Integration of Case-Based and Image-Based Reasoning

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Introduction

Within the psychology community, mental imagery is considered as a major medium of thought. People often describe the sensation of visualizing, manipulating and inspecting "pictures in their heads" during problem solving. Recently, researchers in artificial intelligence have been considering how to best reason with image or diagrammatic representations (Glasgow, Narayanan, & Chandrasekaren 1995). This paper is concerned with how we can incorporate such work on computational image-based reasoning in the context of CBR. In particular, we discuss how CBR might be applied in domains where reasoning and decision making relies heavily on visual or spatial information derived from images. Examples of such domains are medicine, where information derived from X-rays, NMR images, etc. may be important to decision making, geographical information systems, where satellite image information plays a crucial role, and molecular biology, where the understanding of the three-dimensional geometry of a molecular structure is often essential to problem solving. Combining imagery and CBR could also prove fruitful for robotic motion planning, where sensory data could be effectively integrated with experiential knowledge. Although these applications appear diverse, they are related in the sense that they can benefit from CBR systems, and they all rely on the ability to represent, pattern match and possibly adapt image representations.

We briefly review some of the related research in the area of image-based reasoning. This is followed by a discussion on how such reasoning techniques can be integrated with techniques from CBR, particularly for the purpose of building decision-support systems that rely on image data stored in a computer. The paper also includes a presentation of the role of image analysis and feature extraction techniques in image-related CBR application.

Reasoning With Images

Reasoning with images (pictures, diagrams, analogical representations) has been the topic of recent interest in the artificial intelligence community. The issues involved in this research are not so much how to interpret image data (as in image processing or machine vision), but rather how to represent and reason with image information in order to carry out the problem solving.

The concept of constructing knowledge representations that mirror the structure of the world is not new. Hayes (1974) discusses *direct* representations in which there exist similarities between what is being represented and the medium of the representation. Sloman (1975) has also argued the pros and cons of analogical representations, and concluded that a variety of representation formalisms – including those specialized for spatial reasoning – are important to AI problem solving (Sloman 1993). Hybrid approaches have also been suggested for visual-spatial and model-based reasoning. Barwise and Etchemendy (1992) have proposed a system called *Hyperproof* which integrates diagrammatic reasoning with sentence-based logics. Hyperproof uses both diagrams and logic notation to teach students how to reason logically. In subsequent work, Barwise and Etchemendy (1993) presented a formal semantics for reasoning with Hyperproof diagrams. Habel and colleagues (1993) have developed a hybrid system consisting of a propositional and depictorial partonomy (organization of parts) for reasoning, where the depictorial partonomy reflects the hierarchy proposed in representations for visual processes. They suggest that the advantage of the depictorial representation in their system is that it facilitates an efficient attention-driven method for reasoning. Myers and Konolige (1992) treat model-based manipulations as a form of inference within a classical logic system. More specifically, they store partially interpreted sensor data using an analogical representation that interacts with a general-purpose sentential language. A similar approach has been taken by Chandrasekaran and Narayanan (1990), who have proposed an architecture where analogical representations derived from visual perception are used in combination with symbolic (propositional) representations. A technique for qualitative spatial reasoning, based on the directional orientation information made available through perceptual processes, has been presented by Freksa and Zimmermann (1993). In this work, orientations in two-dimensional space are defined by the relation between a vector and a point.

Visual-spatial reasoning techniques have also been considered in the context of specific application domains. Funt (1980) represents and manipulates a visual analog of a world in order to predict potential instabilities and collisions in a physical domain. Several others have applied diagrams or analogical representations to qualitative physics problems (Forbus 1983; Gardin & Meltzer 1989; Habel, Pribbenow, & Simmons 1993; Narayanan & Chandrasekaran 1992). For the domain of route planning, Kuipers (1978) has developed a program that determines a path between points by considering a hierarchical network of region representations. McDermott and Davis (1984) describe a more general representation for route planning that stores the shapes and locations of entities in the world. Facts in this system are represented as propositions and spatial reasoning is carried out by special-purpose modules that incorporate both theorem proving and numerical computations. Other problem domains where diagrammatic reasoning has been applied include biology, architecture, geometry and theorem proving (Narayanan 1992).

Research in geographical information systems and spatial databases has long been concerned with the issue of representing spatial knowledge. Samet (1989) has proposed a method for storing geographic knowledge based on the recursive decomposition of space. In this work, the term *quadtree* is used to describe binary array data structures that iteratively subdivide regions into segments until blocks are obtained that consist entirely of 1s or entirely of 0s. These structures (and their three-dimensional counterpart, termed *octrees*) are efficiently stored and implemented as trees, where each node of the tree corresponds to a region in the decomposition hierarchy. The idea of quadtrees has also been explored by Ahmad and Grosky (1997) for spatial similarity-based retrieval. Similarity of images is computed as similarity of quadtrees. An alternative approach to reasoning in geographic systems has been described by Papadias and Sellis (1993). In their work, a symbolic two-dimensional array structure is used to preserve a set of spatial relations among geographic entities. Their approach is similar to a model for geographic information systems based on the array representation scheme proposed in this paper (Glasgow 1993c).

Spatial representations have also been considered in machine vision research. According to Biederman (1987), the representation of objects can be constructed as a spatial organization of simple primitive volumes, called *geons*. The process of image analysis, as defined by Marr and colleagues (1982), depends on a series of representations culminating in a three-dimensional model of the spatial relations among entities which makes explicit *what* is *where*. As in Marr's approach to computational vision, *molecular scene analysis* (Fortier *et al.* 1993) is concerned with discovering what is present in the world and where it is spatially located. The act of determining the structure of a molecule is an interactive process consisting of a state space search of partially interpreted scenes, which can be represented and evaluated as three-dimensional symbolic array models (Glasgow, Fortier, & Allen 1993).

The ideas presented in this paper have partially evolved from research in the area of computational imagery (Glasgow & Papadias 1992; Glasgow 1993a; 1993b), which involves the study of AI knowledge representation and inferencing techniques that correspond to the representations and processes for mental imagery. In the previously proposed scheme for computational imagery, a mathematical theory of arrays provides a basis for representing and reasoning about visual and spatial properties of entities in the world. Although results of cognitive studies offered initial motivation for the representations and functionality of the formalism, the ultimate concerns of research in computational imagery are expressive power, inferential adequacy and efficiency.

Integration of Imagery and CBR

This section will consider the issues of case representation, retrieval and adaptation in the context of image-based reasoning.

Case Representation

How is image information best represented in a case? Unfortunately, there is no one answer to this question; how we choose to represent an image depends on the type of questions we seek to answer. By making particular features of the image explicit, we can provide for efficient pattern matching, retrieval and adaptation in our CBR system. Take, for example, the multiple representations of a molecular structure illustrated in Figure 1. If we wish to determine how many atoms of carbon are contained in a molecule, then the formula in Figure 1 a) is sufficient. However, if we need to derive connectivity, angle, distance or shape information, then more complex image representations, such as those in Figure 1 b) and c) are more appropriate.

We propose that image information may be stored explicitly, such as in a digital bit map, or implicitly, perhaps using shape descriptor that could be used to reconstruct a bit map. An image may be stored preserving all relevant visual information, or as a simplified model (such as a graph or an array representation), depending on the features we wish to extract. Some form of indexing is required for sizeable image databases.

Image Retrieval and Adaptation

As with any CBR system, a key issue in image domains is to determine what features are important for determining similarity for the purpose of case retrieval. There are many dimensions over which images can be compared: shape, color, size, spatial configuration, component membership, etc. Following, we discuss some mechanisms for image comparison.

Previously we have considered issues in structural similarity and equivalence (Conklin & Glasgow 1992). In this work, we measured the similarity between two images in terms of the transformations necessary to bring them into equivalence, where transformations may include replacing, deleting or moving a part, or rotation of the entire image. This approach to spatial analogy has been applied to the problem of comparing and classifying molecular structures (Conklin, Fortier, & Glasgow 1993; Conklin *et al.* 1996).

Jagadish (1991) proposes an organization of objects in a spatial database, which permits efficient retrieval using shape similarity: two shapes are similar if the area where they do not match is smaller than an error margin when one shape is placed on top of the other (Jagadish 1991). The error margin is not constant and is used to control the number of retrieved cases. This approach is similar to the contrast model (Tversky 1977).

In addition to traditional symbolic approaches to similarity assessment, biomedical domains require visual/spatial similarity comparisons among image representations. Most of the current applications that combine CBR and image databases are passive in a sense that they use images only as examples (Macura & Macura 1995). Haigh and Schewchuk (1994) present a case-based planning system extended to handle two-dimensional graphs that are used to index into the case base. In contrast, our goal is to combine CBR systems with active image processing.

There are several ways of combining image- and case-based reasoning:

- Include image descriptions or depictions as part of a case. For example, in order to provide a diagnosis for a given patient, find patients with similar symptoms and similar X-ray results.
- Use image-based reasoning to focus case retrieval. For example, suggest a treatment plan by finding patients with similar X-rays and then explore the symbolic representation. This requires that either fast image retrieval is available (Petrakis & Faloutsos 1997) or that fast model-based shape recognition is in place (Lamdan, Schwarz, & Wolfson 1990).
- Use CBR to focus image analysis only on the relevant portion of the image database. Efficient case retrieval can focus the search space of applicable images and thus reduce the image analysis complexity.
- Use image analysis to extract important features from images. This approach might result in the loss of some visual information but would enable traditional symbolic retrieval and reasoning techniques to be applied efficiently.

Regardless of the method chosen, image retrieval and adaptation may require *image segmentation* – a process that identifies objects within the image, and *image analysis* – a process that analyzes image and objects within the image.

Image segmentation algorithms can be applied to locate objects within an image (Xu, Olman, & Uberbacher 1996) or to separate objects during classification (Agam & Dinstein 1997). There are two main approaches available: region-oriented segmentation, which are based on searching for connected regions with similar gray-level values, and edge-oriented segmentation, which involve searching for abrupt change in gray levels that are likely to indicate an edge between neighboring objects. An interesting step toward integration of knowledge-based techniques to help during the segmentation task is presented in (Tresp *et al.* 1996). Here, a knowledge base is used to determine what objects should be recognized when they have fuzzy boundaries. The method allows for specifying a bias, i.e., domain knowledge about the object.

Automatic image indexing is used to make complex visual image comparison algorithms scalable for large image databases (Zheng & Leung 1996). Feature-based retrieval methods (Adam & Gangopadhyay 1998) use image features, such as color, shape or texture to access relevant images. Because these features describe content of an image, such techniques are also referred to as content-based retrieval. Current query-by-image-content retrieval techniques (Flickner *et al.* 1995; Ogle & Stonebraker 1995) use symbolic or numeric

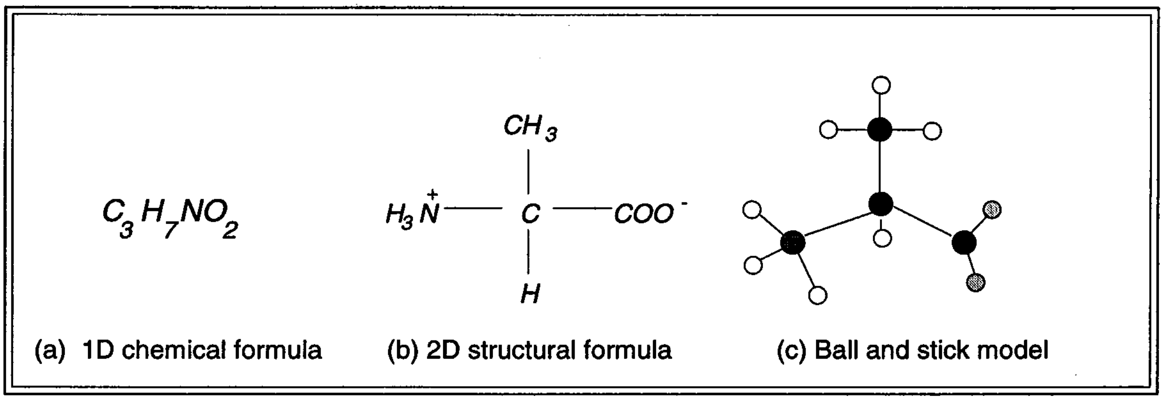

Figure 1: Alternative representations for molecule

features that characterize images. Image features my either be encoded by human experts or determined using simple features extraction (such as color or texture). The query features can be provided by the user in several forms: by selecting an example (forming a query-by-example retrieval), by providing drawings or sketches, or by selecting colors and textures from menus. The complexity of the image segmentation and analysis tasks prevents application of automatic feature extraction techniques. However, in domains with limited scope automated techniques can be applied, especially when the domain expert can control and guide the process. Also, the existence of domains knowledge (in the form of cases, rules or models) can be used to form a knowledge-based image analysis.

Psychological studies have provided evidence that suggest the existence of an isomorphism between physical and imagined image transformations (Shepard & Metzler 1971). Similarly, we can propose a set of primitive computational transformation operations that can form the basis for image adaptation. For example, Ohkawa *et al.* (1996) describe protein classification method using structural transformations, such as deletion or creation, magnification, rotation, movement, exchange or change of kind. In their work, authors compute similarity between proteins on the basis of the cost of individual transformations and their number. Thus, if many transformations are needed or expensive transformation are required then protein structures are marked dissimilar.

Image Analysis and Feature Extraction

Image analysis can be used to extract features from images for more efficient image retrieval or for decision support. Recognized features can enhance CBR and knowledge discovery. A combination of image analysis techniques and CBR can thus serve as: 1) a feature extraction technique, which enables us to use traditional retrieval algorithms for fast image access; 2) an indexing approach, which makes content-based image retrieval scalable; and 3) an analysis tool, which brings additional insight into relations among images and between image and symbolic features.

The application of CBR to biomedical image domains is limited without support for similarity-based image retrieval and image analysis. Computational vision offers many techniques that can be applied. In general, there are two possible integrations of such techniques with CBR: combining CBR system with a computational vision system, or using image analysis techniques to extract important features from existing images (these could then be stored in symbolic form).

Many approaches have been proposed for the problem of identification of image features. These include: polynomials for fitting curves (McInerney & Terzopoulos 1996) or planes (Leclerc 1997); similarity invariant coordinate systems (SICS) that represent images as points and vectors (Li 1997); attributed relational graphs (ARG) (Petrakis & Faloutsos 1997); and transformation sets (Basri & Weinshall 1992; Conklin & Glasgow 1992; Ohkawa *et al.* 1996).

Deformable Models

Deformable models are model-based techniques for image analysis. They have been successfully used for image segmentation, matching and deriving image object size, shape and location (McInerney & Terzopoulos 1996). Thus, they play a significant role in medical image analysis.

Possible tasks where deformable models can be a useful enhancement of CBR include: representation and compression, storage and archiving, comparison (direct and via extracted features), indexing, analysis, feature extraction, abstraction of images, segment identification, track motion or evolution.

Current systems for content-based image retrieval concentrate either on using an expert's abstractions or on simple image characteristics (i.e., color, shape, or shade). This obviously has only a limited applicability. Retrieval by image content involves the problem of obtaining image attributes. This problem can be solved by applying model-based reasoning with deformable models. Here, available models are previously recognized images and deformable models are used for image alignment and thus recognition.

Another important use of deformable models is automated image feature extraction. Here, a deformable model can be used to find image features, such as shape or size. This can be used to classify the image, which in turn can be used in conjunction with other symbolic attributes during decision making. Image feature extraction is identification of image metadata, which can be used as:

- indexes to the image database, supporting scalable similarity-based retrieval;
- models of prototypical features (e.g., tumors in brain scans), implementing model-based retrieval;
- a mechanism for content-based compression (i.e., prototypes and differences are stored).
- auxiliary information in combination with CBR and knowledge-discovery techniques.

Deformable models can also be applied to identifying dynamic properties of images. Namely, a group of models may be compared to another group to identify evolving images. Alternatively, a spatio-temporal similarity measure could be used to identify segments on sequence of images (Choi, Lee, & Kim 1997).

An Application

Our previous studies showed that CBR can successfully be applied to treatment prediction in complex medical domains (Jurisica *et al.* 1998) – in particular for *in vitro* fertilization. In this study, we have also presented an attribute-oriented, knowledge-discovery algorithm. However, because the system was using only symbolic information, the potential of information present in embryo development images could not be explored.

Morphometry comprises techniques for measurement of the size and shape of biological structures. In *in vitro* fertilization, morphometry is used to assess the quality of embryos and oocytes (Garside *et al.* 1997; Roux *et al.* 1995). However, there are problems with analyzing morphology of embryos: First, measurement of embryo and oocyte size is hampered by segmentation, i.e., difficulties in detecting and localizing the boundaries of structures in images. As well, time-series analysis is limited by the ability to accurately find corresponding points in scans taken at different intervals (registration problem).

We propose to use computer-based morphometry to precisely and objectively identify the quality of oocytes and embryos. Extracted morphological information can be linked with symbolic information to better predict pregnancy outcome, because the embryo quality will be objectively characterized. It is believed that embryo morphology is an important factor during treatment planning and outcome rediction. In addition, linking embryo morphology to clinical results may bring insight into which morphological features of embryos are important factors.

Figure 2 shows how deformable models, called snakes (McInerney & Terzopoulos 1996) are used to identify the shape of an embryo. Morphological analysis is performed in steps, each of which requires different parameters to be chosen for the snakes. First, the embryo's diameter is identified. In the subsequent step, the zona pellucida surrounding the embryo is detected and its thickness computed. Thickness of zona pellucida affects the fertility results (Ducibella 1998; Garside *et al.* 1997) and thus its objective calculation is important.

Embryo image analysis allows for the evaluation of morphology and developmental features of oocytes and embryos (including cell number, fragmentation, cellular appearance, zona thickness, etc.). Although individual steps during morphological analysis require different parameters of the snake to be used, the number of analysis tasks is limited and thus these parameters can be preset for individual tasks (e.g., to recognize embryo shape, recognize zona pellucida).

Concluding Remarks

The idea of combining image-based reasoning and CBR is new, and there are many avenues that need to be explored. Above we have presented just a brief glimpse at some of the issues involved in integrating these two approaches to reasoning and problem solving. In particular, we have focused on how CBR could be applied in image domains.

We are currently considering the use of CBR in several domains involving image data. We have applied CBR to the problem of *molecular scene analysis* (Glasgow, Conklin, & Fortier 1993). This work focuses on determining how structural protein data can be organized to permit efficient and rapid retrieval from a case base of molecular scenes. In particular, CBR is used to anticipate 3D substructures that might occur within a novel protein image (constructed from an X-ray diffraction experiment). CBR is also being considered as an approach for planning crystallization experiments for proteins, where a visual image of the potential crystal resulting from an experiment is stored in the case and potentially used in the retrieval process.

Medicine is another area with potential for integration of CBR and image-based reasoning. Previously, we have demonstrated how CBR can be applied to the problem of prediction and diagnosis in a medical domain (Jurisica *et al.* 1998). The early prototype of our system worked only with symbolic patient data. Later, more detailed information was collected, including oocyte and embryo images. These images are analyzed by embryologists and the extracted information is used by doctors to potentially provide an explanation of multiple failed implantations. Image analysis evaluates morphology and developmental features of oocytes and embryos (including cell number, fragmentation, cellular appearance, zona thickness, etc.). Although humans can analyze image more flexibly, computer vision helps to make the process more objective and precise.

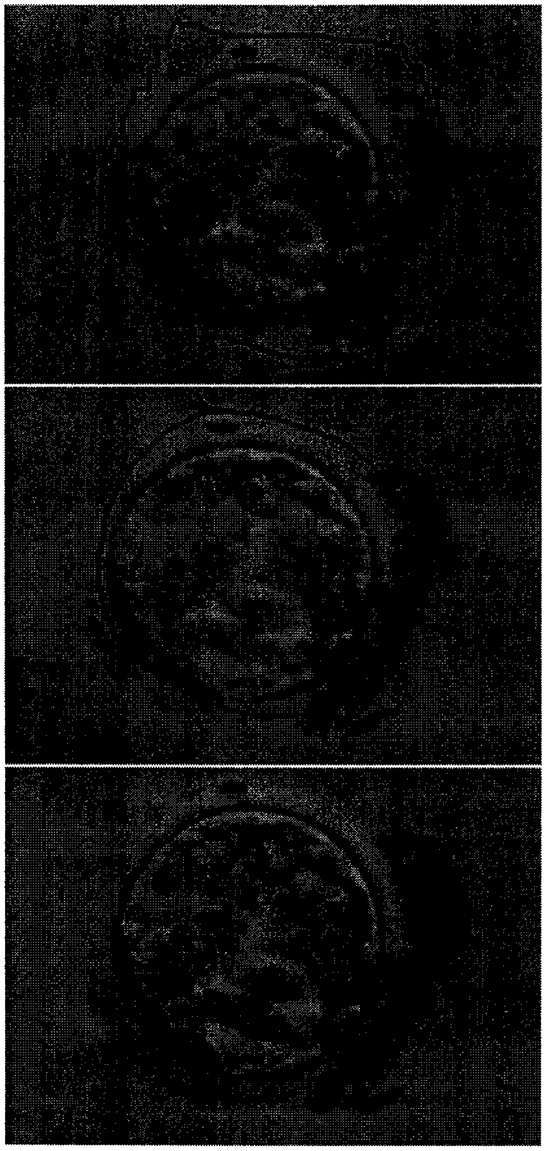

Figure 2: Feature extraction in IVF. Example of an embryo morphology analysis using deformable models to find important image features. The first image shows the initial placement of the snake around the area of interest; the second image illustrates an intermediate result; and the last image demonstrates how the snake recognized the embryo boundary.

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