



CONTEXT-ENHANCED INFORMATION FUSION

The concept of *context* has been used in computer science for several decades, with early work dating back to the 1980s. However, the popularity of context-aware computing has significantly increased in recent years due to advances in mobile and ubiquitous computing, the Internet of Things, and the proliferation of data from various sources. The term “context” has been used in various subfields of computer science, including artificial intelligence (AI), human–computer interaction, information retrieval, and data management. The importance of context has been recognized in various application areas, including healthcare, transportation, and smart cities. However, a clear definition is still lacking due to the diversity of applications.

Following the positive response that special sessions on context-enhanced information fusion (IF) have received at the International Conference on Information Fusion, this short paper aims at providing an overview of current research, presenting works covering aspects that include contextual elements in the fusion process. The reader is referred to [1], [2], a survey and collection of works on context-enhanced IF.

DEFINITION OF CONTEXT

Context refers to the circumstances or situation in which something exists or occurs and can affect its meaning, interpretation, or significance. Context can include various factors, such as the physical environment, cultural background, social norms, historical events, prior experiences, and related factors.

In communication, context plays a crucial role in understanding the meaning of a message, as it provides the necessary background information and clues for interpreting the message correctly. For example, the meaning of a word or phrase may change depending on the context in which it is used.

In broader terms, context is also used to describe the overall framework or perspective that shapes how we view and interpret information, events, or situations. Understanding the context of a particular situation can help in making more informed decisions, forming more accurate judgments, and communicating more effectively with others.

Many definitions have been proposed in the literature; here we report the one proposed by Steinberg [3] that highlights the relational nature of context: a *context* is a *situation*. More specifically, if a situation is a set of relationships, then a context c could be understood as the subset of a situation s that can be used to resolve (estimate or infer) a set of random variables X .

THE PROBLEM

Over the past few years, it has become increasingly clear that simply combining data from multiple sources may not be enough

to improve fusion systems’ performance. Even with a potentially large number of sources, unexpected results may occur if the value being estimated, the error characteristics of the sources, and the fusion process itself are not properly contextualized. For example, the state of a target may depend on various factors such as the environment, nearby entities, time of day, and weather conditions. When estimating the position and speed of a car in city traffic, various factors such as the bends and turns of the road, condition of the asphalt, traffic signs, and overall traffic conditions can affect the state of the car.

Generally, context awareness involves considering and using information and knowledge about the environment or current situation surrounding the focal element of interest. However, the understanding and application of context in IF systems are still limited, with domain knowledge being traditionally acquired ad hoc and applied to stovepiped solutions. To improve adaptability and performance, context should play a crucial role at any level of a modern fusion system.

EXAMPLES OF APPLICATIONS

The possibilities of applications for context-based IF are diverse (improved estimation and classification, sensor characterization and management, decision making, situation sense-making, etc.). Some examples of recent applications in different fields are reported in the following. In [4], an example in the domain of electronic combat is used to illustrate context formalization through ontologies. It shows how context can facilitate the representation of entities at different fusion levels to make possible inferencing among levels, with a consistent representation of entities, the states at different levels and relationships. An example in the domain of environment perception for automated vehicles is presented in [5], where accurate detection models are required for safe operation. The authors address the evaluation of false object hypotheses in complex scenarios with high density in order to verify the existence of a tracked object with a probabilistic model, considering the influences of multiple digital map elements on each track’s existence for every track in urban scenarios. In [6], a probabilistic approach is used for forecasting vessel trajectories. Context is exploited through a

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discrete probabilistic model with typical vessel behaviors using dynamic Bayesian networks to predict the speed and orientation of a vessel with a discretized representation of the space. In [7], context-aware data fusion is used in the design of personalized monitoring systems. In this domain, the specific vocabulary, facilities, and events of interest are modeled in order to develop customized monitoring solutions. In [8], an example in the domain of airborne passive localization of stationary ground-based emitters is used, including roadmap-assisted target tracking and integration of terrain map data for target localization. The authors show the integration of contextual knowledge into target tracking algorithms, exploiting the constraints on the target state both in the prediction step and in the measurement update step of a tracking filter. In [9], pretrained word embeddings, typically used for natural language processing, are fused to estimate word concreteness. The authors analyzed how much contextual information can affect final results and how to properly fuse different word embeddings in order to maximize their performance for a word concreteness task. Finally, the example in [10] shows how geographic datasets of roads and buildings can be enhanced with more contextual information by means of automatic processes exploiting available sensors onboard vehicles, like lidar and 360-degree cameras.

FUTURE DIRECTIONS

In the area of AI, building “explainable” solutions has become an emergent research trend, as indicated in surveys like [11]. A fundamental challenge for next-generation AI systems will be the ability to adapt to contextual conditions. In this sense, a “context-aware” system is a paradigm in the AI community where the interaction with users improves significantly when high-level concepts are used by the system to explain outputs, in opposition to black-box solutions. Therefore, it seems reasonable to expect that next waves of AI will put more focus on how to perform inferences, also considering contextual factors and incorporating contextual models over time in the learning process. For instance, the model of “rational rules” [12] combines the inferential power of Bayesian induction with the representational power of mathematical logic and generative grammars for concept generalization. Similarly, Markov logic networks integrate probabilistic models with first-order logic to enable inferences under uncertainty [13]. In both cases, the possibility of using a symbolic representation of the concepts learned allows the system both to generalize and to adapt to specific conditions for each domain.

A fundamental challenge identified in both AI and IF future systems is “understanding” context, the capability to represent and relate how relevant the context is to the inference problems addressed, along with mechanisms to adapt the inference processes to this context. In this parallelism, the challenges include perception, reasoning, and context adaptation toward deploying

AI and IF systems to support knowledge representation and situation understanding. A key objective is the capability to learn interpretable models from contextual data to bind observations with knowledge and use the semantics provided by context. In conclusion, recent developments in research show a convergence in IF and AI systems for situation understanding, where efforts are being made to develop representations and models that allow automatic adaptation to domain conditions.

ACKNOWLEDGMENT

J. García was partially supported by the Spanish Ministry of Science and Innovation in projects PID2020-118249RB-C22, PDC2021-121567-C22 and TED2021-131520B-C22.

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