Data and knowledge manangement in field studies
A case for semantic technologies *

Hans Georg Schaathun †‡ Que Tran† Mikael Tollefsen†
Etienne Gernez §

Abstract

Ship design is a knowledge-intensive industry. To design safe ship systems for demanding operations, there is an increasing need for comprehensive knowledge of the operational context. Field studies is an important source of relevant knowledge, but current methods and information systems do not realise their full potential. In this paper, we discuss how the field data can be modelled semantically, integrated with relevant domain models, and be more effectively made available to the organisation. We propose a data model and a software architecture to facilitate the collaborative data analysis and modelling process favoured by designers.

1 Introduction

Field studies is an effective, and well-established method in industrial design. In the maritime industry, the interest in field-studies is spreading to other disciplines, including engineering, business analysis, and strategic decision making. These field studies are expensive to undertake, and they produce massive amounts of multi-modal and heterogenous data. In current practice, field studies are commissioned as part of specific design projects, and the data are analysed with respect to current needs. The result is a report which addresses the current project, but which has very limited transfer value.

The current, manual process of managing field data is not satisfactory. Users report a need for new tools, to organise and share field data and insights therefrom, both during the analysis immediately after the study, and long-term. Ship design is an inter-disciplinary exercise, so the data must be related not just to one, but to many application domains, and they must be interpreted in light of available domain knowledge. The field researcher cannot possibly cover all the domains involved. Hence, a knowledge management system should integrate the field data with existing domain models. An efficient information system could both cut costs and increase the benefits of field study.

We have analysed current field study processes in maritime design as it is used among our collaborators and reviewed the nature of the data involved. We propose a data model and a software architecture to improve the analysis and presentation of the results. A

*The work is funded by the Norwegian Research Council (grant no. 244235), DNV GL, Ulstein International AS, and Pon Power Scandinavia.

†Corresponding author ⟨georg@schaathun.net⟩

‡NTNU, Noregs Teknisk-Naturvitskaplege Universitet; Inst. IKT og Realfag, PB 1517; N-6025 Ålesund

§AHO, Arkitektur- og Designhøgskolen i Oslo, PB 6768 St. Olavs plass, N-0130 Oslo

This paper was presented at the NIK-2017 conference; see `http://www.nik.no/`.

key feature of the proposal is the use of ontologies to link the data to existing and novel domain models, including ship models, task models, and organisational models. This is important to facilitate semantic search in the data. The proposal is designed to improve the cost/benefit ratio of field studies in three ways. Firstly, facilitating analysis and reporting will cut costs. Secondly, we can integrate data from multiple field studies to facilitate a more reliable analysis. Thirdly, we can provide long-term access to the original data, giving designers and engineers access to more information than what they can get with current reporting techniques.

2 Methodology

This paper is the result of an inter-disciplinary and participatory method. The project team, including both designers and computer scientists, has worked simultaneously on analysis of field data, methodology for field studies, data models for field data, and software tools. Thus insights from one area have contributed to progress in others. The methodology is based on *cooperative inquiry* [10], and the main principles are common for many methodologies in design and other human sciences.

We have used an iterative research process, where development phases are interleaved with workshops. In the development phases, the team members work individually or in smaller, single-discipline teams, to explore a problem, draft solutions, and develop prototypes (incl. domain models, interface mockups, and executable software demos). The workshops are used to review, reflect on, and evaluate the output of the preceding cycle, and to prioritise research questions for the next cycle. The interdisciplinary participation ensures a broad perspective in the workshop.

Co-operative inquiry is not aiming for objectivity in the strictest sense, and indeed Heron argues that the world is *subjective-objective*. In our context, we take that to mean that the realitity which we study depends both on systems, such as the ships, governed by physical laws which can be objectively stated, and also a human factor with subjective elements for which objective statements fall short. Reliability of the results in ensured by a certain *intersubjectivity*, where we converge to models which are compatible with each of the subjective realities perceived by the different team members.

3 Background

The maritime sector is an important part of European economy. Increasing subsea and offshore activity make *demanding marine operations* a hot topic, and safety is a critical challenge. According to Rothblum [22] 75–90% of accidents are wholly or partly due to human error, and very often, suboptimal user interface design contributes to the human errors. Lurås *et al.* [17] cite a number of studies confirming that current design of ship technology does not support the mariners in a satisfactory manner. The traditional assumption has been the expert crew do not need user-friendly systems. This assumption is being challenged, and Norwegian maritime industry has seen an increasing use of designers to work on the man-machine interaction in ship development [17].

Field Studies

User-centricity is a buzz word in many disciplines. The user and user needs have often been forgotten in the design of new products, but there is an increasing awareness that this is not acceptable. Designers have sometimes been critised for not listening to users, but the problem may just as well be that the necessary information is not available [1]. Very often designers rely on secondary sources to understand the work context and the user needs [17]. Field studies are critical to understanding the context of work and use [16].

Arnold [1] defines field studies as «activities during the product development process where the designer gathers information about the user while in the user's environment». Building on methods from ethnography and social science, the use of field studies in design has been increasing over many decades, reflecting a shift from the largely artistic 'old' design, to a more research-driven 'new' design [1]. Even so, there are distinct differences in the objectives between design and science, and different standards may guide the management and analysis of data.

Lurås and Nordby [16] identify three objectives for field studies.

1. *Experience life at sea* refers to the first-hand experience of being submerged in the context of the user.
2. *Design reflection* refers to the designer reflecting on designs while being in the user's context.
3. *Data mapping* is the collecting and recording of specific data needed by the designers.

The tacit knowledge from the first objective is often seen as the primary outcome of field studies, but invested in the individual field researcher, the long-term value to the organisation is limited. The knowledge from design reflection and data mapping are to a larger extent propositional, and could, with adequate tools, be transferred to the organisation to leverage long-term value.

Knowledge Management

Ship design is a knowledge-intensive industry. It is the knowledge possessed by a firm's engineers which gives competitive advantage [25]. Methods to facilitate the sharing, distribution, creation, obtaining and understanding of a firm's knowledge is known as *knowledge management* [25], which has existed as a field of study for more than 30 years [8]. Knowledge comprises, in addtion to data and items of information, also the relationships between information, their classification, and their metadata [23]. Effective knowledge management is well illustrated in the words of General Electric engineer Andy McKeran [11].

> *«One of the big benefits of working here is that someone in some other part of the company may have already solved your problem. We call it the GE store, except that you don't have to buy the solution, you get it free.»*

A good example of a knowledge management system to support a design process in chemical process engineering, can be found in Brandt *et al.* [3]. Where traditional Data Warehousing organises fixedly structured data, they use a flexible ontology to be able to integrate knowledge from a large number of different sources and tools. They note a conflict between scalability and full logic expressiveness, and chose a trade-off prioritising scalability.

Ontologies

Ontologies is a common tool in the design of knowledge management systems. The term comes from philosophy, where it includes the study of the basic categories of being and their relations. In computer science, Studer [26] defined an ontology as *a formal, explicit specification of a shared conceptualization*. The underlying conceptualisation is a model of the world, describing the things and the relations studied in the application domain(s).

A formal and explicit specification of the conceptualisation makes a *computational* model of the world.

Ontologies have a key role in the integration of data from heterogenous sources [26]. Many projects have focused on syntactical integration of different systems. Ontologies support seamless connectivity at a semantic level [29]. They can be applied to different aspects of the systems, giving rise to of different kinds of ontologies [26]. In our project, we make use of the following three. Domain ontologies represent shared knowledge of the domain experts, and it needs to shared with other systems used within the domain. Generic ontologies are valid across domains and designed for reuse, examples include FOAF (friend of a friend) which model people and their relationships, and OWL-Time for time concepts. Application ontologies are designed specifically for a given application to facilitate its computational needs.

Ontologies as sensemaking

Ontology development can be a useful excercise to *make sense* of an application domain [7]. The formalisation into an ontology can be used in an iterative process to catalyse the development of the shared domain understanding. Sensemaking as an academic notion can be traced back to the early 1980s [13], and it can be used to describe many modelling processes. The data/frame theory [14] is a useful perspective which applies both to the ontology design, the analysis of field data, and the development of domain models.

Studer *et al.* [26] describe a paradigm shift in knowledge engineering. The traditional paradigm viewed knowledge engineering as a transfer of knowledge from the human experts to the computerised expert system. The more modern paradigm views it as a *modelling process*. This implies that the resulting model is an approximation of reality, and typically faulty, due to subjective interpretations. Modelling is a cyclic process, in principle infinite, and the model must be revisable at every step to approach an ideal representation.

Obviously, the creation of a new ontology from scratch is a task which should not be undertaken lightly. It is a difficult and time-consuming process, but more importantly, if an existing ontology exist, creating a new one defeats the purpose of ontologies as shared conceptualisation. Usually, ontologies are modular, and to facilitate reuse, each module should be small with high internal cohenrence and limited interaction with other modules [26].

Ontologies as database

Ontologies provides an alternative to the well-known relational databases. Conversely, as Martinez-Cruz *et al* [19] says, «the ontology community labels databases as light weight ontologies due to the way in which they represent the structure of the information and what the purpose they serve». A database schema is a static representation designed for a particular application and purpose. When the requirements change, the viewpoint and the schema will need modification [28]. In contrast, ontologies as shared conceptualisations operate on a higher level of abstraction [19], and they are designed for reuse across different applications [29].

Resource Description Framework (RDF) defines an abstract syntax to define ontologies. An RDF graph is a set of triples, which can be interpreted either as logic propositions (subject—predicate—object), or as a directed, labelled graph (source—edge label—target). Many different formats exist to serialise the abstract syntax of RDF.

Database backends which store RDF are known as *triple stores*. An RDF graph can define both the schema (classes) and the data (instances). Thus ontologies can mix schemata and data and reason over both [29]. Resources (nodes and edge labels) in RDF are identified by URIs (Universal Resource Identifiers), so that they can be identified uniquely even when several ontologies are combined.

RDF itself provides the basic representation syntax. Ontology languages, such as Web Ontology Language (OWL), add semantics by defining relationships between resources. This makes it possible to define ontologies which proved provide a more correct and precise domain conceptualization than what is possible with relational databases [6]. Database access is established through the use of the ontology [19] which adds meaning to the data, but the ontology is only loosely coupled with the database.

Ontologies in the maritime domain

Several authors have developed ontologies for different domains related to maritime and offshore industries. An early navigational ontology was proposed by Raphael Malyankar [18], focusing mainly on geospatial information. Subsequent authors have built on this work, for instance Pietrzykowski *et al.* [21], who presented a general concept of communication system for maritime transport. A similar work comes from Paweł Banaś [2] aiming to allow automatic communication between computer systems on board and ashore.

Several projects have developed ontologies for oil and gas, Kharlamov et al. [12] considered the business critical data required for analysis in the petroleum company Statoil. The main challenge, which was solved using ontologies, was the time-consuming process of gathering data from different access points. Skjæveland et al. [24] converted the Norwegian Petroleum Directorate's Fact-Page into other representations, including relational database, a linked open data dataset and an ontology.

Another interesting application of ontologies is anomaly detection. Most of this research is based on ship trajectories, e.g. [5, 4]. Vandecasteele *et al.* [30] proposed integration of concepts of semantic events and semantic behaviors. Their work includes a semi-supervised framework to extend an existing ontological framework [31]. To support maritime surveillance, Gupta *et al.* [9] focused on classifying maritime objects from video data. Instead of considering each object individually, they tried to transform a maritime scene into a graph of spatially related objects. A maritime ontology was used as a knowledge base in the transformation process.

4 The Problem

The immediate objective in this study is to improve the process for field studies and make better use of the field data. The field study consists of three phases: planning (pre-field), data gathering (in field), and analysis (post-field). In this paper we restrict the scope to the analysis phase only. We did some early field trials attempting to formalise and structure data during planning and data gathering, but the results were negative. As is often the case with marine operations, the field study had to be planned on short notice with little information about the mission ahead. Hence, little modelling and structuring could be done until the analysis phase.

Although the distinguishing feature of field studies is that data are gathered «while in the user's environment», we do also include field data which can be harvestedrwithout necessarily visiting the field in person, such as ship sensor data, weather data, etc.

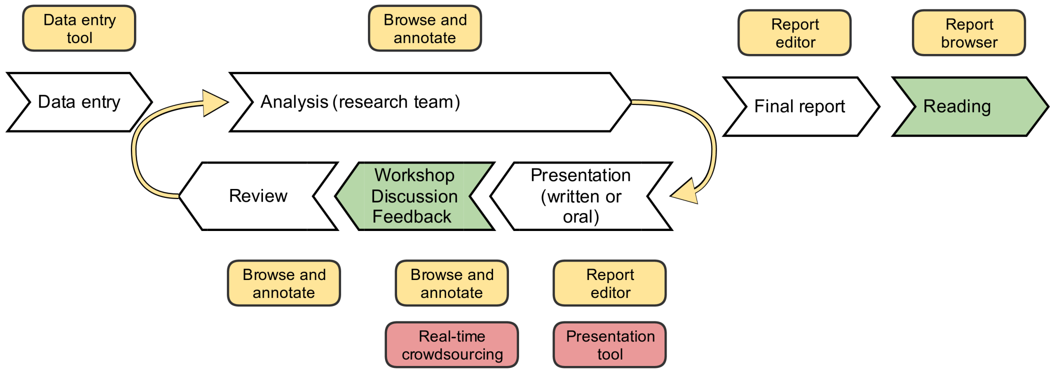

Figure 1: The process of analysing field data.

The analysis process

Returning from the field, the field researchers will type up and sort their notes, before the data are analysed. Different projects require different analysis teqhniques, but typically the result is one or more idiogrammatic models, using techniques such as task analysis, scenario mapping, etc. Conventionally, the field researchers present their findings in one or more internal workshops for discussion. Feedback from the discussion is used in the further work to develop the written report.

Figure 1 visualises the process. Once the initial data have been gathered, an iterative process starts, centering on the workshops. Before each workshop the researchers analyse the findings to be presented on the workshop. In the workshop, a wider community takes part in the review and analysis. After each workshop, the researchers review data from the workshop which feeds into the next cycle.

The workshops as a collective creative exercise form a central element in how designers work. This is a significant difference between field studies in design and qualitative research in social sciences, where the analysis is conducted by a small research team, and only the final report is shared with a larger audience. The workshops are critical to including perspectives from different disciplines in the interpretation.

It should be noted that the workshop serves not only as a collaborative exercise, but also to disseminate insights from the study to the rest of the organisation. This dual nature is especially important when tight deadlines mean that the analysis of data is carried out concurrently with the design process requiring the same data. This is the challenge Millen [20] addresses when he proposes *rapid ethnography*.

Limitations of current process

The existing field study process is limited by the lack of efficient information management tools.

1. Only standard office tools are used to process the data, and the data must be structured and restructured manually for each iteration.
2. The input emerging in the workshop is recorded on flip-over paper and yellow stickers, leaving a tedious task of typing up the notes to the research team.
3. The report format is limited to highlights relevant to the current design problem. All the other data from the study are accessible only to the research team.
4. We have no means to search semantically in the data.

Existing software tools for qualitative research (CAQDAS) could probably mitigate some of the limitations, at least where the field researchers are trained in academic research methods. However, CAQDAS tools are not designed for the open collaborative approach of design, nor to provide end-user access to the data set. We also note that the manpower to analyse the field data and complete the report is limited, and typically more limited than what is expected from an academic research project. This increases the importance of a streamlined process with support software which guides the users efficiently through the process.

Our goal

Our goal is an information system to support the process described above. Figure 1 shows different tools needed at different stages of the process, including

1. the data entry tool.
2. a browse and annotate tool, where any registered user can navigate existing data, and add reflections, interpretations, and other annotations.
3. a report editor.
4. a report reader, where cross-references to raw data can be browsed on a whim.

To support the analysis, we need to be able to code (tag) the data similarly to existing CAQDAS tools. Codes can identify themes, topics, specific research questions, moods, etc. to identify the relevance of the data to the research questions. Qualitative research usually employs a codebook with no defined semantics. In the collaborative design process, semantics is imperative. The designers work closely with domain experts, from several different disciplines, and it is important that the coded data relate to established domain models. A shared understanding of the codebook is essential for smooth communication in the workshop. Furthermore, semantic search and retrieval will make analysis much more effective, especially for end users who want to reanalyse data from several different field studies for new purposes.

One distinguishing feature of the field study is the diversity of data. Typically, the field data include both images and video, observations and descriptions recorded as text, and numerical data. Numerical data include the signals from the ship sensors and other systems, as well as data from external sources, such as weather data. The observations and descriptions are the most used data types in the current process. Images and video are used as illustrations, but are too time-consuming to analyse in depth. There is demand, especially from engineering stakeholders, to increase the use and availability of numerical data, but better techniques are needed to integrate the numerical data in the existing qualitative analysis.

The time it takes to categorise and analyse such a body of data is a major cost factor, and many projects simply lack the resources to complete the final report is never We believe that we need to shift the effort from the traditional report to a living knowledge base, where the end user can access raw data via semantic search.

5 Data Model

The data model is best presented as a series of submodels. The data item model handles observations and other qualitative data. A separate signal model is used for numerical time series. The actor model is used to define human actors, including both observers and the subjects observed. Finally, there is the tagging system to code data and link them to domain models. For the tagging system, the use of an ontology is essential, in order to support text and data mining and integration with various domain models. We have chosen to use ontologies throughout, except where we have found good reasons to do otherwise.

The data item

Common practice in qualitative research is to split all text into atomic fragments and tag each fragment [15]. Ideally, each fragment should say only one thing, to make the tag as precise as possible. Such fragmentation is often the natural format of recording, for instance as bullet points in hand-written notes. We capture such fragments as the field item class in our model. A field item can contain a short text or a media attachment. In some cases, typically quotes from the crew, longer prose has to be handled as a single item. The author is a critical element of the metadata, both as information about the authority behind the recording, and to imply update permissions.

Data is not limited to the raw data from the field. We continue to record data as the field data are analysed, discussed, reflected upon, and used in the design process. Such data are recorded as annotation items which are attached to other items.

A field study is organised hieararchically. The field study is a set of sessions, and a sessions is a list of field items. A session corresponds to a well-defined period where the researcher is actively observing in the field, as opposed to down-time which can be used to relax or to organise notes. Field item, session, field study, and annotation are subclasses of the same data item class. All data items include similar metadata, including authors and time. Reports are defined using a very similar, hierarchical model.

Tagging system

The tagging system is the main case for using ontologies. Instead of tagging with free text, we want to tag with *concepts* which can be found in relevant domain models, and which have an agreed and unambiguous meaning. Concepts can be drawn from ship system models, deck plans with locations, organisational charts with user roles, task models, etc. Standard industry taxonomies, for example the SFI group system need to be available in the tagging system. However, taxonomies do not have the rich internal structure of ontologies [26], and they should be extended with semantics. The tag system need to be modular so that new domain models and ontologies can be imported at any time.

Other models

Most of the **numerical data** of interest are signals or time series. Each signal is a sequence of numerical measurements with timestamp (samples). The numerical data are related to the qualitative data, and to the same domain models, and must be linked appropriately. For each signal, we identify the system which produce the signal, as well as any system or concept described by the signal.

An **actor** is a person, be it an observer or a person observed. Actors should always be identified by a job title or role description. If it is necessary to anonymise the data, this could be the only information stored. Alternatively, we can identify it with a (physical) person (using foaf:person). A person who appears in different roles over different field studies, would be recorded as one and the same person, but as different actors. Other properties, such as an employer, can be added to the actor.

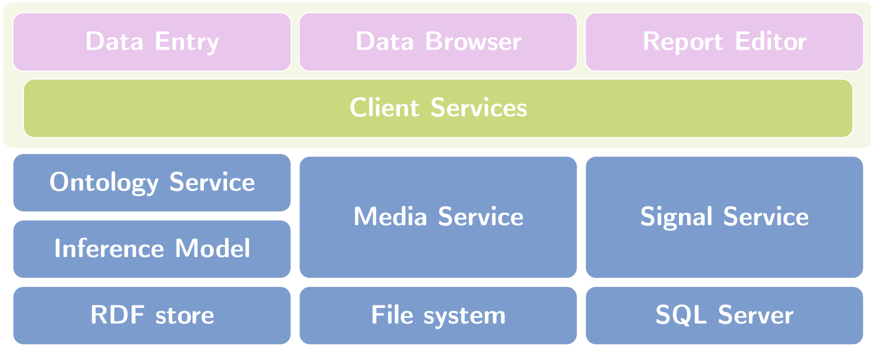

Figure 2: Software layers.

6 Software architecture

The ONSITE software suite allows the users to record, augment, and review field data to support the analysis process described in Section 4. The design is modular as shown in Figure 2. At the top, we can see three client-side tools, to enter data, browse and annotate data, and to compile reports. These are the tools identified in Section 4, except that the tools to browse field studies and to browse reports are the same.

On the server side, we adopt the philosophy of microservices [27], aiming for small, independent, and robust server side components. The microservices approach follows the ideas of a traditional Service Oriented Architecture (SOA), but have more stringent requirements to the size and manageability of each service. Each service is responsible for its own persistance and each one provides a ReST style API over HTTP. The client service layer manages communication with the server and caches a local data model on behalf of the different client tools.

Services

Three services are shown in the diagram. The ontology service is the core of the system, implementing the data model described in Section 5. Authors can edit their own items, and any registered user can add annotations to any items. Users can create a new field study or report, and will automatically be an author with rights to define additional authors. This open access model eliminates the need for most dedicated administrator tasks.

The inference model in the ontology service employs a reasoner to serve a richer model than what is physically stored in the database. Rule sets for the reasoner are written in a simple declarative syntax, which is easy to edit and maintain.

The media service can be an exceedingly simple file store. It is kept separate from the ontology store to avoid having to manage BLOBs (binary large objects) within the database. It is primarily intended for images and video, but could serve any file type. Files in the media service can be referenced from the ontology using a URL. It will be useful to extend the media service to transcode, crop, or downsample media on the server. For instance, video is sometimes recorded in 4k format, which require a lot of bandwidth and is rarely useful for normal viewing. However, the 4k resolution is extremely valuable when zooming in on details in the picture. In such cases it may be necessary to zoom in on the server to save bandwidth.

The signal service handle numerical data, mainly time series. Processing the numerical data, in contrast, is very different from processing the qualitative data in the

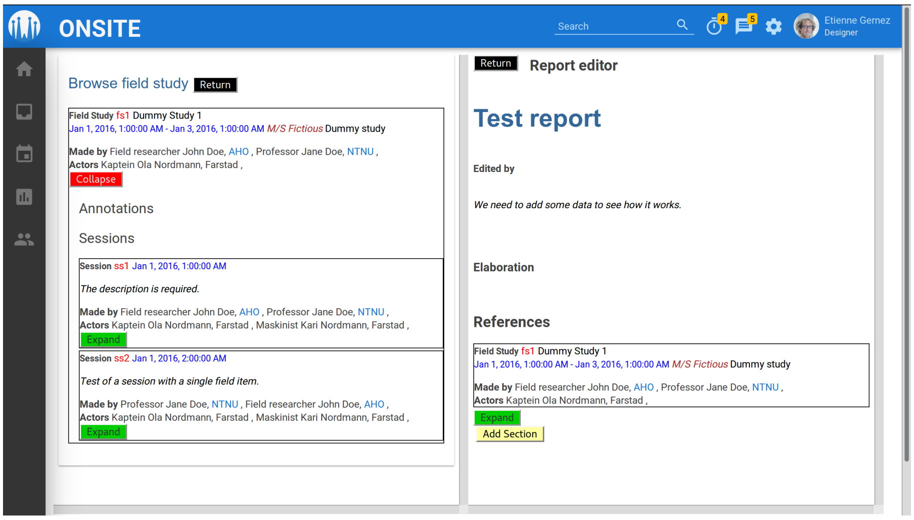

Figure 3: Screenshot showing the report editor.

ontology, and can be done more efficiently with a simple single table database. Splitting the services also makes each one less complex and more maintainable. Metadata, such as the meaning and the URL for each signal, are still stored in the ontology service.

7 Prototype

We implemented a first prototype of the proposed system for testing and evaluation. Some routine features, such as user management, have been omitted, focusing instead on new ideas. Throughout the system, we have used state-of-the-art frameworks, where most of the plumbing code is replaced by simple declarative syntax.

The client is implemented using the Google Angular 2 framework. The separation of the client service and client components (tools in the architecture diagram) follow Angular 2 recommendations. The framework encourages a concise separation loosely based on the Model-View-Controller architecture, which harnesses the complexity of a modern web-client. The code is written in Typescript which is compiled into JavaScript, as well as HTML and CSS files. We use UI components from the PrimeNG library, with the Barcelona Layout page templates. Using such libraries and templates makes it possible to satisfy the user with a reasoably attractive front-end, with little extra effort.

The web services have been implemented in Java EE with jax-rs, with each service as an independent application. They are deployed using a Payara application server on Docker images. The ontology support is implemented using Apache Jena, which is a collection of ontology libraries for Java, including the Inference API to provide the reasoner and TDB which is an RDF triple store with transaction support.

The media service stores individual media resources directly as files on the native file-system. A UUID is used both as the filename and as part of the URI specifying the resource. The signal service stores the numerical data in memory-mapped flat files.

8 Evaluation and conclusion

We have presented a data model and a software architecture to handle data from field studies. Unlike existing software designed for social sciences, ours is designed to support the iterative and collaborative sensemaking process used in design, and to integrate closely with domain models.

The data models are the result of inter-disciplinary team work. Users, domain experts, and computer scientists have engaged in an iterative sensemaking process, to converge towards a model which serves both computers and people. This is the best assurance we can have that the models are valid for the relevant domains and that the software proposal is closely aligned to the design processes where it will be used. This process can be described as participatory research, co-operative inquiry, or participatory design.

This is still work in progress. The ontologies used are still rudimentary, and need to be extended, both to cover the breadth of relevant domain models, and to support efficient search and retrieval.

A very interesting extension would be a fully distributed, inter-company database. Companies in the maritime industry have a dual relationship of close collaborators and fierce competitors, as they compete for the same contracts, but may well subcontract some of the work. An inter-company database would allow partners to share relevant information, but dynamic, fine-grained access control is needed to keep other information confidential. From the user perspective, the aggregate knowledge should appear seamlessly as a single knowledge base.

References

[1] J. Arnold. Big ideas: A history of field research in industrial design in the united states. in joining forces. In *International conference on design research*, September 2005.

[2] Paweł Banaś. Using the protégé environment for building ontology for automated communication system at sea. *Zeszyty Naukowe/Akademia Morska w Szczecinie*, pages 12–17, 2012.

[3] Sebastian C Brandt, Jan Morbach, Michalis Miatidis, Manfred Theißen, Matthias Jarke, and Wolfgang Marquardt. An ontology-based approach to knowledge management in design processes. *Computers & Chemical Engineering*, 32(1):320–342, 2008.

[4] Stefan Brüggemann, Konstantina Bereta, Guohui Xiao, and Manolis Koubarakis. *Ontology-Based Data Access for Maritime Security*, pages 741–757. Springer International Publishing, Cham, 2016.

[5] GKD De Vries, V Malaisé, M Van Someren, P Adriaans, G Schreiber, A Nijholt, M Pantic, M Poel, and G Hondorp. Semi-automatic ontology extension in the maritime domain. In *Proceedings of the Twentieth Belgian-Dutch Conference on Artificial Intelligence, University of Twente, Faculty of Electrical Engineering, Mathematics and Computer Science*, pages 265–272, 2008.

[6] Tharam Dillon, Elizabeth Chang, Maja Hadzic, and Pornpit Wongthongtham. Differentiating conceptual modelling from data modelling, knowledge modelling and ontology modelling and a notation for ontology modelling. In *Proceedings of the fifth Asia-Pacific conference on Conceptual Modelling*, volume 79, page 7–17. Australian Computer Society, Inc., 2008.

[7] Thomas C Eskridge and Robert Hoffman. Ontology creation as a sensemaking activity. *IEEE Intelligent Systems*, 27(5):58–65, 2012.

[8] John Girard and J Girard. Defining knowledge management: Toward an applied compendium. *Online Journal of Applied Knowledge Management, 3 (1), 1*, 20, 2015.

[9] Kalyan Moy Gupta, David W Aha, and Philip Moore. Case-based collective inference for maritime object classification. In *International Conference on Case-Based Reasoning*, pages 434–449. Springer, 2009.

[10] John Heron. *Co-operative inquiry: Research into the human condition*. Sage, 1996.

[11] Tomas Kellner. If ships could fly: Big data dawn on the high seas, July 2015. `http://www.gereports.com/post/117966015130/if-ships-could-fly-big-data-dawn-on-the-high/`.

[12] E Kharlamov, D Hovland, E Jiménez-Ruiz, D Lanti, H Lie, C Pinkel, M Rezk, M G Skjæveland, E Thorstensen, G Xiao, et al. Ontology based access to exploration data at statoil. In *International Semantic Web Conference*, pages 93–112. Springer, 2015.

[13] G. Klein, B. Moon, and R. R. Hoffman. Making sense of sensemaking 1: Alternative perspectives. *IEEE Intelligent Systems*, 21(4):70–73, July 2006.

[14] G. Klein, B. Moon, and R. R. Hoffman. Making sense of sensemaking 2: A macrocognitive model. *IEEE Intelligent Systems*, 21(5):88–92, September 2006.

[15] Richard A. Krueger and Mary Anne Casey. *Focus Groups: A Practical Guide for Applied Research*. SAGE Publications, Inc, 4th edition, October 2008.

[16] Sigrun Lurås and Kjetil Nordby. Field studies informing ship's bridge design at the Ocean Industries Concept Lab. In *Human Factors in Ship Design & Operation*, February 2014.

[17] Sigrun Lurås, Birger Sevaldson, and Margareta Lützhöft. Meeting the complex and unfamiliar: Lessons from design in the offshore industry. *International Journal of Design*, 9(2):141–154, 2015.

[18] Raphael Malyankar. Creating a navigation ontology. In *Workshop on Ontology Management*, pages 48–53, 1999.

[19] Carmen Martinez-Cruz, Ignacio J Blanco, and M Amparo Vila. Ontologies versus relational databases: are they so different? a comparison. *Artificial Intelligence Review*, 38(4):271–290, 2012.

[20] David R. Millen. Rapid ethnography: time deepening strategies for HCI field research. In *Proceedings of the 3rd conference on Designing interactive systems: processes, practices, methods, and techniques*, pages 280–286. ACM, 2000.

[21] Z Pietrzykowski, G Hoáowiski, J Magaj, and J Chomski. Automation of message interchange process in maritime transport. *International Recent Issues about ECDIS, e-Navigation and Safety at Sea: Marine Navigation and Safety of Sea Transportation*, pages 119–124, 2011.

[22] A. M. Rothblum. Human error and marine safety. In *National Safety Council Congress and Expo, Orlando, FL*, October 2000.

[23] Ioana Rus and Mikael Lindvall. Knowledge management in software engineering. *IEEE software*, 19(3):26, 2002.

[24] Martin G Skjæveland, Espen H Lian, and Ian Horrocks. Publishing the norwegian petroleum directorate's factpages as semantic web data. In *International Semantic Web Conference*, pages 162–177. Springer, 2013.

[25] Marina Z Solesvik. Collaborative knowledge management: case studies from ship design. *International Journal of Business Information Systems*, 8(2):131–145, 2011.

[26] Rudi Studer, V Richard Benjamins, and Dieter Fensel. Knowledge engineering: principles and methods. *Data & knowledge engineering*, 25(1-2):161–197, 1998.

[27] J. Thönes. Microservices. *IEEE Software*, 32(1):116–116, January 2015.

[28] Thanh Tran, Holger Lewen, and Peter Haase. On the role and application of ontologies in information systems. In *Research, Innovation and Vision for the Future, 2007 IEEE International Conference on*, page 14–21. IEEE, 2007.

[29] Michael Uschold and Michael Gruninger. Ontologies and semantics for seamless connectivity. *ACM SIGMod Record*, 33(4):58–64, 2004.

[30] Arnaud Vandecasteele, Rodolphe Devillers, and Aldo Napoli. A semi-supervised learning framework based on spatio-temporal semantic events for maritime anomaly detection and behavior analysis. In *CoastGIS 2013-The 11th International Symposium for GIS and Computer Cartography for Coastal Zone Management*, pages 4–pages, 2013.

[31] Zhixian Yan, Dipanjan Chakraborty, Christine Parent, Stefano Spaccapietra, and Karl Aberer. Semantic trajectories: Mobility data computation and annotation. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 4(3):49, 2013.