A KNOWLEDGE BASED FRAMEWORK FOR THE DETECTION OF MEASUREMENT UNCERTAINTIES IN DERIVED SEA SURFACE CURRENT FIELDS

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ABSTRACT

In [6] we presented an approach to measure sea surface currents from satellite images by computing the displacement vectors of distinctive image features or measuring the optical flow between successive images of the same scene. These algorithms are based on the assumption that the image flow observed is caused by the motion of surface films with the currents to be measured. Optical flow due to other image features, e.g. ship wakes, does not correspond to the motion field and causes systematic errors. The decision whether a derived measurement is valid or not by domain experts is very time-consuming. We present first steps towards an automatic knowledge-based approach that uses description logic to validate the measurements of sea surface currents. The terminological knowledge is based on the expert's knowledge of the domain in conjunction with a geographical database containing factual knowledge about the scene. The combination of different sources of knowledge makes it possible to infer about the validity of sea surface current measurements from image data by reasoning based on the local context of the image features.

Index Terms— oceanography, sea surface currents, uncertainties, description logics

1. INTRODUCTION

In this paper we present a conceptual framework that uses a knowledge based description logic approach to decide whether or not a computed motion vector corresponds to a sea surface current. For this decision we need to take different sources of knowledge into account.
In [7] we have shown that low level image processing algorithms can be used to improve the derived motion fields by means of smoothness. However there are still cases where this correction may result in unwanted motion measurements that do not correspond to the sea surface currents. To solve problems like this, image interpretation systems have proven to be adequate [5].

2. DERIVATION OF HIGH-RESOLUTION SEA SURFACE CURRENTS FROM SATELLITE IMAGERY

Currently there exist two well-known families of algorithms for the computation of sea surface currents from at least to satellite images of one region: the feature-based and the Optical Flow-based approaches. Both have in common that there have to be current tracers (e.g. sea surface films) visible in the images to be analyzed. The local sea surface currents cause the motion of these tracers, which allows an indirect and high-resolution measurement of the currents [6].

Before the feature-based local approaches can be used, we have to find the features of interest (e.g. algae signatures) in at least one satellite image a priori. After the detection of features different feature matching methods can be used (e.g. fast normalized cross-correlation or shape-context matching). These methods usually assign a confidence value to each matching (see [6]).

The Optical-Flow-based approaches do not depend on knowledge about specific features. They result in a global motion field that represents the displacement of one satellite image relative to the other. The Optical Flow methods do not explicitly assign a confidence value to each motion vector.

In this paper, we concentrate on results of feature-matching approaches based on surface film tracking on synthetic aperture radar (SAR) satellite imagery. The results of these approaches provide explicit information about the uncertainties of each motion measurement. Although the feature-matching methods are well known, and are highly optimized, there is always some chance of a measurement error. We distinguish between two error cases:

1. A high correlation value of a motion that does not correspond to a real sea surface current and
2. A low correlation value of motion that corresponds to a real current element.

Due to the matching strategy, the first case occurs more often than the second one and cannot be compensated by low-level post-processing steps [7]. The origin of these erroneous motion measurements is the tracking of unsuitable features. These features can be ship wakes or wind induced surface anomalies that result in similar signatures in the SAR images. To solve this ambiguity, we need to classify the motion target with scene specific knowledge.

3. SOURCES OF KNOWLEDGE

We distinguish between two sorts of knowledge: dynamic factual knowledge about the scene depicted in the current image that is analyzed and static interpretation knowledge that allows the automated reasoning over the facts. Examples of factual knowledge about the scene comprise wind information, tidal information, position of ships and waterways, chlorophyll ratio, and sea surface temperature information for each selected feature at each spatiotemporal point. The factual knowledge changes dynamically for each measurement. This may cause a huge amount of data, which cannot be represented inside the description logic efficiently. Hence, there is a strong need of a multi-layer architecture with bottom-up reasoning for the task of detecting unreliable measurements.

The interpretation knowledge is often compact enough to be represented inside such a system. Moreover there are static interpretation rules given by domain experts, like:

- Biogenic surface films are often associated with a locally enhanced chlorophyll-a concentration
- SAR signatures of wakes and surface films may look similar.
- Wind and tidal forces mainly affect surface currents.

The representation of this “higher knowledge” is independent from the factual knowledge. Knowledge engineers can revise it according to domain experts and their knowledge [3].

4. DESCRIPTION LOGICS

Description logics (DLs) are a family of knowledge representation languages, which originated from early attempts in the 1970s to model knowledge with class- or concept-based knowledge structures, i.e., Minsky’s Frames, and the so-called Semantic Networks. Nowadays, DLs provide the semantic basis for the Semantic Web (e.g., OWL DL is basically a description logic).

Most contemporary DLs can be considered as subsets of first-order logic, and hence, the inference services offered by the corresponding systems are well defined.

Knowledge in DL systems comes in two disguises: class- or concept-based knowledge, and individual-specific knowledge. The knowledge is kept in two separate boxes, the TBox and ABox. Concepts are described by concept descriptions and denote sets of individuals in the modeled domain of discourse. In order to interrelate individuals in the domain of discourse, binary relations are used which are called roles in DLs. If R is such a role, and C and D are concept descriptions, then the following grammar defines the syntax of concept descriptions in the basic DL ALC, starting from atomic concepts (concept names):

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concept ::=    atomic-concept | top | bottom
concept ::=    (and C D) | (or C D) |
               (some R C) | (all R D) |
               (not C)
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According to this specification, “(and woman (some has-child person))” is a concept (description). The semantics of such a concept / the denoted set of individuals in the domain of discourse, is specified inductively by means of a so-called Tarski-style interpretation function I, which maps concepts to subsets of some non-empty universe of discourse, Δ, and roles to binary relations over Δ, such that the following equations are satisfied:

$$
\begin{aligned}
I((\text{and } C\ D)) &= I(C) \cap I(D) \\
I((\text{or } C\ D)) &= I(C) \cup I(D) \\
I((\text{some } R\ C)) &= \{\, i \mid \exists j \in \Delta\colon j \in I(C),\ (i, j) \in I(R) \,\} \\
I((\text{all } R\ C)) &= \{\, i \mid \forall j \in \Delta\colon (i, j) \in I(R) \Rightarrow j \in I(C) \,\} \\
I((\text{not } C)) &= \Delta \setminus I(C)
\end{aligned}
$$

I(C) is also called the extension of C (w.r.t. an interpretation). A concept C is said to be satisfiable or consistent iff there is at least one interpretation function and non-empty domain Δ such that I maps C to a non-empty subset of Δ; otherwise, C is called inconsistent or unsatisfiable. An interpretation, which satisfies C is also called a model of C.

An important relationship between concepts is the subsumption relationship. It is said that C is subsumed by D if the extension of C is a subset of the extension of D in all models of C and D. Then, C is called the more specific, subsumee, and D the more general concept or subsumer.

In terms of first-order logic, a concept description corresponds to a first-order logic formula with one free variable, like “woman(x) ∧ ∃y. has-child(x,y) ∧ person(y)” and thus, checking satisfiability amounts to checking the first-order satisfiability of this formula in terms of first-order predicate logic.

In order to interrelate concept descriptions, the so-called terminological box, or TBox, contains concept specialization and concept definition axioms, thus allowing to define the vocabulary of a domain of discourse. For example, the concept definition axiom “mother ↔ (and woman (some has-child person))” enforces equality of the extensions of these two concept descriptions in all models of the knowledge base. A concept specialization axiom enforces that the extension of the first concept is a subset of the extension of the second concept, e.g., “woman → person”. The notion of a model is extended to TBoxes in the obvious way by requiring that a model must satisfy the corresponding equations for the different types of axioms. From a first-order logic perspective, the given axioms correspond to the sentences

$$\forall x : \text{mother}(x) \leftrightarrow \text{woman}(x) \wedge \exists y.\ \text{has-child}(x,y) \wedge \text{person}(y)$$
$$\forall x : \text{woman}(x) \rightarrow \text{person}(x)$$

Important inference problems for TBoxes are, again, satisfiability (does the TBox admit a model?), TBox coherence (are there unsatisfiable concept names other than "top" in the TBox?), and TBox classification. The latter inference service computes the so-called taxonomy of a TBoxwhich represent the direct subsumption (direct subconcept) relationships between concept names (atomic concepts) by means of a directed, acyclic graph (DAG).

Whereas the TBox models conceptual knowledge, the so-called assertional box, the ABox contains a set of so-called assertions, where assertion is defined by the following grammar rules: A knowledge base typically consists of a pair (T,A), where T is TBox and A is an ABox. Formally, an ABox is a set of ABox assertions. Let "i, j" be ABox individuals (constants), R be a role, and C be a concept:

assertion ::= concept-assertion | role-assertion
concept-assertion ::= (instance i C)
role-assertion ::= (related i j R)

For example, from the ABox {betty: woman, (betty, charles) : has-child} it follows that betty is an instance of the concept mother. From a first-order logic perspective, an ABox is simply a set of ground facts. The interpretation function is extended in such a way that it maps ABox individuals to domain individuals of Δ. As usual, a model of an ABox satisfies all assertion. A concept assertion is satisfied if the element of Δ denoted by the ABox individual is indeed a member of the extension of the concept C, and analog for role assertions. Important inference problems are ABox consistency (w.r.t. a TBox), and ABox query answering (w.r.t. TBox). Current DL systems support at least so-called grounded conjunctive queries. E.g., the answer to the conjunctive query (denoted in predicate logic)

$$\text{ans}(?x, ?y) \leftarrow \text{mother}(?x), \text{has-child}(?x,?y)$$

is {ans(betty, charles)}. Note that reasoning was required in order to realize betty as an instance of the concept mother (this was not stated explicitly in the ABox): thus, ABox query answering has to consider the effects of the TBox axioms.

5. THE DESCRIPTION LOGIC SYSTEM RACERPRO

In this work, the DL system RacerPro is used [1]. RacerPro implements the expressive description logic SHIQ(Dn), which offers transitive, functional and inverse roles, role specialization hierarchies, reasoning with datatypes (e.g., strings, reals, integers, booleans), and some additional concept constructors (e.g., the qualified number restrictions of OWL2). Racer was the first system of a new generation of highly optimized DL systems [1] that also supported ABoxes.

RacerPro offers many advanced proprietary features, such as (grounded) first-order queries, rules, programmatic "server-sided" scripting, extensibility, and some innovative inference services (such as abductive query answering). After more than 10 years of continues improvements, RacerPro is one of the fastest ABox reasoning system nowadays whose scalability for certain standard ABox benchmarks has been shown recently [2]. As such, it is an ideal basis for knowledge-intensive applications which require ABox reasoning and ABox query answering and was thus selected for this research. In addition, Racer has proven to fit well for reasoning by means of computer vision scene interpretation [4].

6. KNOWLEDGE BASED DETECTION OF VALID SEA SURFACE CURRENT MEASUREMENTS

We developed a prototypical framework that models the domain expert's knowledge inside the TBox and uses the derived currents in conjunction with the other factual knowledge about the scene as ABox contents (Figure 1). To transfer the quantitative information into the ABox, we use an abstraction on the middle layer of the framework that maps the quantitative values to qualitative symbols. One example of a very simple TBox could be like this:

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water → (not land)

high-chlorophyll → (and (not medium-chlorophyll)
(not low-chlorophyll))
medium-chlorophyll → (not low-chlorophyll)

coastal ↔ (and (some next-to water)
(some next-to land))

valid-current → (or (not (some next-to ship))
(not (some next-to waterway)))

valid-chlorophyll-amount → (or high-chlorophyll
medium-chlorophyll)

valid-current → (all next-to valid-chlorophyll-amount)

The abstraction from quantitative to qualitative values can be observed e.g. in the case of the chlorophyll amount. Instead of model floating-point values we use three categories: high, medium and low. Another abstraction can

be found at the spatial neighborhood that is modeled as role "next-to". Note that the system can derive knowledge about a "coastal" relationship using a TBox equivalence rule.
We now present an example for an ABox:

(instance motionA	valid-current)	
(related motionA	water	next-to)
(related motionA	land	next-to)
(related motionA	high-chlorophyll	next-to)

In this ABox, we assume that the measured motion is a valid current. We perform a so-called ABox consistency check, to finally get the answer to our question: Is the measured motion vector representing a valid sea surface current or not? Please note that the example above is a very simple one, just to demonstrate the basics needed for our approach.
For this example, the measured motion "A" represents a valid current given the TBox above, because it is next to some higher chlorophyll amount than usual, and is not next to some waterway or ship.

7. CONCLUSIONS

We have presented the main concepts of a flexible knowledge based framework and have given a first example of an application. A conceptual diagram is given in (Figure 1). Due to the multi-layer architecture of the framework and the RacerPro DL system, it is highly scalable and can therefore be used for reasoning in many areas of remote sensing.
One of the key features is the separation of knowledge into static expert knowledge and highly dynamic knowledge. We implemented a prototype, which results in promising but yet preliminary results [5]. The next steps are the integration of other knowledge sources and of more expert knowledge to improve the automatic reasoning.

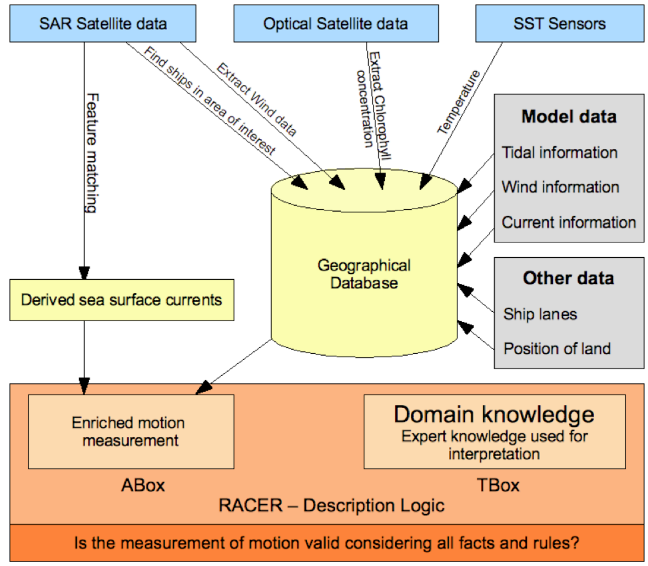

Fig . 1. Diagram of the conceptual Framework showing the bottom-up reasoning approach. The geographical database represents the middle (integration) layer.

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