematic review of the literature regarding fuzzy logic approaches for SA is proposed in this article. From an initial screening of over 250 papers from 2010 to 2021, 139 works have been selected according to the PRISMA methodology and included in the final review. The paper provides a comprehensive overview of the main fuzzy formalisms used in SA, highlighting the advantages and drawbacks of each approach. The main research challenges that have been identified relate to limited support to the SA projection phase, which is critical for decision-making, and the increasing complexity of systems and environments which demands for novel hybrid approaches for situation identification that takes into account data streams and evolving situations. The main future research direction that emerged from the analysis is the Granular Computing paradigm that, for its characteristics and principles very similar to the SA model, can represent a unifying framework on which to define the methodologies, models, and techniques based on fuzzy logic for SA.

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