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A Review and Proposal for Developing of Data Fusion Models and Frameworks for Decision Making Systems

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Abstract

An adequate decision making is heavily dependent on data fusion processes. The only way a decision making agent can infer a decision which is adequate to the current state of an environment is through gaining a situation awareness regarding relevant aspects of it which is achieved through data, information, and knowledge fusion. The following paper covers some of the latest proposals for frameworks and architectural approaches to building fusion-based decision making systems, both formal and conceptual. The article also proposes a new architectural approach to building more extensible fuison-based systems through adding an explicit prediction block. The motivation for that architectural solution was the blistering pace of learning-based prediction systems development witnessed by scientific and engineering communities during the last decade which brought us a plethora of well-established methods and methodologies.

Keywords: Decision Making, Data Fusion, System Architecture, Formal Data Fusion Models, Conceptual Data Fusion Models

1. Introduction

In order to tackle a situation adequately, situation awareness (SA) decision-making systems rely upon data and information acquired from sensors, knowledge bases, databases, and experts. However, no matter how many sources of information are used, there exists an issue of integration and interpretation of those pieces of information, and more importantly a problem of inferring an adequate representation of the state of an environment in a broad sense, i.e. gaining a situation awareness through information fusion.

Information fusion in computer systems is traditionally seen as multilevel process where lower levels are characterized by higher degree of detailing. The higher the level of fusion, the higher the extent of abstraction. JDL data fusion model (Figure 1) is often used as the architectural reference for describing fusion models, although it is rarely used for practical purposes now due to its age (it has been developed in mid 80s). In order to follow the well-established pratice, this article refers to it as well.

It is not an easy task to classify data fusion models (Sokolov et al., 2017) since they cover topics of an incomprehensible scale. However, there exists an option to do so on the basis of how those models are represented. Steinberg et al. (1999) propose a simple classification of data fusion models (figure 2) which essentially divides data fusion models into 2 categories by the degree of formalization they are described with.

As for sensor fusion which lower level fusion processes often rely upon, academia has to offer numerous algorithms (Fridman and Kurbanov, 2016) and generic approaches capable of very precise estimation such as Kalman or Alpha Beta filters. But when it comes to higher levels of fusion, building of those kinds of sys-

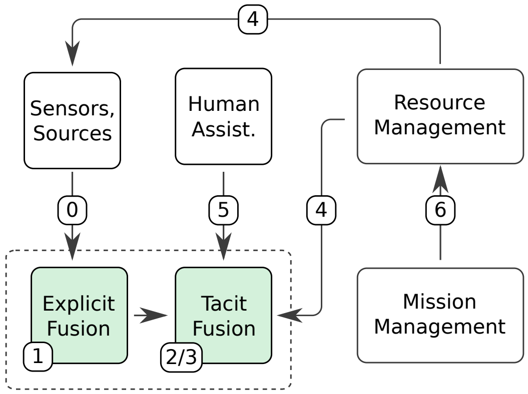

Figure 1. JDL model describing 7 levels of data fusion: 0. Source Preprocessing, 1. Object assignment, 2. Situation Assessment, 3. Impact Assessment, 4. Process Refinement, 5. User Refinement, 6. Mission Refinement

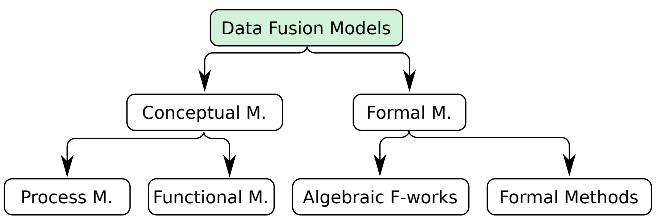

Figure 2. Classification of Data Fusion models according to (Steinberg et al., 1999)

tems is often a matter of human ingenuity mixed with a fair share of interdisciplinary research.

This article presents a review of approaches to building higher level (JDL-3 or higher) data fusion systems capable of gaining situation awareness. Those approaches are either complete architectures of such systems, data fusion models, or cover significant parts of those.

We also offer a proposition of our own which is a modification of one of conceptual architectural approaches to building data fusion system with prediction capabilities.

2. Formal models

Jousselme and Maupin (2007) propose a *formal* agent-based state model for situation analysis named *interpreted system* covering levels 2 and 3 of JDL model. The proposed framework for *interpreted system* $F_{\mathcal{I}}$ can be represented as a tuple:

$$Fs_{\mathcal{I}} = \left\langle \mathcal{A}, L_i, S, \mathcal{R}, ACT_i, P_i, P, \gamma, \Phi, \mathcal{L}(\Phi), \pi(\mathcal{L}(\Phi)) \right\rangle, \quad (1)$$

- where $\mathcal{A} = \{1, 2, \ldots, n, e\}$ is a set of *agents* including special agent e representing environment,
- L_i is a set of *local states* encapsulating information about *agent* i,
- S is a set of *global states* defined by all agents' local states,
- $\mathcal{R}$ is a *system* defined as a set of *runs*, where *run* r is a function from *time* m, sequence of global states $s^1, s^2, \ldots$ describing change of an entire system,

$$\mathcal{R} = \{(r, m)\}$$

- ACT_i is a set of *actions* defined for *agent* i,
- P_i is a *protocol* defined for each *agent* i mapping its *local states* L_i to *actions* ACT_i,
- P is a set of all protocols named *joint protocol*,
- $\gamma = \langle P_e, S_0, \tau, \Psi \rangle$ is a context where
  - P_e is a protocol for the *environment* e,
  - S_0 is an initial state of the system
  - τ is a *transition function*

$$\tau : S \times P \to S$$

  - Ψ is an *admissibility condition*, a "filter" excluding inadmissible runs r.
- Φ is a set of *facts* about the system,
- $\mathcal{L}(\Phi)$ is a *language* based on propositional logic defined for *facts* $\{\Phi\}$
- $\pi(\mathcal{L}(\Phi))$ is an interpretation of *facts* about the system

In terms of the framework, the *interpreted system* $\mathcal{I}$ is represented as a pair $\mathcal{I} = \langle \mathcal{R}, \pi \rangle$, i.e. interpreted system is a combination of a *system* over *global states* S and an interpretation of the system. The analysis of a situation is performed through analysis of a graph-like structure of *agents'* trajectories produced by running their protocols.

The proposed framework may be considered quite generic since it incorporates a set of models which are quite common to complex systems: use of agent model, integration of the state abstraction, etc.

In the realm of formal models, there also exist another approaches, one of which was described by Mykich and Burov (2016). The paper proposes a new unifying algebraic framework for situation awareness modeling which enables incorporation of other methods of SA-modeling within it.

The framework rests upon formal metalanguage called *Algebra of Systems (AoS)* (Koo et al., 2009), although transforms it rather substantially. In comparison with the original AoS, the new framework retains its *domain of properties* (renamed to *attributes domain*) and *boolean domain* while omitting *composition domain*, and also extends it with new entities. Considering changes, the framework comprises the following entities:

- $A = \{A_1, \ldots, A_n\}$ – facts ,
- $E = \{E_i = (Name, A_i, EOP)\}$ – concepts, an abstract data type. EOP represents a set of basic set operations,

- $At = \{(key, value)\}$ – domain of *attributes*. Equivalent to AoS' *properties domain*
- $Cs = \{(TRUE, FALSE)\}$ – boolean domain. Equivalent to one of AoS,
- $T = \{T_i = (E_i, At_i, Cs_i)\}$ – domain of concepts with attributes. An itermediate entity. Both this and
- *domain of relations*,
- *ontology* (On):

$$On = (T, Rl, Cs)$$

Unlike *interpreted systems* which rely on state model, this framework does not imply mathematical structure of any kind, although permits use of graph-like structures by including a concept of relations.

The idea behind the new framework is that it provides a comprehensive set of low-level facilities which serve as some sort of "common language". This feature enables one to use different methods within single "platform", and most likely reap benefits of synergy emerging from that.

3. Conceptual models

According to the model of knowledge creation proposed by Nonaka et al. (2000), conversion of knowledge comprises 4 stages which the knowledge is being morphed through. Those transformations are related to transition of tacit (implicit) knowledge to explicit one, and vice-versa. Despite the fact that this model primarily concerns human-oriented administrative processes, there are applications of the model for designing decision-support and decision-making systems (Chikh, 2011; Yang et al., 2018).

Decision-making systems operating upon awareness about environment and current situation require relevant domain knowledge, which is often stored in a knowledge base. However, this kind of knowledge is of explicit kind, whereas according to Nakanishi and Black (2018) both explicit and implicit kinds of knowledge may appear vital parts of decision making, especially with regard to situation awareness, which implies ad-hoc decision making taking all (or most) of the situation aspects into account.

To address this problem, Yusof et al. (2016) proposed an approach considering integration of (Endsley, 1995) Endsley's Situation Awareness (SA) Decision Making model into Nonaka's model of knowledge conversion (otherwise known as SECI model). As shown in figure 3, this is achieved through inclusion of SA-related part of Endsley's model into Nonaka's model as an intermediate phase between Combination and Internalization stages.

Usage of the model as the architectural underpinning of a decision-support (decision making) system possesses some valuable qualities. The SA-related phase of the new model may extend a system with filtering

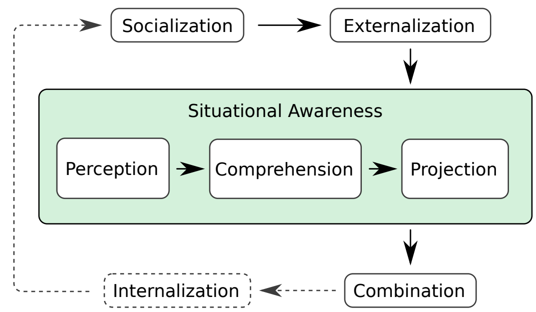

Figure 3. Incorporation of SA-related part of Endsley model into SECI knowledge creation framework. The process of internalization is drawn with dotted line denoting optionality, as digital systems do not necessarily imply a presence of *human* $\rightarrow$ *machine* $\rightarrow$ *human* loop

and interpretative capabilities, meaning that domain knowledge will be construed with regard to a current situation's context, and only relevant pieces of domain knowledge will be selected for decision inferring.

Along with the issue of SA acquision, there exist a problem of SA assessment which possesses harsh challenges due to lack of any quantitative features of situation awareness. Mitaritonna et al. (2019) propose a descriptive approach of multidimentional scaled assessment of the degree of agent's SA called 3D-SAM model. The approach is based on incorporation of different models enabling one to assess agent's SA along the following dimensions:

- SA stage;
- Workspace awareness;
- Modality.

Ensley's SA model (Endsley, 1995) enables determination of a stage an agent operates at, namely:

- Perception,
- Comprehension,
- Projection.

Modality dimension comprises physical aspects of environment comprehension:

- Visual,
- Audial,
- Haptic.

Gutwin and Greenberg's model (Gutwin and Greenberg, 2002) describes agent's awareness of workspace. Among all the components it takes into consideration, there are mutual relations of agents, purpose of their actions, and spatial features of a workspace. The complete list is shown in table 1.

Despite the fact that the proposed approach still lacks the capacity to provide a researcher with an exact numerical expression of situation awareness, there still exist possibilities to incorporate those multidi-

Table 1. Elements of workspace awareness according to Gutwin and Greenberg (2002)

Category	Element	Comment (question)
Who	Presence	Who is present?
	Identity	Who is participating?
	Authorship	Who is doing what?
What	Action	What is an agent doing?
	Intention	What is the goal of an agent?
	Artifact	What is the object of agent's work?
Where	Location	Where is agent working?
	Gaze	What is agent observing?
	View	What is agent able to observe?
	Reach	Where can agent reach?

mentional assessments into quantitative models. This can be achieved through use of mathematical model of preferences and related works.

Use of automated data-driven models implies use of multiple data sources along with processing of data acquired from those sources. This in turn inevitably leads to numerous challenges related to processing, managing, filtering, and integration of data into processes. In distributed automatic or automated systems, those challenges transform into even more daunting task, since additional integration issues between system's entities should be taken into account as well. Therefore, a model envisaging presence of constantly changing computational and business processes, human operators, decision makers, multiple sources of data while also enabling alignment of data and information with organizational processes is required.

Classical models covered here do not cover those issues in their entirety. E.g. JDL model considering data fusion on its intermediate levels does imply human-performed data fusion rather than the one performed by a machine. As for Endsley model, it doesn't encompass details of data processing, and neither does it elaborate on details of decision-making process.

Dynamic Node Network (DNN) fusion architecture proposed by Bowman (2004) addresses some of these problems (figure 4). It consists of 2 large entities performing tasks of resource management (planning) and data fusion. Although 2 nodes operate in parallel, they are provided with means of communication enabling them to adjust their mutual and individual objectives.

Figure 4 does not highlight mapping between DNN and JDL models explicitly. However, it is acceptable to consider sub-nodes of Data Fusion node a replacement for levels 0 through 4 of JDL model, since they carry similar functions. The same is true for Resource Management node, although it should be viewed as an auxillary entity backing tasks performed by Data Fusion node.

DNN is a solid framework covering fair share of processes described by JDL, and it also does not rely on presence of a human in computational chain, which is no less important. But it regards the decision making stage (JDL, level 3) as the one of external origin, rather than viewing it as an encapsulated part of the model. Sliva et al. (2015) propose a new DNN-based model that tightly integrates decision making process and parts of DNN within one robust model named Dual Node Decision Wheels (DNDW) model (figure 5).

The core of the model retains most of DNN's features including connections between Data Fusion and Resource Management nodes. DNDW extends DNN with decision-making component named Mission Planning. The cyclicity of the decision-making process enriches it with a possibility of continuous adjustment as a reaction to the constant flow of additional information.

DNDW envisages presence of human operators performing intervention when needed (including intervention in lower levels of information fusion), although it does not exclude possibility of their partial or complete substitution with automatic decision making systems. This kind of extensibility is especially helpful for systems with long life cycle, such as electric grid control facilities and other critical objects of civil or military infrastructure, because it enables them to be modified with the latest technical equipment on a rolling basis while preserving the architectural structure.

Along with comprehensive set of data fusion capabilities, DNDW delineates responsibilities between sub-nodes rather strictly. In practice, it implies that separate nodes become less dependent on each other since they carry out completely different (yet complementary) tasks. Decoupling leads to more sustainable modular architecture enabling employment of service-oriented approaches.

4. Domain-specific models and practical applications

Another issue arising from data / information fusion processes is quality of data. Depending on an environment and used data / information sources, SA decision making system may have adequate and clear information as well as rather noisy unreliable one. The last is especially the case when the system uses human-generated data as an input, e.g. social network posts. Information acquired from that kind of environment may be inadequate in multiple dimensions, since it is often produced in an indolent manner without having any long-term purposes. However, sometimes this is the only information a system has at its disposal, therefore, quality assessment is required for such cases.

To address the problem of low information quality, Botega et al. (2017) presented a new situation awareness quality-aware ontology-based fusion model called Quantify (*Quality-aware Human-Driven Information Fu-*

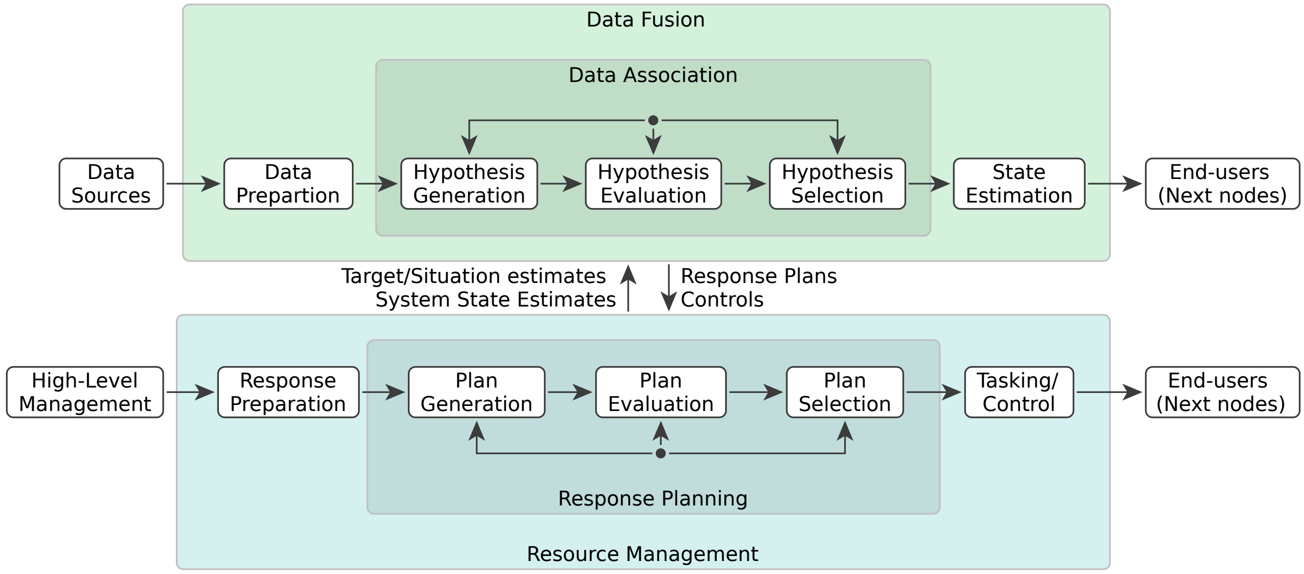

Figure 4. DNN model architecture

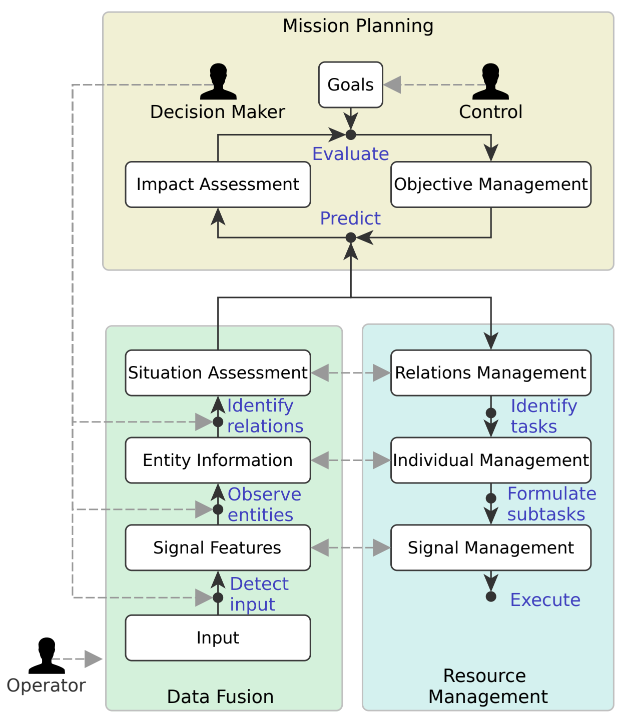

Figure 5. Architectural scheme of DNDW model

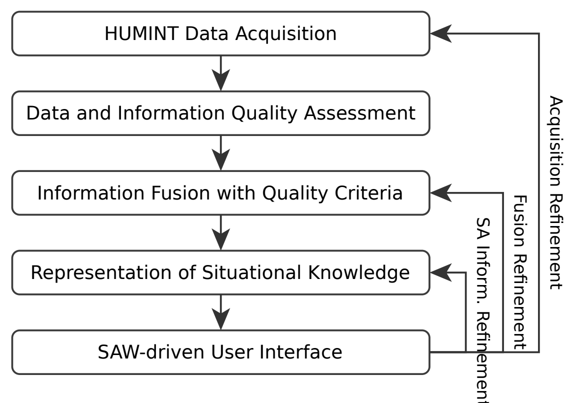

Figure 6. Architecture of *Quantify* model

sion Model, Figure 6).

As the name implies, the main idea behind the new architecture is that information / data fusion process is enriched with quality control and management processes. The base component of the system is the module performing acquisition of the information and data produced by human intelligence (in short: HUMINT). The data acquired on that stage then gets passed through stages covering levels 1 through 3 of JDL model.

HUMINT data acquisition stage carries data gathering and preprocessing of data, namely:

- cleansing;
- pre-classification;
- transformation for getting processed on further stages.

This stage implies use of ML-based techniques for performing data filtering and information extraction such as NLP.

The goal of the next stage, *Data and Information Quality Assessment*, is to assign quantifiable metrics to distinct features of gathered data and information. Timeliness, completeness, consistency, and relevance may be among them. No limitations were imposed on kinds of processess and models used here.

Information Fusion with Quality Criteria stage is oriented toward update of an existing ontology. It comprises 2 sub-stages:

- search of synergistic information;
- multicriteria association.

On the 1st sub-stage, a *preliminary ontology* is created. This ontology represents newly-gathered data and information and is used for extraction of new information from it. The extracted information is then gets decorated with attributes, properties, and quality measures which are produced with regard to the existing ontology.

The 2nd sub-stage gets the information through the process of its incorporation into the existing ontology. Pieces of information that meet a required threshold get fused into the exsiting ontology thus modifying it.

This 2-stage process updates situation awareness on one hand, and restrains the existing information from being displaced with the new one on the other.

Representation of Sutiational Knowledge stage concentrates on post-processing of the updated ontology. Its main purpose is to infer semantics from exsiting information.

The last stage called *SA(W)-driven User Interface* is a human-computer interface. Its aim is to construct a comprehensive representation of the existing ontology in a comprenesive manner, and also provide mechanisms enabling a user to interfere in earlier stages of information fusion and make necessary adjustments. Although there is no clear definition establishing features of the interface, Botega et. al. claim that the workflow occuring within boundaries of the interface shall adhere to Endsley's SA-developing principles.

As for more specific architectural propositions, Muccini and Sharaf (2017) offer a new conceptual model named CAPS, which comprises 3 modelling languages, plus one "binding" language used for establishing semantic connections between created models. The new approach primarily concerns non-distributed cyber-physical systems (CPS) operating within static environments such as smart homes and mid-size production sites.

The model is based on the idea of division of a complex CPS into 3 groups:

- Software Entites,
- Hardware Entities,
- Physical Environment,

each of which abstracts out basic kinds of CPS entities affiliated with it. Complete list of entities is represented by table 2.

The proposed approach enables to achieve SA through fusion of both data received from sensors and knowledge about physical (especially spatial) configuration of the environment.

Table 2. Entities of CAPS modeling language

Software Entities	
Component	Separate program entity
Data	Piece of data possessed by *Component*
Mode	Intrinsic state of a *Component*
Messages	Pieces of data transferred btw. *Components*
Events	Some events, intrinsic to software *Components*
Actions	Some actions components take
Conditions	Behavioral element implementing branched evaluation
Hardware Entities	
Computational Resources	Microcontrollers
Memory	In-chip storage facilities
Energy	Batteries, AC/DC sources, etc.
Sensors	Sensing systems, such as barometers, magnetometers, etc.
Actuators	Subsystems performing some physical actions, primarily mechanical ones
Physical Entities	
Area	Physical area
Artifact	Artifact contained within Area
Coorinates	Coordinates of Area or Artifact

Another practical application is described by Mitaritonna et al. (2019) reviewed in section 3. The paper proposes a prototype implementation of a military augmented reality system called RAIOM. The proposed prototype utilizes 3D-SAM SA assessment approach for configuration of a VR system's user interface (UI). The system assesses user's SA stage, modality of a request, type of workspace awareness, and produces a relevant response presented in a form of contextually-adjusted UI.

5. An architecture of a replicable fusion system with prediction capabilities

Another challenge decision making (support) systems face is prediction. The entire decision making process is aimed at achieving the best result using information a decision making agent/system has in its possession, which involves making an assumption on how a situation would develop. Despite the fact that almost every one of the aforementioned models highlights presence of prediction processes of some sort, none of them proffered an implementation of a dedicated forecast sub-system. Sokolov et al. (2015a) proposed a gen-

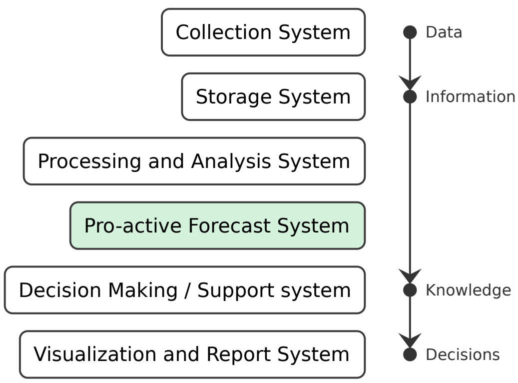

Figure 7. Architecture of a System for Complex Objects Proactive Monitoring and Control

eralized 6-level architecture of a system for complex objects proactive monitoring and control (Figure 7) that envisages that kind of functionality, and has a number of successful practical implementations (Avtamonov et al., 2017; Okhtilev et al., 2020).

The proposed model was a high-level "blueprint" of physical manifestations of 2 applied theories: Theory of Complex Objects Life-cycle Proactive Control (Sokolov et al., 2015b), and Theory of Multicritera Estimation and Situational Choice of Models and Multimodel Complexes (Sokolov et al., 2018). As a result, it is primarily focused on problems of control and multimodel complexes management what is self-evident from the description of the model below. However, its generic structure and approach impose no limitations on subject area or mathematical apparatus whatsoever.

The basic level of the model called *Collection System* gathers data across different sources such as sensors and sub-system events. It also offers basic data cleansing capabilities.

Storage System, as the name implies, stores data, information, knowledge, sorts data, and performs data structures optimization.

Processing and Analysis System performs search, data analysis, complex modelling, parametrical and structural model adaptation, and synthesizes methods and algorithms for automatic data analysis.

Pro-active Forecast System assists a decision making agent with envisaging of all possible outcomes of a current situation. It analyses information on current state of a system, performs factor analysis aimed at eduction of entities making the highest contribution to situation development, and adapts models in a way that enables them to represent a dynamically changing situation adequately.

Decision Making / Support System is a subsystem that infers a suitable solution from a given set of objectives, constraints, and forecasts, and provides a decision making agent with a set of possible solutions and

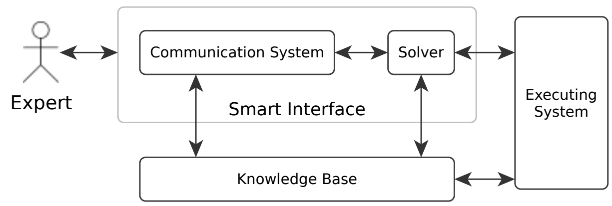

Figure 8. General architecture of the system

explainations for them.

The last system called *Visualization and Report System* is aimed at human-computer interaction. Its purpose is to represent results of system's work in a human-readable way, what is achieved through use of visualization techniques, interactive user interfaces, spatial visualization, etc.

Undoubtedly, a system with predictive capabilities will have an upper hand in every possible situation. Considering latest advancements in the realm of data analysis and adjacent areas, it would be a practical solution to create a dedicated prediction sub-system.

A huge progress notwithstanding, each and every case is unique since it exists within its own subject area and decorated with all kinds of particularities. Therefore, the one who needs to solve a practical problem has a meager supply of options which, in essence, are limited to coding or hiring a coder with solid knowledge of a cutting edge field, neither of which is cost- or time-effective.

The encouraging part of that bleaky picture is that, on lower level, most of data-processing algorithms operate on similar data structures. At least, those can be categorized with a classification of a reasonable scale. Therefore, data processing algorithms have a potential to be parameterized and repurposed. This enables an access to replicability which, in turn, reduces complexity thus decreasing cost. Based on this premise, we propose an architectural approach to building replicable data fusion systems for decision making with prediction capabilities which elaborates on aforementioned 6-level generalized architectural approach.

On a higher (although less abstract) level, the architecture defines 3 components, namely *Knowledge Base*, *Smart Interface*, and *Executing System* (Figure 8), which are, in essence, in accordance with the structure of an expert system (ES). However, since the model envisages use of prediction facilities, its *Smart Interface* (Figure 9) differs from that of a stereotypical ES.

To provide flexibility, we propose to divide data into 2 categories: measured data and calculated one, for each of which *Smart Interface* envisages a dedicated storage. Those storage facilities preserve history of a controlled system. In practical context, those facilities are supposed to contain sensor data and its "derivatives".

State Assessment and Control Synthesis is the sub-

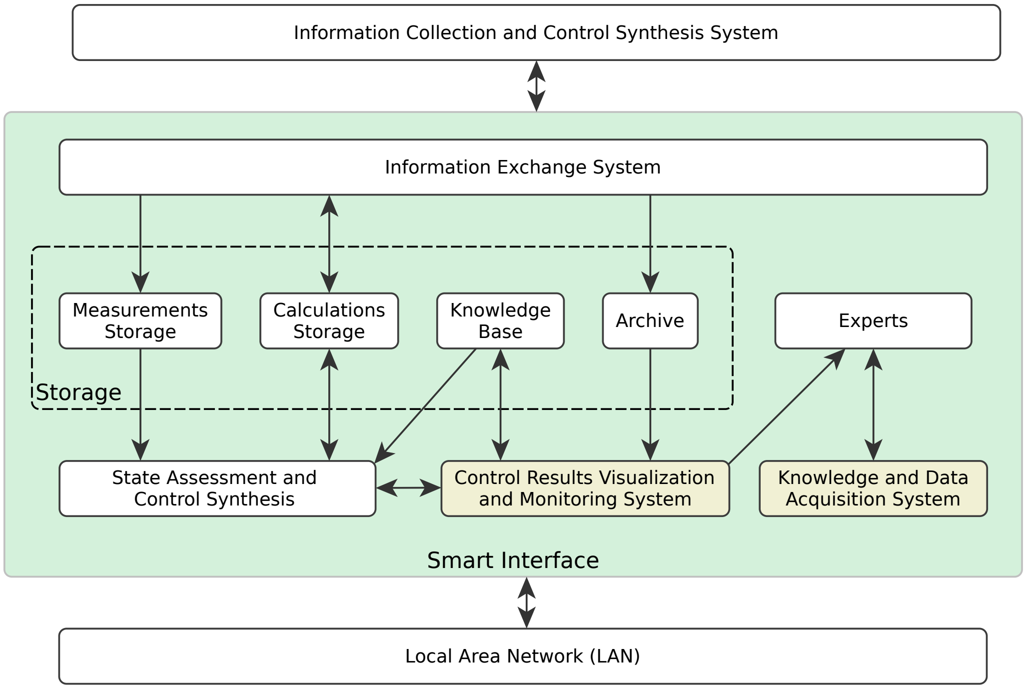

Figure 9. Architecture of Smart Interface

module that performs lower-level fusion. We envisage the possiblitiy that the module performs fusion of higher levels, so we added a connection with *Knowledge Base*, although this feature is rather optional.

Since every system has its own unique artifacts, we offer a separate storage called *Archive* which is intended to store service information.

The key element of the architecture is *Knowledge and Data Acquisition system*. It not only serves as an interface for *Knowledge Base*, but also as a "programming" tool enabling an expert to create a tailored environment which fulfills particular needs. The complete list of the submodule's capabilities reads as follows:

- Designing of databases,
- Designing of UI,
- Knowledge Management,
- Programming.

The term "programming" is used in its figurative meaning. It means use of logical description of the real-world object controlled and observed by the system in terms of a particular subject area. This approach involves visual programming, constraint satisfaction, custom combination of predefined algorithms, and other techniques made to encapsulate all the programming-related complexity and provide experts with a unified toolset, which they will be able to use across various application cases, and which enable maintenance of the created system without being relied on programmers.

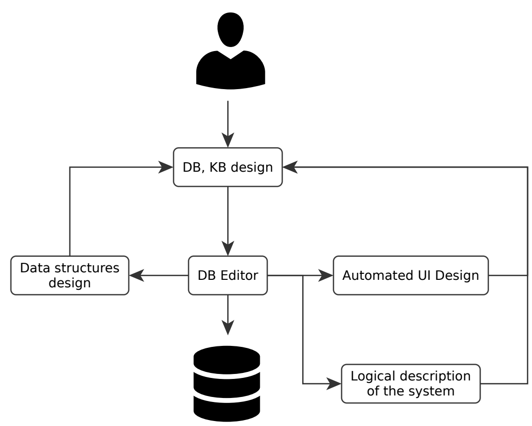

Figure 10. Workflow of an expert

The workflow of an expert (Figure 10) implies the following stages: design of data and knowledge bases, creation of UI, description of subject area. If necessary, the user may step a few stages back and adjust configuration when needed. A designed and configured system would then be immediately deployed.

6. Conclusions

This article presents a review of some high level data fusion models covering different aspects of decision making based on situational awareness. The reviewed models differ in scale, level of detailing, genericity, and formality.

The article also proposes a modification of the 6-level architecture of data fusion system for decision making with prediction capabilities. The core architectural element of the proposed system is the configuration/design system enabling seamless implementation, deployment, and maintenance of cost-effective solutions. The idea behind the approach is similarity of data structures which data processing algorithms work with. That kind of similaty enable replicability, so it becomes possible to create a system with a broad set of repurposable algorithms.

Among the directions of further research, we reckon that formalization of our and other approaches would be of a great value. Graphical representation is very convenient it conveys the core idea very clearly, and, considering the engineering and architectural experience being in place, an expert could construe them unambiguously. However, there is not much one could infer from representations of that kind, because visual tools lack the capability of providing necessary means for formal development of the idea. So we believe that development of proper mathematical apparatus would be extremely useful.

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References

Avtamonov, P., Bakhmut, A., Krylov, A., Okhtilev, M., Okhtilev, P., and Sokolov, B. (2017). Application of decision support technology at various stages of the life cycle of space facilities in assembly with the information system of technical condition and reliability. *VESTNIK of Samara University. Aerospace and Mechanical Engineering*, 16:173.

Botega, L. C., Valdir, A. P., Oliveira, A. C. M., Saran, J. F., Villas, L. A., and de Araújo, R. B. (2017). Quality-aware human-driven information fusion model. In *2017 20th International Conference on Information Fusion (Fusion)*, pages 1–10.

Bowman, C. (2004). A descriptive framework of workspace awareness for real-time groupware. *AIAA Intelligent Systems Conference*.

Chikh, A. (2011). A knowledge management framework in software requirements engineering based on the seci model. *Journal of Software Engineering and Applications*, 04.

Endsley, M. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 37:32–64.

Fridman, A. J. and Kurbanov, V. G. (2016). Information technology to integrate spatial data into the situational modelling system. In Yusupov, R. M., editor, *SPIIRAS Proceedings*.

Gutwin, C. and Greenberg, S. (2002). A descriptive framework of workspace awareness for real-time groupware. *Computer Supported Cooperative Work (CSCW)*, 11:411–.

Jousselme, A.-L. and Maupin, P. (2007). Interpreted systems for situation analysis. *FUSION 2007 - 2007 10th International Conference on Information Fusion*, pages 1 – 11.

Koo, B. H. Y., Simmons, W. L., and Crawley, E. F. (2009). Algebra of systems: A metalanguage for model synthesis and evaluation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 39(3):501–513.

Mitaritonna, A., Abasolo, M. J., and Montero, F. (2019). Situational awareness through augmented reality: 3d-sa model to relate requirements, design and evaluation. In *2019 International Conference on Virtual Reality and Visualization (ICVRV)*, pages 227–232.

Muccini, H. and Sharaf, M. (2017). Caps: Architecture description of situational aware cyber physical systems. In *2017 IEEE International Conference on Software Architecture (ICSA)*, pages 211–220.

Mykich, K. and Burov, Y. (2016). Algebraic model for knowledge representation in situational awareness systems. *2016 XIth International Scientific and Technical Conference Computer Sciences and Information Technologies (CSIT)*, pages 165–167.

Nakanishi, H. and Black, J. (2018). Implicit and explicit knowledge in flood evacuations with a case study of takamatsu, japan. *International Journal of Disaster Risk Reduction*, 28:788–797.

Nonaka, I., Toyama, R., and Konno, N. (2000). SECI, ba and leadership: A unified model of dynamic knowledge creation. *Long Range Planning*, 33:5–34.

Okhtilev, M., Klyucharyov, A., Okhtilev, P., and Zyanchurin, A. (2020). Technology of automated information and analytical support of the product life cycle on the example of unified virtual electronic passport of space facilities. *Izvestiâ vysših učebnyh zavedenij. Priborostroenie*, 63:1012–1019.

Sliva, A., Gorman, J., Bowman, C., and Voshell, M. (2015). Dual node decision wheels: an architecture for interconnected information fusion and decision making. page 94640F.

Sokolov, B., Ohtilev, M., and Yusupov, R. (2015a). Teoreticheskie i technologicheskie osnovy konceptsii proactivnogo monitoringa i upravleniya slozhnymi ob'ektami. In *Izvestiya SFedU. Engineering Sciences*, pages 162–174.

Sokolov, B., Pavlov, A., Yusupov, R., Ohtilev, M., and Potryasaev, S. (2015b). Theoretical and technological foundations of complex objects proactive monitoring, management and control. In *Automated Systems and Technologies*, pages 103–110.

Sokolov, B., Sobolevsky, V., Mikoni, S., Zakharov, V., and Rostova, E. (2018). Quality evaluation of models and polymodel complexes: Subject-object approach. pages 305–310.

Sokolov, B., Ziuban, A., Pimanov, E., Ivanov, D., Micony, S., and Burakov, V. (2017). Theory and practice of information fusion models' quality estimation and models' quality control. In Affenzeller, Bruzzone, Jiménez, Longo, and Piera, editors, *Proceedings of the European Modeling and Simulation Symposium, 2017*.

Steinberg, A. N., Bowman, C. L., and White, F. E. (1999). Revisions to the JDL data fusion model. In Dasarathy, B. V., editor, *Sensor Fusion: Architectures, Algorithms, and Applications III*, volume 3719, pages 430 – 441. International Society for Optics and Photonics, SPIE.

Yang, S., Liu, Y., and Liang, M. (2018). Teachers' personal knowledge management tools and application strategies exploration based on the seci model. In *2018 International Joint Conference on Information, Media and Engineering (ICIME)*, pages 341–346.

Yusof, W. S. E. Y. W., Zakaria, O., and Zainol, Z. (2016). Establishing of knowledge based framework for situational awareness using nonaka's and endsley's models. In *2016 International Conference on Information and Communication Technology (ICICTM)*, pages 47–50.