DESIGN OF VIRTUAL EXPERTS FOR IMAGERY REGISTRATION AND CONFLATION

Boris Kovalerchuk, Professor
Artemus Harper, Student
Michael Kovalerchuk, Researcher
Dept. of Computer Science,
Central Washington University
Ellensburg, WA, USA 98926-7520
borisk@cwu.edu
harpera@cwu.edu
kovalerm@cwu.edu

ABSTRACT

The unique human expertise in imagery analysis should be preserved and shared with other imagery analysts to improve image analysis and decision-making. Such knowledge can serve as a corporate memory and be a base for an imagery virtual expert. The core problem in reaching this goal is constructing a methodology and tools that can assist in building the knowledge base of imagery analysis. This paper provides a framework for an imagery virtual expert system that supports imagery registration and conflation tasks. The approach involves tree strategies: (1) recording expertise on-the-fly and (2) ex-extracting information from the expert in an optimized way using the theory of monotone Boolean functions and (3) use of iconized ontologies to build a conflation method. The paper presents an ontological iconic registration/conflation method based on this methodology that is implemented as an ArcGIS Plug-in. To be able to do this we build an OWL ontology for the Feature Attribute Coding Catalog(FACC) with more than 600 terms. This ontology is available free for download from the CWU server.

INTRODUCTION

The goals of this paper is to determine how to build an **Imagery Virtual Expert System** (**IVES**) for imagery analysis, create tools to capture imagery specific information and knowledge for IVES, and create tools to foster intelligent consultation with IVES.

The goal of *imagery registration* is providing geospatial coordinates to the image. The goal of the *imagery conflation* is correlation and fusion of two or more images or geospatial databases. “The process of transferring information (including more accurate coordinates) from one geospatial database to another is known as ‘conflation’” (FGDC, 2000). Typically, the result of the conflation is a combined image produced from two or more images with: (1) matched features from different images and (2) transformations that are needed to produce a single consistent image. Note, registration of a new image can be done by conflating it with a registered image. Such a way of registration can be useful if there is a lack of reliable metadata that provide registration directly. This consideration motivates us to concentrate on the conflation task in this paper. Recently the conflation has been viewed as a *matching technique* that fuses imagery data and preserves inconsistencies (e.g., inconsistencies between high and low resolution maps, “best map” concept, (Edwards, Simpson, 2002). This approach tries to preserve the pluralism of multi-source data. The traditional approach (USGS, 1998) uses an “artistic” match of elevation edges. If the road has a break on the borderline of two maps then a “corrected” road section starts at some distance from the border on both sides and connects two disparate lines. This new line is artistically perfect, but no real road may exist on the ground in that location.

Why design virtual experts for conflation? Can the conflation problem be solved by designing a sophisticated mathematical procedure without relying on an expert’s knowledge? In essence, the conflation problem is a **conflict resolution** problem between disparate data (Cobb et al., 1998). n solving a conflation problem, experts are unique in extracting and using **non-formalized context** and in linking it with the task at hand (e.g., finding the best route or comparing roads without a formal criterion). Unfortunately, few if any contexts are explicitly formalized and generalized in mathematical models for use in conflating other images. It is common that the context of each image is unique and not recorded.

There are two known approaches to incorporate context: (1) *formalize context* for each individual image and task directly and (2) *generalize context* in the form of expert rules. In the first approach, the challenge is that there are too many images and tasks and there is no unified technique to for context formalization. The second approach is more general and more feasible, but in some cases may not match a particular context and task, thus a human expert needs to take a look.

Building IVES includes: (a) determining how to build knowledge-based and expert systems for use in supporting imagery analysis, (b) creating tools to assist the knowledge engineer to capture domain specific information and build the knowledge base, (c) incorporating the use of semantics into an imagery knowledge management environment, (d) integrating multimedia information in a user-friendly, human-computer interface, and (e) creating tools to foster intelligent consultation of the virtual expert' knowledge base.

To show the challenges of building IVES we refer to the extensive DARPA Rapid Knowledge Formation (RKF, 1999) program that identified what is hard in building virtual experts. It is a **knowledge acquisition bottleneck**, that is a transition: (1) from natural language to formal mathematical language, (2) from reasoning by analogy to logical deduction, (3) from **image-based knowledge** to symbol-based knowledge, (4) from **built-in spatial reasoning** to explicitly defined knowledge and (5) from "common sense" to something that is not clearly identified in machine knowledge. In geospatial domain the challenge is in all of these areas, but image-based knowledge and spatial reasoning are especially relevant and challenging for imagery analyses that are often not verbal at all. In addition, imagery analysis involves (6) complex mathematical models for image manipulations, such as conflation, registration, feature extraction, change detection and target recognition.

SHORTCOMINGS OF PREVIOUS ATTEMPTS TO DEAL WITH THE SUBJECT

Currently, even large knowledge bases cannot answer many questions, which are in their scope. The real world is too dynamic, uncertain, and complex for even modern knowledge bases. The conflation/registration problem is an example of such a real world problem. DARPA's program The DARPA program "Rapid Knowledge Formation" (RKF, 1999) formulated new requirements that include parallel entry of knowledge by teams of 25-50 individuals (end users) for test tasks such as crisis management and battlespace understanding. According to DARPA using High Performance Knowledge Base technology, a 5-person team can create knowledge at a rate of *40 axioms* per hour and *100K* of axioms per year. After that, DARPA stated a new goal: the creation of new knowledge at a rate of *400 axioms* per hour. Next, DARPA identified the criterion of *comprehensiveness* of the knowledge base at the level of *a million axioms***.** The PARKA project research team at the University of Maryland extracted *125913 assertions* (facts) from CIA World Fact book pages on the World-Wide Web using a *web robot* [VLKB, 1998]. Notice that these assertions are not rules, but *facts* such as "economy_imports#tajikistan#$690 million {1995}." For the conflation task, there is *no text available* to use as a source for a web robot and we need to extract rules from experts directly. In RKF program the maximum number of axioms was 90,000 per 10 months. Note that $90,000 < 2^{17}$, which means that for designing a complete knowledge base with 17 binary attributes we need even more axioms.

Building comprehensive virtual experts. A knowledge base will be called **complete** if for a given set of attributes the knowledge base can generate an answer for every combination of values of these attributes. We will say that a knowledge base has **comprehensive coverage** if a set of attributes of rules in the knowledge base covers most of attributes used in the domain. For instance, we may include in the knowledge base all the attributes used in NIMA's Vector Product Format (VPF) to get a comprehensive coverage. Nevertheless, this knowledge base may not be complete because rules cannot produce answers for many questions formulated as combinations of VPF attributes. However, there are some *positive examples* of a complete knowledge base in medical imaging, e.g., [Kovalerchuk, et al., 1996, 2001]. The challenge is that it is unlikely that the expert will enter complex rules involving, say 12 attributes. Later testing may show that the expert rule with only 3 attributes is wrong for some cases. The refinement can take years. The problem is that this process can be exponential in time. For instance, having 14 binary attributes we may search among $2^{14} = 16384$ potential rules.

To avoid refining and testing the knowledge base for years, we need to be sure that the set of rules is complete enough from the beginning. Asking the expert does he believe that 10 rules he entered are complete may not be the right choice. We need to be sure that the rest of potential 16384-10=16374 rules are not rules at all. Thus, DARPA's design time should also measure both rules included in the knowledge base and the rules **rejected.** If we know that something is not a rule, this is also useful knowledge. DARPA's current goal of 1,000,000 axioms, would correspond to a design of a complete knowledge base with less than 23 binary attributes. Note that the problem of designing a complete knowledge base above the limit of 20 attributes (10^9 potential rules) is especially critical when knowledge is not presented in any printed form (book, articles) and should be extracted from an expert as a sole knowledge body. This is the case of the virtual expert for imagery conflation/registration problem.

IVES SYSTEM ARCHITECTURE

There are three views of the system: (1) an imagery analyst view (end user view), (2) knowledge engineer's view (system support view), and (2) developer's view (tools development view). The support of an **imagery analyst's view** means defining *imagery analysis* from the Decision Making Level and to the Subpixel Level, implementing analysis tools, providing *quality assurance* tools, and specific tools for imagery *conflation.* The support of a **knowledge engineer view** includes providing tools for *discovering imagery analysis rules* including recording conflation process and discovering conflation rules.

The support of **a developer view** means providing conceptual and algorithmic base for building methods and software for *mission-specific solutions* that include: (1) new *optimized rule extraction procedures* using monotone Boolean functions; (2) a contradiction analysis method for extracted rules and for *deconflicting* rules obtained from different sources; (3) a recording method for capturing expert knowledge *on-the-fly*, and 4) Image-DAML (*I-DAML*) language, DAML ontologies, and agents. The complete system design contains seven components (see Figure 1). Currently IVES contains three integrated components: (1) Analysis and Recording Tool (ART), (2) Multi-Image Knowledge Extractor (MIKE), and (3) Joint Outline Notator with icon markup (JON).

The first component - Interactive on-the-fly recording of expert's actions during registration/conflation serves as major source of the raw information for rule generation. It is also useful as a quality control tool of the analyst's conflation results (a kind of airplane "black box"). An interactive optimized rule generation procedure based on the theory of monotone Boolean functions (TMBF) is intended to speed up direct generation rules by the imagery analyst. These two components are implemented in Java as a web portal. These components are described in more detail in the following sections. The data mining component (block 3) is designed to generalize the record of an expert's actions. The results of such generalizations are conflation rules. The major problem for successful mining of rules from recordings is that the system actually records lower level expert's actions, such as rotation, scaling, translation. Mining these lower level rules may not be very beneficial, thus the system provides a tool for the expert to record an identification of upper level categories such as "selecting main feature", "conflating main features", etc. The system design includes recording expert's actions and mined rules in XML format, for rules it is RML (rule markup language).

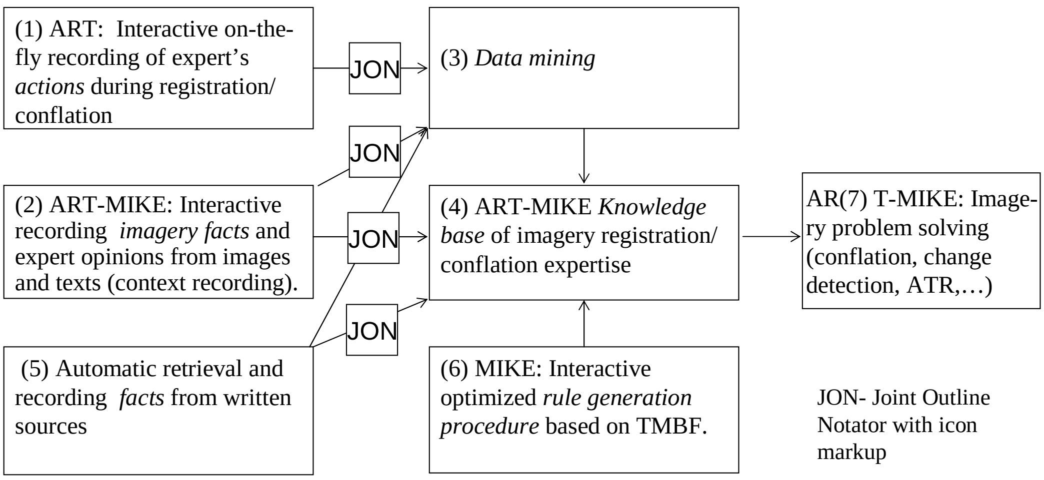


Figure 1. Imagery Virtual Expert System (IVES) architecture

Automatic retrieval and recording of facts from written sources (Block 3) is designed to fulfill functions similar to PARKA project (VLKB, 1998). At this moment, we do not consider this source as a main source to fill the KB with facts related to registration and conflation of images, but potentially it can provide useful facts for the KB. In contrast, interactive recording of imagery facts from images and texts (Block 6) can be one of the major sources of conflation related facts right now. The reason is that such recording provides *context* for conflation and registration tasks.

IMAGE-DAML LANGUAGE FOR IMAGERY RULE RECORDING

The state of the art in building expert systems assumes that a knowledge base in recorded and formalized as propositional if-then rules such as "If A and B then C", or as first order logic rules such as "If A(x,y) and B(x,z) then C(y.z)" It is also assumed that concepts (predicates A,B,C) and variables x,y,z are specified in advance for each individual expert system and knowledge base.

A **virtual expert system** is envisioned as a system that looks like a unified local expert system for a user but in fact it is distributed system on the web with components physically located in different places without a unified format and set of concepts. To deal with such distributed environment a markup language is necessary to encode predicates, variables, and rules. Currently DARPA Markup Language DAML and its more recent extension DAML-OWL is a primary markup language of the semantic web, but this language lacks 2-D, 3-D, and 4-D versions that are needed for virtual expert systems that will support multimodal imagery and video. Currently DAML is a one-dimensional text-based language. Thus the first problem is extending DAML approach to imagery by creating an **Image-DAML (I-DAML)** language with 2-D, 3-D, and possibly 4-D versions. Solving this problem can open an opportunity for a knowledge engineer to **record imagery analyst practice on the fly** using I-DAML.

Extending DAML to work with images has several aspects one of them is annotation of images. It can be done adding text annotation as a separate DAML file for each image. This approach has disadvantages – it does not provide a direct reference objects in the image and it does not provide a reference in the form of images (icons). For instance maps are annotated with icons that are not text annotations. Incorporation of NIMA symbology GeoSym, and Mil Std 25-25 and symbology is one on the goals in building I-DAML image annotation facilities. Similarly these facilities will benefit from adding mission specific icons such as fighting terrorism.

The development of original DAML that marks up text (not images) took years of work of several research teams. To avoid designing a completely new language with a new syntax, semantics and implementation we came up to the I-DAML development approach as follows: (1) Combining already available markup technologies to build I-DAML such as Java graphics libraries, scalable vector graphics (SVG), DAML-OWL, Rule Markup Language (RML), ontologies that can be related to image processing, (2) Developing iconized ontologies, (3) Developing an innovative GUI approach that can combine listed technologies together. The Mil Std 2525 symbology exists in SVG format. We developed its ontology concept tree that has now 8 levels with the number of concepts in each level as follows: 5, 24, 110, 229, 412, 292, 225, and 46 with total 1343 concepts involved. This ontology is being associated with Mil Std 2525 symbology (icons) in SVG format for imagery annotation and imagery expertise recording.

Extending DAML approach for imagery by creating an Image-DAML language with 3-D, 4-D versions is a challenging task. 3-D annotation means that we annotate objects in 3-D scene shown in the screen and 4-D annotation is the annotation of video. The Digital Elevation Models (DEM) and other 3-D models can be described in I-DAML and shown visually in 2-D screen but cannot be annotated by the same drag-and-drop GUI we have developed for 2-D IVES. Thus, for 3-D the approach is as follows: (1) Presenting 3-D scene as a set of 3-D objects, (2) Activating each 3-D object or its component interactively using user-friendly GUI, (3) Annotating the 3-D object in the same way as we did in 2-D, (4) Annotating 4-D scenes (3-D video) that contain a time component is designed by applying the previous steps to a selected 3-D frames, and (5) Incorporating Mil Std 25-25 symbology in Image-DAML language.

INTEGRATED DATA MINING AND "EXPERT MINING"

The next IVES problem is developing an **integrated** data mining and "expert mining" methodology to extract consistent imagery knowledge-base rules using format of semantic knowledge captured in Image-DAML. Below we describe a methodology that we have developed. It uses our original interactive procedures with a dynamic set of questions (Kovalerchuk et al., 1996). In the dynamic set of questions the next questions to the expert depend on answers to previous questions and are minimal for the worst-case scenario.

The fundamental challenge in this problem is that knowledge of imagery analysts is not recorded and formalized to discover rules using a data mining technique. We start from raw knowledge recorded in I-DAML. This knowledge can be queried using search technologies including queries based on I-DAML. Thus an imagery analyst can benefit from such raw knowledge in a traditional way for a knowledge management technology adapted by semantic web technology. This is important conceptually, but we are interested in a more sophisticated IVES. A traditional search technology finds related records but does not help directly in decision making. It does not provide a solution. A more sophisticated IVES intends to generalize raw rules (knowledge) going through three steps:

Step 1. Recording knowledge (rules) written in I-DAML. For instance **raw knowledge** could be: match (conflate) section (x,y) of feature A from in Image 1 with Feature B from (v,w) in Image2.

Step 2. Formalization of context of knowledge (rules) written in I-DAML as a set of parameters **Q** that represent relations between components in involved images. **Formalized knowledge example**: If **Q**(Image1, Image2) then match section (x,y) of feature A from in Image 1 match with Feature B from (v,w) in Image2.

Step 3. Relational Data Mining step: generalization of a set of formalized rules {R}. Assume that a set of rules {R} is large and there are many rules with the same then-part V, but different If-parts $\mathbf{Q}_i$, If $\mathbf{Q}_i$ Then V. In this case a relational data mining technique (Kovalerchuk, Vityaev, 2000) can automatically explore these rules and find their generalization in the form "If $\mathbf{Q}_s$ Then V", where $\mathbf{Q}_s$ is a set of parameters derived from sets $\mathbf{Q}_i$ such that "If (If $\mathbf{Q}_s$ Then V) Then (If $\mathbf{Q}_i$ Then V)".

CONSISTENT KNOWLEDGE BASE

Testing for contradiction between rules extracted from data using data mining techniques and "extracted" from experts using "expert mining" techniques is another problem in building IVES. Such techniques did not exist previously in general and for imagery analysis also. The imagery analysis specific challenge is that rules extracted from data using data mining do not exist yet and may not be discovered in a traditional for data mining way because the data are not collected and data types are much more complex than in traditional data mining. Thus, the process of building automatic conflation rules (algorithms), R_D, can differ from what is known in traditional data mining.

The method for testing rule contradiction has been developed. This method assumes that automatic rules $\{R_D\}$ and rules $\{R_E\}$ extracted from experts using the method described above in (2) are already recorded. The method makes rules $\{R_D\}$ and $\{R_E\}$ comparable in their languages by designing special knowledge representation techniques using ontologies and incremental rule parameter formalization, and compares uniformly presented rules for their differences. In our approach we: (i) start from a non-formalized set of parameters **Q,** (ii) obtain expert rules expressed using these parameters **Q**, (iii) run rules on real images after parameters **Q** are formalized and used to build an automatic conflation rule (algorithm) R_D, (iv) check that data are really conflatable using rule R_D, and (v) compare outputs of R_D and R_E .If data are conflatable by R_E, but are not conflatable with R_D, then a rule contradiction is discovered. This is important because it can influence the redesign of the rule (algorithm) R_D or correct a human rule R_E. This technique can be extended for many domains where consistency of knowledge is critical and should be tested.

Deconflicting rules obtained from different sources by deleting parts that are in conflict and testing against trusted sources and cases using case-based reasoning. Such techniques did not exist previously in general. We are planning to implement it. The imagery challenge has significant specifics here too because of involvement of complex mathematical operations for image transformations applied to millions of pixels. This process starts from the point where process of testing rules is finished and we know that the rules are contradictory. It is assumed that rules R_D and R_E may use own subsets $\mathbf{Q}_D$, $\mathbf{Q}_E$ of set of parameters **Q**. If $\mathbf{Q}_D \neq \mathbf{Q}_E$ and one of them, say $\mathbf{Q}_D$ is a subset of another one, $\mathbf{Q}_E$, $\mathbf{Q}_D \subset \mathbf{Q}_E$ then the rule R_E that uses more parameters $\mathbf{Q}_E$ should be explored first as a preferable candidate of an adequate rule. Such exploration includes testing that if according to R_E images should be conflatable, R_E(Im1,Im2)=1 for images Im1 and Im2, but rule R_D was not able to conflate images, (R_D(Im1,Im2)=0 then we need try to modify rule R_D by deconflicting it with rule R_E by using more parameters in R_D. The situation about rule preferences is more difficult when $\mathbf{Q}_E$=$\mathbf{Q}_D$, R_E(Im1,Im2)=1, and R_D(Im1,Im2)=0. Rule R_D does not conflate those images and should be modified to be able to conflate, but it is not clear how. No parameters are given to add to rule R_D to start modification. What can be done in this situation? In a traditional data mining approach it is a straightforward -- use more data within the same set of parameters $\mathbf{Q}_E=\mathbf{Q}_D$ to learn a better rule. In the imagery situation this approach is not very feasible because the situation is much more complex and lacks formalized data for automatic learning. A simulation approach is more realistic here, where data will be generated by the simulation and a machine learning method could be applied.

INFORMAL CONTEXT AND ALGORITHM-CENTERED KNOWLEDGE ENGINEERING TECHNOLOGY FOR IMAGERY ANALYSIS

The IVES challenge is harder than generally assumed in knowledge engineering approach because it requires a **direct reference to images** and **informal imagery context** as Figures 2 and 3 show. These problems involve direct references to raster or vector images with rules such as

IF the situation is as shown in Figure 3
THEN match a section (x,y) of feature 2 in Image A with the section (v,w) of feature 1 in Image B and do not match with section (y,z) of feature 3 in Image B.

Figure 3 shows this conflation situation where two red lines are from image A (lines 3 and 1) and lines 2 and 4 are from image B. Two alternative matches are possible for line 2. It can be matched with line 1 or 3 in image A. If conflation is done without an image context, then line 2 can be matched with line 3 because it is closer to it than line 1, but conceptual observations will alter this match. Below we present this reasoning in the form of the rules, showing the process of rules formalization from direct reference to the lines in the image by formally capturing the structure of relations between lines. Here the IF-part of the rule "the situation is as shown in images 1 and 2" that provides a **context of the reasoning is not formalized**, although specified. In the traditional approach it is assumed that the situation (context) is formalized as a set of parameters $\mathbf{Q}=\{Q_1,Q_2, \ldots, Q_n\}$. To address this problem we developed a new methodology. Our approach is to avoid unrealistic formalization of the situation in a single step, but offering a technology to build formalization as set of parameters **Q** step-by-step. We call this methodology an **algorithm-centered knowledge engineering methodology** for imagery analysis. In this methodology the process of recording and formalization of the rule presented above goes through several steps. Below we show three steps from an initial formalization of the rule ant its context to the pseudo code level of formalization.

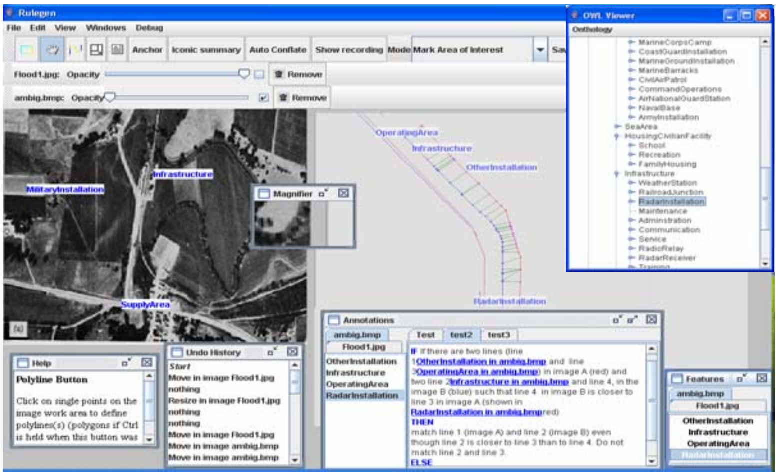


Figure 2. Direct reference to the image in imagery knowledge base rules with an example of I-DAML rule recording to resolve conflation ambiguity.

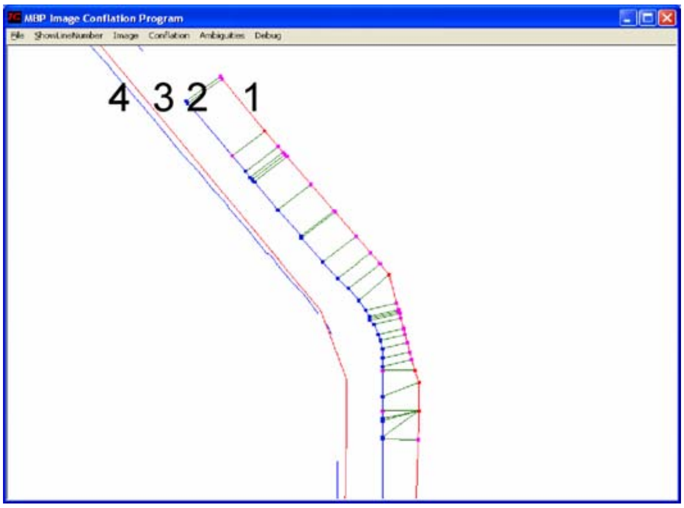


Figure 3. Conflation situation (informal context)

Initial formalization:

> If there are two lines in the image B such that line 4 is closer to line 3 from image A
> Then match line 1 and line 2

This formalization is justified since line 3 and line 4 match well, and line 3 should not match line 2. Figure 4 shows recording this rule in Image-DAML language with direct references to the objects (lines) in the images A and B.

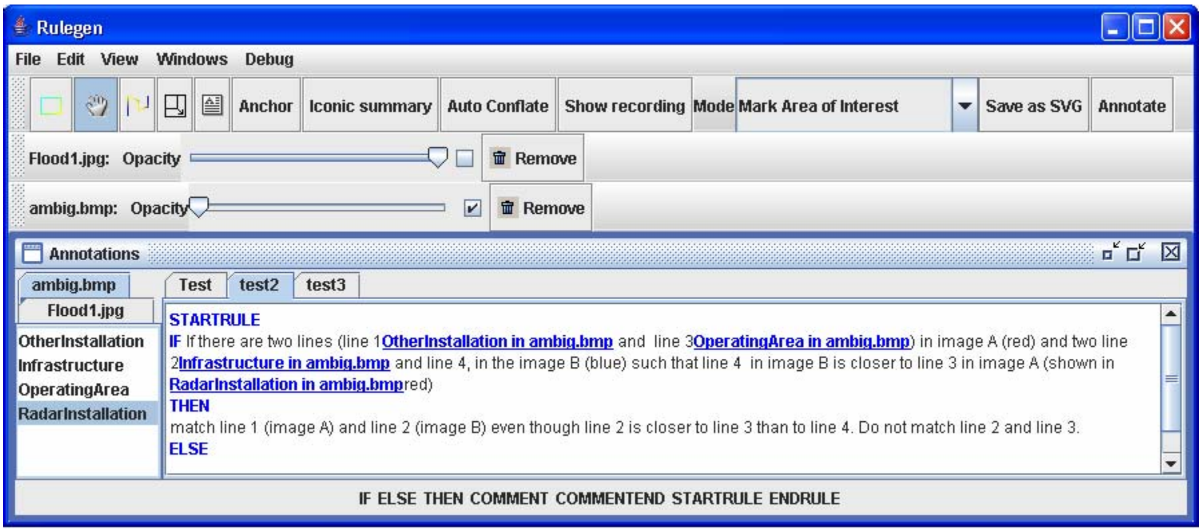


Figure 4. I-DAML rule recording interface

Formalization phase 2:

If

> there are two lines (line 1 and line 3) in image A (red) and two line 2 and line 4, in the image B (blue) such that line 4 in image B **is closer** to line 3 in image A (shown in red)

Then

> match line 1 (image A) and line 2 (image B) even though line 2 is closer to line 3 than to line 4. Do not match line 2 and line 3.

Formalization phase 3:
IF

Line 4 be the **best match** for *line2* from *Image A* excluding *line1*
Line 5 be the **best match** for *line3* from *Image A* excluding *line2*
q1 be the **quality of the match** for *line2* with *line4*
q2 be the **quality of the match** for *line3* with *line5*
If *q1* **is a better match** than *q2*

Then

suggest that *line1* matches with *line3* with confidence of q1-q2.

Else

suggest that *line1* matches with *line2* with confidence of q2-q1.

INTERACTIVE ON-THE-FLY ANALYSIS AND RECORDING AND I-DAML

The IVES system component called the Interactive on-the-fly **Analysis and Recording Tool** (**ART**) is implemented as a web portal that allows an expert to conflate images while having the knowledge presented by conflating these images recorded on-the-fly. A part of IVES is also implemented as an ArcMap Plug-in. ART currently allows the user to load a set of images and conflate these images using basic scaling, translation and rotation tools. The user can view these images overlapped and change the opacity of the images for conflating. The system provides facilities for marking up the sections of the images using various shape tools. Each of these markups can be named by the user using a basic name of his/her choice or by choosing from a list of predefined terms from a variety of ontologies. Such marking permits to build the bridge between the image and the domain that will describe the image in a deeper context.

Currently, the system ontology base includes three ontologies:

- DAML-OWL Geofile ontology [DAML Geofile, 2001],
- DAML-OWL CIA World Fact book ontology [DAML WFB, 2002],
- DAML-OWL NIMA Feature and Attribute Coding Catalogue [FACC].

Other ontologies also can be loaded. The Geofile ontology consists of about 70 terms on the low level and 6 terms on the top level of the tree next to the root. The World Fact book ontology consists of about 190 terms on two levels and the Feature and Attribute Coding Catalogue ontology consists of 540 terms on the low level, 59 terms on the next level and 8 terms on the level on level next to the tree root. ART supports tree view of these ontologies with the following functionality: browsing, editing (adding new terms and deleting terms), expanding and shrinking tree view, adding icons to terms and drugging icons to images.

Selected parts of images can be marked up with terms from these ontologies (see block 1 in Figure 5). There is also a detailed list of actions the user has performed that can be undone and redone to any point. A basic magnifier is available for taking a detailed look at the image. Any of these markups and conflations can be applied to multiple images to allow two (or more) images already conflated to be conflated to a third image or simply zoom in all images. All of these actions are recorded, can be presented in a human readable form and are available for playback.ART includes three categories of tools: *basic tools*, *conflation tools* and on-the-fly user *action recording tools*. Basic and conflation tools allow the user to load a set of images, and conflate them using scaling, translation and rotation and affine control points and shape based conflation tools. These tools provide a foundation for interactive tools on-the-fly recording of expert's actions is implemented as a web portal. Thus the system allows an expert to conflate images while having the expert knowledge presented by conflating these images recorded on-the-fly.

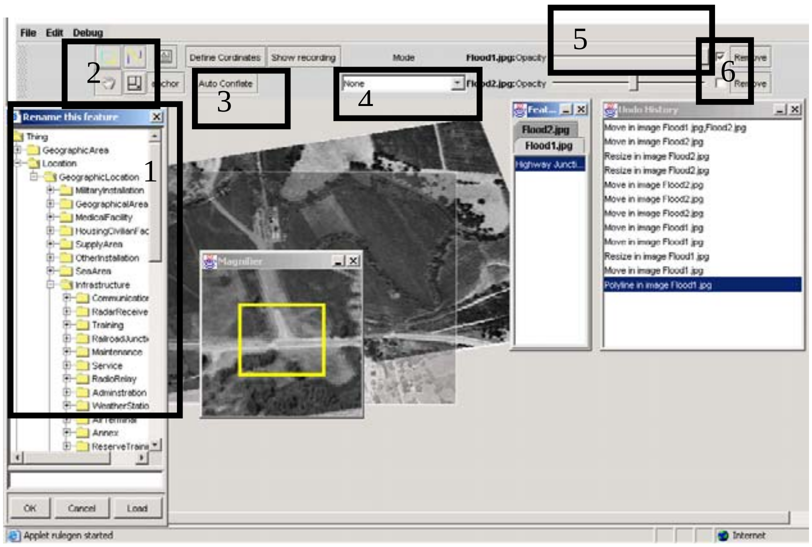


Figure 5. Image of sample conflation using the case recorder tool.

The user can view these images overlapped and change the opacity of the images for conflating. The system provides facilities for marking up the sections of the images using various shape tools. Each of these markups can be named by the user using a basic name of his/her choice or by choosing from a list of predefined terms from one of the ontologies, e.g., DAML-OWL Geofile ontology. There is also a detailed list of actions the user has performed that can be undone and redone to any point. A basic magnifier is available for taking a detailed look at the image. Any of these markups and conflations can be applied to multiple images to allow two (or more) images to be conflated. All of these actions are recorded, can be presented in a human readable form, and are available for playback. Figure 5 shows a conflation sample with user action recording using ART. The list below presents comments to numbered items shown in Figure 5:

1. The Markup tools can be used to mark major features on the image and name them, these names can be defined in a variety of ontologies.
2. The move, resize, and rotate tools are basic operations used to conflate images
3. The Auto Conflate tool allows the user to choose 3 points on two images and using transformations, match those points together (and hopefully the images as well).
4. The Show recording button allows the user to see how the conflation was broken up via the current mode that was used in various segments of the conflating.
5. The Opacity slider is used to set the transparency of the images, allowing one image to be seen through another.
6. The checkboxes are used to select the image(s) that will receive the operations such as move or draw polyline. This allows a user to resize or rotate both images together, or once two images have been conflated together, a third image can be brought in and conflated against the other two together.

MULTI-IMAGE KNOWLEDGE EXTRACTOR

A **Multi-Image Knowledge Extractor** (**MIKE**) assists an imagery analyst in rule extraction and recording. The common way to extract rules is asking an expert to write down rules and providing software for converting the rules to computer-readable knowledge base (KB) form. The major problem with this straightforward approach is that: (1) typically experts have limited time available for rule entering, refining, testing and debugging, (2) the refinement time can grow exponentially with adding more attributes, (3) experts are unlikely to enter complex rules because it is difficult to keep in mind more then 7±2 attributes, (4) in life critical applications, the process of rule refinement and debugging has to finish before the system is used. The rule generation contains five steps depicted in Figure 6, and Figure 7 illustrates its implementation.

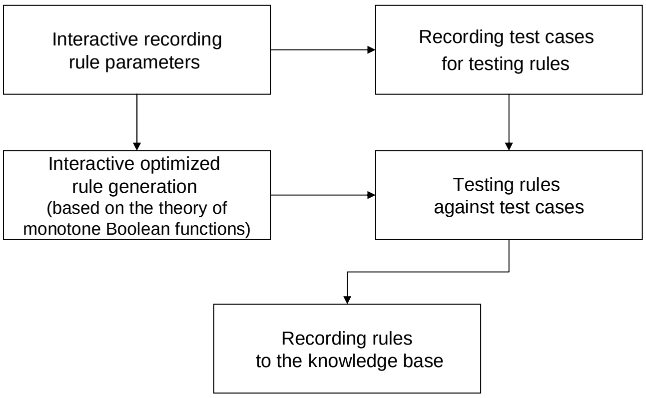


Figure 6. Interactive rule generation

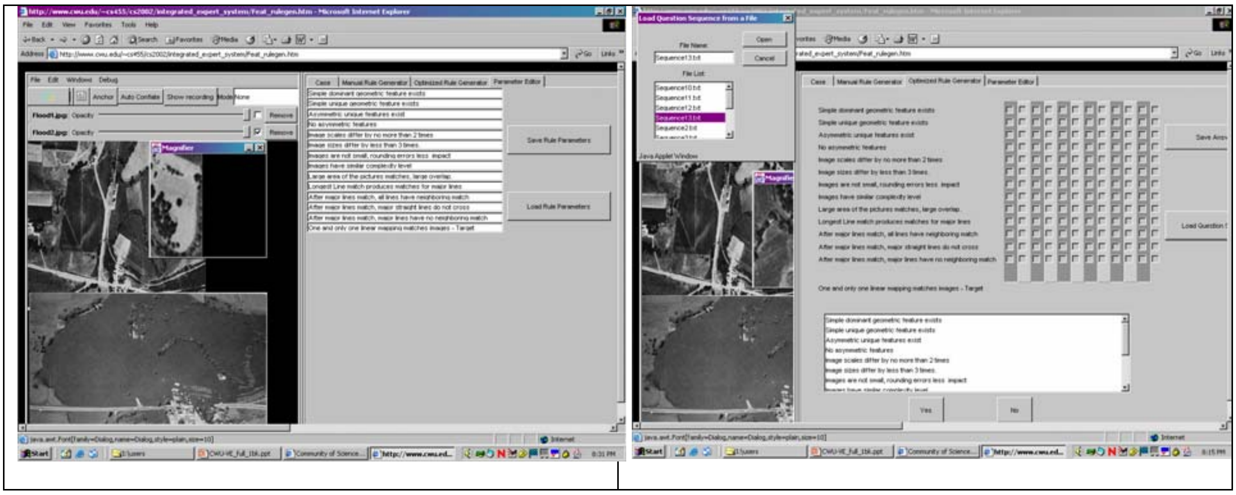


Figure 7. Multi-Image Knowledge Extractor (MIKE)

ICONIC ONTOLOGICAL CONFLATION

General Iconic Conflation is implemented as an extension of ART-MAKE software. This system: (1) loads images, (2) loads ontologies including iconized ontologies, (3) edits ontologies, (4) marks up images using a selected ontology, (5) marks up images with icons associated concepts in ontologies (each images can be annotated using a mixture of ontologies), (6) generates ontological iconic annotation of images to be able to compare and conflate images on conceptual ontological level, (7) stores marked up images in a database, loads marked up images, runs iconic conflation to find matched images and conflates images using ontological similarity measure.

Below we describe a conflation task of two images taken from [Lillesand, Kiefer, 1987]. In essence these images cover the same area, but one of them covered by water as a result of flood. The flood area is almost half of the image. We assume the scenario where person A annotates image flood1 independently of person B who annotates image 2 using the same or different ontologies. Because persons A and B do not coordinate image annotation process, they can pick up different terms from ontologies to mark the same spot in two images. This is a typical situation in GIS where the same object may have several individual and group manes associated.

We start with *Person A.* We assume that person A's only goal is to annotate the image with useful icons so it can be later used as a tool in conflation. This person even may not possess skills to accomplish conflation.

The screenshot in Figure 8 shows the steps of the iconic conflation process after opening a blank workspace of ART, loading an OWL Goefile ontology and a raster image. The tree-based ontology is marked up with icons. These icons appear in the iconic annotation of the images. Since Geofile didn't come with icons, synthetic ones are used instead. These icons can be raster images or SVG files. The user drags icons onto the image in order to mark it up. This is the starting situation for the creation of the bridge between the image and the domain information in the form of DAML-OWL ontology when an image and an ontology are loaded.

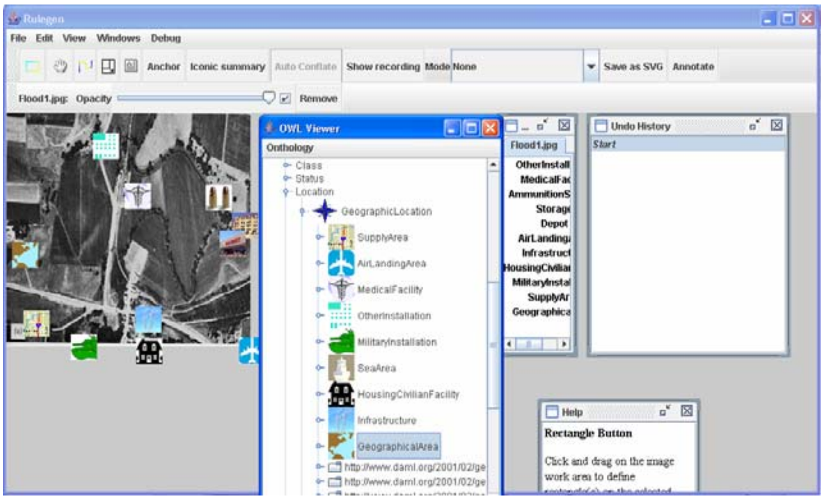


Figure 8. Image with various iconic annotations from the DAML-OWL Geofile ontology shown in the middle.

The next step is to record the annotated image 1. The user can store annotated images and after that ART-MIKE software no longer has just a raster image to work with, but knows the location of various key features via iconic annotation. Finally the annotation is committed to a database where it can be later pulled for reference data. Person A's goal for this image is done. Now we move onto person B. Person B just received a photo of a flooded area and needs to know what was beneath that water area. These steps show the completion of one task (annotating images) and the start of another task (**conflating images**). Expert requests the system for a suggestive match. The system tries to determine a match based on the similarities of the annotations in each image and shows the results for the expert to evaluate.

An automated approach to match up iconic annotations from one image to another is based on similarities of ontological concepts in the ontology tree. The similarity of two annotations (annotated features), F_1 and F_2 is measured by *upper matching category (UMC)* in the ontology that is: (1) the node itself if both nodes are the same, (2) one of the nodes, if one of the nodes is ancestor for another, and (3) a closest ancestor for both annotations otherwise. For instance, in the iconic summary in the bottom in Figure 9 on the left (see also ontological match in Figure 10) concept "other installation" and concept "air landing area" have concept "geographic location" as their closest ancestor. Concepts "sea area" and "geographic location" have "geographic location: as a common closest ancestor and concept "supply area" appeared in both images has itself as UMC. The match level for each pair of these iconized concepts is the level of UMC in the ontology tree. For instance, the node "geographic location" is a root and other concepts belong to lower levels. Thus, we have three matched points (identified by matched icon locations) in two images and an affine transform can be run to conflate images. Figure 10 shows the result of such type of conflation using our ArcGIS Plug-in.

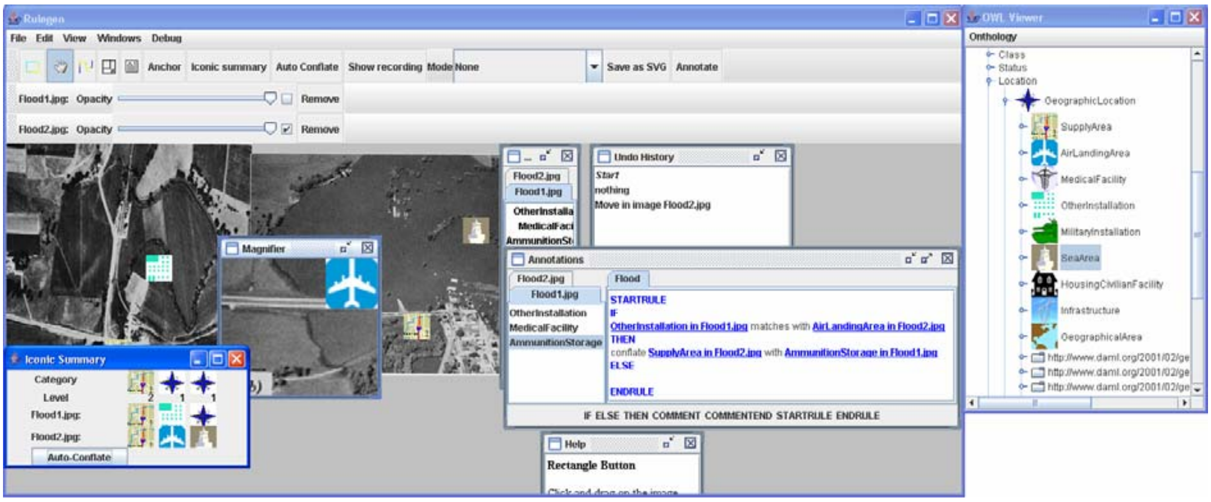
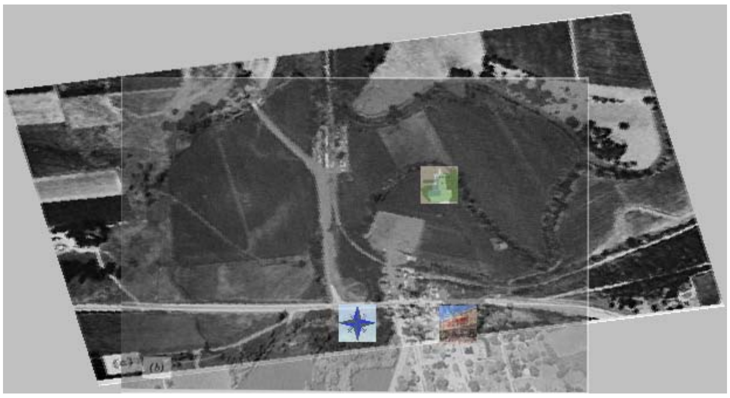
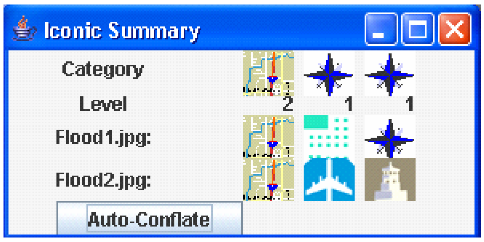


Figure 9. Annotated images and iconic conflation





Ontological match for Figure 9

Figure 10. Result of affine conflation based on an ontological match

CONCLUSION

In moving toward the goal of preserving human expertise in imagery analysis and capturing non-formalized context, virtual expert tools have been developed to assist knowledge engineers and image analysts in populating the knowledge base of the virtual expert. The first tool records an imagery analyst's actions on the fly, assists the analyst in marking up imagery with iconized ontology terms and provides an ontological image conflation. The second tool generates expert rules by questioning the imagery analyst and minimizing questioning time using the theory of Monotone Boolean functions. These tools are implemented as a web portal using Java.

Future work for a knowledge engineer includes developing tools for discovering imagery analysis rules, implement tools for recording conflation process, and developing tools to apply imagery analysis rules to conflation.

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