On construction method of shipborne and airborne radar intelligence and related equipment knowledge graph

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Abstract. Knowledge graph construction in military intelligence domain is sprouting but technically immature. This paper presents a method to construct the heterogeneous knowledge graph in the field of shipborne and airborne radar and equipment. Based on the expert knowledge and the up-to-date Internet open source information, we construct the knowledge graph of radar characteristic information and the equipment respectively, and establish relationships between two graphs, providing the pipeline and method for the intelligence organization and management in the context of the crowding battlefields big data.

1. Introduction

The capability of radar intelligence collection and analysis is a vital aspect of national military comprehensive strength, and it is significant for strategic situation evaluation to timely and accurately collecting and analyzing radar intelligence. Under the circumstances of information extracted from mass data overloading during the operation, a problem surfaced that it is essential to converting the information advantage to decision strength, which requires accumulating the intelligence superiority by flattening the information sharing and convergence [1].

Knowledge base is the fundamental techniques of artificial intelligence and intelligent service applications [2]. Since the Google’s proposition of building the knowledge graph utilizing the big data in 2012, it has raised wide attention as a new type of knowledge representation and service technology for both academic and industry sphere [3]. The research sphere of knowledge graph includes information extraction, knowledge representation, knowledge reasoning, database management, etc. It is a burgeoning domain, originated from information retrieval, now applied in the search engine, medical research, bioinformatics as well as finance analyzing. However, study of it in the military intelligence domain is still scarce. Jiang Kai [4] proposes an intelligence based military knowledge search framework. Yijun Yan [5] designs a reconnaissance situation synthesis system to deal with the intelligence acquired from multiple source. The most successful application case of knowledge graph related domain in intelligence analyzing is Palantir’s Dynamic Ontology, which helped international antiterrorist campaign in the Middle East.

The association of radar intelligence and equipment information benefits battlefield knowledge management, effectively reducing the information barrier, connecting the signal layer, information layer and decision layer together and better realizing the integrative joint operations. Knowledge graph’s strong semantic query capabilities provide richer expression and more accurate results, so that it can be more widely used in the lack of expert knowledge combat environment. The Decision Support System (DDS) roots in the knowledge graph and assists commanders to plan and solve various actions.
2. Graph Modeling

The knowledge graph is a semantic network that describes the various entities, concepts, and relationships between them in the real world. The difference between the knowledge map and the expert system is that the expert system is more concerned with the rules building and reasoning, but the bottlenecks of knowledge and the portability of the system are obvious while knowledge graph focus more on the existing entities and relations [6]. By integrating multi-source heterogeneous data into the form of graph, taking good advantage of some unstructured or isolated data becomes possible, and a good purpose for multi-data type fusion decision will achieves. In the light of this, the radar intelligence graph pays more attention to the association information mining, rendering knowledge representation and knowledge reasoning a significantly stronger ability [7].

2.1. Knowledge Graph Framework

According to the coverage of knowledge range, knowledge graph includes general type and domain type, and the construction methods are also slightly different for them. The general knowledge graph is constructed from a bottom-up approach, which facilitates the discovery of new patterns of knowledge. The domain graph focuses on the hierarchical structure of knowledge, usually need top-down approach to build the graph, and then expanding the entity network [8].

![Radar Intelligence and Equipment Knowledge Graph Construction Framework](image)

We combine two approaches mention above that design two subgraphs, one is radar intelligence graph, and the other is equipment knowledge graph and then using expert knowledge as well as open source knowledge to establish relations between the entities of them and on the top of them, we design a concept ontology to organize the whole graph. The former subgraph contains the shipborne and airborne radar signal features and the co-occurrence association rules, the task of which is to establish a
semantic web model to represent, visualize and store association rules. The latter one is comprised of equipment entities, the task of which is extracting equipment knowledge from open source projects and integrating new confidence entities into them, including the tasks of entity extraction, entity resolution and link prediction, etc. In the process of knowledge accumulation, we need to deal with the tacit knowledge and explicit knowledge. The explicit knowledge is extracted from big data and it’s a long-term process to gradually accumulate. The tactic knowledge, embedded in the human brain, cannot expressed easily and require the collaborative work. These make the radar knowledge graph modeling more specifically in domain, a long-term progress and build up technically.

The main source of intelligence knowledge is the association rules mined from frequent radar signal item, and the equipment knowledge is mainly from the Internet open source domain knowledge base and some specific intelligence documents including academic papers and intelligence magazines such as Jane's Defense Weekly. The framework of knowledge graph is as Figure 1.

![Figure 1. Knowledge Graph Framework](image)

2.2 Model Terminology

Our ontology modeling methods employs Ontology Development 101 and comprehensively refers to the Radar Handbook, World Airborne Radar Manual, and Airborne Radar Handbook, Jane's Defense Weekly and various academic papers and military encyclopedias to define the terminology. Figure 2 is the up-layer ontology model.

By means of top-down approach we build the hierarchy of classes, and based on this the properties are essential to enrich the semantic information of ontology layer of knowledge graph. We have four main top layer classes:

Country, formation, aircraft, radar system and the naval craft. The object properties are designed as follows:

1) **subclassof**: Describing the child relationship of concept;
2) **armament**: Describing the relationship between radar and equipment;
3) **cooperatewith**: Representing the cooperative relation between combatant equipment;
4) **hasfunc**: Describing the properties radar type has;
5) **ispartof**: Describing the dependency of equipment. **ispartof**: Describing the dependency of equipment.
6) **operator**: Describing the relation that the equipment is the armament of a country.

![Figure 2. Up-layer Ontology Concept Model](image)
3. Construction Techniques

3.1. Radar Intelligence Subgraph Construction

This paper focuses on the construction of radar intelligence association rules in the format of semantic web. Graph is an intuitive pipeline to visualize the complex association rules of feature signals and the semantic web provides expressive and convenient way for querying. The data source of the radar intelligence graph is the rule mined from radar intelligence information, which is born with confidence and good operability. We propose two semantic relationship in the subgraph: “isfeatureof” and “meantime”. The “isfeatureof” describes the relationship between radar and its feature signals, and the “meantime” shows the co-occurrence relationship between signals.

![Figure 3. Radar Intelligence Subgraph Structure](image)

As for those multiple-to-one rules, we introduce new node into the graph to express the meaning “and”. For example, the rule “Meantime (1, 2, 3) → (4)” is represented as figure 3. Every node in the graph is allocated with a Uniform Resource Identifier (URI) and the intermediate node is named after “Meantime” plus the identifier of signal.

3.2. Equipment Subgraph Construction

The equipment subgraph is a vertical knowledge graph that focus on the depth of knowledge and the overall hierarchy. It is rational to reuse some existing knowledge projects to help better build knowledge graph. Linked Open Data (LOD) projects such as Dbpedia and Wikidata achieve quite well on the general knowledge graph construction so we reuse, partition and merging them to extract those domain knowledge we need. The Jane’s Defence Weekly, military publications and academic papers provide the entities of equipment subgraph.

This paper proposes an incremental construction method called “one foundation and multi sources” to build up the equipment subgraph. We reuse the domain knowledge of DBpedia as the initial knowledge source and adding new knowledge from Wikidata, intelligence documents and publications. The recursive build-up process is illustrated as figure 4.

The specific steps are as follows:
1) Using the SPARQL query language and Protégé ontology editor to partition the military domain knowledge;
2) Mapping those equipment class concepts to the Wikidata dump, and find all the leaf nodes within 2-length in the Wikidata dump;
3) Using Jena tool to write the new individuals from dump into the knowledge graph;
4) Adding new entities extracted from web, publications and papers;
5) Check the consistency of knowledge graph;
6) Repeat step(2) to step(5).
During the process of dealing with Wikidata, we simplify the property of entities for the reason that the data properties are not uniform. We save the Wikidataid, aliases, label and description of all the properties. The object properties Wikidata uses are identifiers in the format of “P001”, so we retrieve the real name on the internet and substitute it.

The process of entity matching is achieved by defining the distance measurements for the string. If the string similarity is less than the threshold value, the name is the entity mention. The measurements we use are Levenshtein Distance [9] and Jaccard Similarity [10]. The similarity degree of two strings is the bigger score of two measurement.

If the machine could not figure out the corresponding entity of the concept, then the mention would be marked to wait for manual processing.

3.3. Equipment Relationship Extraction
In this part we focus on the relation between two subgraphs, specifically the relation between radars and equipment.

In Wikipedia, military radar information is under the category of "Military radars", but it is hard to find the structured information about radar and equipment, and this sort of information is hidden in the unstructured text. The web page crawling and cleaning work is done by the python package “Beautiful soap”. The extraction steps are listed as below:

1) Crawling the web pages and extract each text under a theme into a “txt” file;
2) Taking advantage of Stanford NLTK natural language processing tool to parse the text, tagging the part of speech;
3) Looking for those sentences with the named entities in the concept graph and match the pattern sentences containing “suitable”, “equipped”, “installed”, “combined”, “used in”, “destroyer”, “carrier”, “frigate”, etc.
4) Use the pattern to match the relationship. If the one sentence has named entities belonging to distinguished category of “radar” and the category of “aircraft” or “naval craft”, saving them into the relationship form.

Table 1 shows an example that extracting information from the Wikipedia page “EL/M-2052” and “APAR”.

The EL/M-2052 has direct relationship to the equipment of aircrafts while APAR only connects to the frigate type, so it requires more work to detail the information. Under this circumstance, we retrieve the key words in the Wikipedia and find the subclass of the equipment and add them into the relationship form.

Figure 4. Equipment Knowledge Graph
Under the light of these methodology the shipborne and airborne radar intelligence and equipment knowledge graph gradually grows bigger and the circle of construction still continues.

Table 1. Relationship Form of Two Kinds of Radars

| Radar type | Equipment type | Radar type             | Equipment type                |
|------------|----------------|------------------------|-------------------------------|
| EL/M-2052  | F-15           | Active Phased Array    | De Zeven Provinciën class    |
|            | Mirage 2000    | Radar (APAR)           | frigates                      |
|            | MiG-29         |                         | F124 Sachsen class frigates   |
|            | Sukhoi Su-27/30|                         | Royal Danish Navy Ivar        |
|            |                |                         | Huitfeldt class frigates      |

4. Consistency Evaluation and Application Scenario

The consistency evaluation is to check the consistency of the knowledge graph and the up-layer ontology. Protégé furnishes some reasoning plugins such as Pellet, HermiT and FaCT++. We use Pellet inference engine to evaluate the consistency and gives an American’s Nimitz aircrafts carrier formation instance. After executing the reasoning machine, the Pellet engine will return the inference result if the ontology is consistent. Otherwise, it will pop up an error window. The reasoning result is shown as Figure 5, the yellow part of which is the inference information.

The shipborne and airborne radar intelligence and equipment knowledge graph can be widely implemented in the target recognition task. The knowledge graph is the decision layer for the situation evaluation. The feature intelligence, analyzed through several steps, is send to the decision layer to identify which kind of target it belongs to by matching the characters defined in the ontology. After identifying the enemy radar, it can figure out the potential enemy armament and formation information as well as other intelligence of the radar and equipment, which rendering power for commanders to make operational decisions.

Figure 5. Consistency Evaluation and Formation Reasoning

5. Conclusion

The knowledge graph construction is a part of knowledge engineering so it is more like a project. This paper proposes a methodology to construct multi-source heterogeneous shipborne and airborne radar intelligence and equipment knowledge graph and verify the feasibility of the method. This method provides a new idea of semantic representation of radar intelligence rules and integrates open source information and expert knowledge, which applies the ontology engineering method and large data semantic network construction technology. Besides this, the graph construction also requires reasoning to enrich the knowledge capacity to meet the consistency and completeness, so this is a process of constantly updating and iteration. The application of the method facilitates improving the level of automatic processing of our military intelligence and lays the foundation for situation evaluation and threat discovery.
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