

# Image processing in case-based reasoning

PETRA PERNER<sup>1</sup>, ALEC HOLT<sup>2</sup> and MICHAEL RICHTER<sup>3</sup>

<sup>1</sup>*Institute of Computer Vision and Applied Computer Sciences, Körnerstraße 10, 04107 Leipzig, Germany;*  
e-mail: pperner@ibai-institut.de

<sup>2</sup>*Health Informatics, Department of Information Science, University of Otago, PO Box 56, Dunedin, New Zealand;*  
e-mail: aholt@infoscience.otago.ac.nz

<sup>3</sup>*Department of Computer Science, University of Calgary, Canada;*  
e-mail: richter@informatik.uni-kl.de

## Abstract

This commentary summarizes case-based reasoning (CBR) research applied to image processing. It includes references to the systems, workshops, and landmark publications. Image processing includes a variety of image formats, from computer tomography images to remote sensing and spatial data sets.

## 1 Introduction

Image processing is a challenging field. The unique data (images) and the necessary computation techniques require extraordinary case representations, similarity measures and case-based reasoning (CBR) strategies to be utilized. Image interpretation is the process of mapping the numerical representation of an image into logical representations suitable for scene descriptions. An image interpretation system must be able to extract symbolic features from the pixels of an image (e.g., irregular structure inside the nodule, area of calcification, and sharp margin). This is a complex process; the image passes through several general processing steps before the final symbolic description is obtained. Image interpretation systems are becoming increasingly popular in medical and industrial applications. However, existing statistical and knowledge-based techniques lack robustness, accuracy, and flexibility. New strategies are needed that can adapt to changing environmental conditions, user needs, and process requirements. Introducing CBR strategies into image interpretation systems can satisfy these requirements. CBR can be used to control the image processing process in all phases of an image interpretation system to derive information of the highest possible quality. Beyond this CBR offers different learning capabilities, for all phases of an image interpretation system, that satisfy different needs during the development process of an image interpretation system. An overview of the challenges of image processing and image interpretation by introducing CBR strategies is given in (Perner, 2001).

## 2 Image processing

Several systems have been developed that apply CBR for image retrieval and interpretation at the symbolic level. Usually the images are not processed, and the symbolic terms are user-specified. Early examples include Macura & Macura (1995) for retrieval of radiological images, Haddad *et al.* (1997) for the detection of coronary heart disease, and Jaulent *et al.* (1998) for the diagnosis of breast cancer in histopathology.

Grimnes & Aamodt (1996) presented a system that integrates CBR into a task-oriented model-based system for interpreting abdominal computer tomography (CT) images. A case-based

reasoner working on a segment case base contains the individual image segments. These cases with labels are considered indices for another case-based reasoner working on an organ interpretation case base. Their system is based on a propose–critique–modify learning cycle. Jarmulak (1998) presented a system for ultrasonic B-scans, which are one-dimensional signals. He presented a tree-based retrieval strategy. A completely different application of CBR to image processing was described by Ficet-Cauchard *et al.* (1999). They applied CBR for the development of the image processing steps of formerly unknown image processing problems by using experiences and plan adaptation. Micarelli *et al.* (2000) applied CBR to scene recognition. They calculated image properties from images and stored them in a case base. They used a wavelet approach that is scale-independent and therefore constrained their similarity measure to consider only object rotations.

Perner has been influential and prolific in this area of image processing using CBR, having authored about 40 publications. In early publications, Perner (1993, 1999) described using CBR for ultrasonic image interpretation and in image segmentation in image segmentation for CT images from the brain. As her research progressed, she used more complex case representations, reasoning and learning strategies, and data mining techniques for pattern recognition. Perner (2000) proposed a system that used CBR to optimize image segmentation at the low-level stage according to changing image acquisition conditions and image quality. The intermediate-level stage extracted the case representation used by the high-level unit employed to dynamically adapt image interpretation. The system worked on different case representations such as a graph representation for the cases of the high-level image description and the raw image matrix for the low-level image representation. Therefore, the system used different CBR strategies for reasoning and learning, where one uses structural similarity and the other uses digital image distance. Different learning strategies in a hierarchy of structural cases are presented in Perner (1998, 2003). Perner (2002) has connected (or) has made a bridge between CBR and dissimilarity classification research methods, which has become important in pattern recognition. The application of case-based image interpretation to health monitoring and biotechnology is described in Perner *et al.* (2003). Learning case representations and improving system performance by controlling the similarity measure is described in Perner *et al.* (2002). Recent research has focused on mining raw information into more general cases (Perner & Jähnichen, 2004) and making object recognition more robust against model variation (Perner & Bühring, 2004).

Most of the work described here was presented at the International and European CBR conferences. A working group for CBR in image processing has also been established under the umbrella of The International Association for Pattern Recognition Technical Committee 17—Machine Learning and Data Mining ([www.ibai-research.de/html/TC17](http://www.ibai-research.de/html/TC17)) that has an annual conference called the *International Conference on Machine Learning and Data Mining*.

### 3 Spatial information processing

An early application of CBR that attempted to use spatial information was focused on meteorological images (Jones & Roydhouse, 1994). They used meteorological images in trying to predict weather patterns based on previous similar spatial patterns. Their research focused on the efficient retrieval of structured spatial information.

A new challenging application field concerns using spatial information from surveying, remote sensing, and aerial photography. This kind of application requires special spatial problem-solving techniques and spatial similarity measures. There are about 60 publications in this area. Holt & Benwell (1996, 1999) reported the first application of CBR to geographic information systems (GIS) and have published about 30 publications on this subject. Their approach consisted of combining CBR with GIS to form a hybrid system to solve spatial problems. Their research now focuses on incorporating spatial topology in cases.

Further recent research described the use of spatial similarity measures to compare the location of objects in aerial photos (Carswell *et al.*, 2002; O'Sullivan *et al.*, 2004, 2005). These authors have published about 10 publications on this subject. Some of their work used raster sketches for digital image retrieval. They also used directional and metric object relationships to evaluate similarity between user-defined query scenes and object configurations. They used digital image software and a series of metrics to calculate values for topology, direction, distance, and shape.

## References

- Carswell, J.D., Wilson, D.C. and Bertolotto, M., 2002, Digital image similarity for geo-spatial knowledge management. *Proceedings of the 6th European Conference on Case-Based Reasoning (ECCBR2002) (Lecture Notes in Artificial Intelligence)*. Berlin: Springer, pp. 58–72.
- Ficet-Cauchard, V., Porquet, C. and Revenu, M., 1999, CBR for the reuse of image processing knowledge: a recursive retrieval/adaption strategy. In Althoff, K.-D., Bergmann, R. and Branting, L.K. (eds) *Case-Based Reasoning Research & Development*. Berlin: Springer, pp. 438–453.
- Grimnes, M. and Aamodt, A., 1996, A two layer case-based reasoning architecture for medical image understanding. In Smith, I. and Faltings, B. (eds) *Advances in Case-Based Reasoning*. Berlin: Springer, pp. 164–178.
- Haddad, M., Adlassnig, K.-P. and Porenta, G., 1997, Feasibility analysis of a case-based reasoning system for automated detection of coronary heart disease from myocardial scintigrams. *Artificial Intelligence in Medicine* **9**, 61–78.
- Holt, A. and Benwell, G.L., 1996, Case-based reasoning and spatial analysis. *Journal of the Urban and Regional Information Systems Association* **8**(1), 27–36.
- Holt, A. and Benwell, G.L., 1999, Applying case-based reasoning techniques in GIS. *International Journal of Geographical Information Science* **13**(1), 9–25.
- Jarmulak, J., 1998, Case-based classification of ultrasonic B-Scans: case-base organisation and case retrieval. In Smyth, B. and Cunningham, P. (eds) *Advances in Case-Based Reasoning*. Berlin: Springer, pp. 100–111.
- Jaulent, M.C., Le Bozec, C., Zapletal, E. and Degoulet, P., 1998, Case based diagnosis in histopathology of breast tumours. *MedInfo* **9**(1), 544–548.
- Jones, E.K. and Roydhouse, A., 1994, Intelligent retrieval of historical meteorological data. *AI Applications* **8**, 43–54.
- Macura, R. and Macura, K., 1995, MacRad: radiology image resource with a case-based retrieval system. In Veloso, M. and Aamodt, A. (eds) *Case-Based Reasoning: Research and Development*. Berlin: Springer, pp. 43–45.
- Micarelli, A., Neri, A. and Sansonetti, G., 2000, A case-based approach to image recognition. In Blanzieri, E. and Portinale, L. (eds) *Advances in Case-Based Reasoning*. Berlin: Springer, pp. 443–454.
- O'Sullivan, D., McLoughlin, E., Bertolotto, M. and Wilson, D., 2004, A case-based approach to managing geo-spatial imagery tasks. *Proceedings of the 7th European Conference on Case-Based Reasoning (ECCBR'04) (Lecture Notes in Artificial Intelligence)*. Berlin: Springer, pp. 702–716.
- O'Sullivan, D., McLoughlin, E., Bertolotto, M. and Wilson, D., 2005, Capturing and reusing case-based context for image retrieval. *Proceedings of the 19th International Joint Conference on Artificial Intelligence (IJCAI-05)*. San Francisco, CA: Morgan Kaufmann, pp. 1574–1576.
- Perner, P., Case-Based Reasoning For Image Interpretation in Non-destructive Testing, In: M. Richter, S. Wess, K.-D. Althoff, F. Mauer, First European Workshop on Case-Based Reasoning, EWCBR-93, SFB 314 Univ. Kaiserslautern, Vol. II, pp. 403–410.
- Perner, P., 1998, Different learning strategies in a case-based reasoning system for image interpretation. In Smyth, B. and Cunningham, P. (eds) *Advances in Case-Based Reasoning (Lecture Notes in Artificial Intelligence, 1488)*. Berlin: Springer, pp. 251–261.
- Perner, P., 1999, An architecture for a CBR image segmentation system. *Journal on Engineering Application in Artificial Intelligence, Engineering Applications of Artificial Intelligence* **12**(6), 749–759.
- Perner, P., 2000, CBR ultra sonic image interpretation. In Blanzieri, E. and Portinale, L. (eds.), *Advances in Case-based Reasoning (Lecture Notes in Artificial Intelligence, 1898)*. Berlin: Springer, pp. 479–481.
- Perner, P., 2001, Why case-based reasoning is attractive for image interpretation. In Aha, D.W. and Watson, I. (eds) *Case-based Reasoning Research and Developments (Lecture Notes in Artificial Intelligence, 2080)*. Berlin: Springer, pp. 27–44.
- Perner, P., 2002, Are case-based reasoning and dissimilarity-based classification two sides of the same coin? *Journal Engineering Applications of Artificial Intelligence* **15**(3), 205–216.

- Perner, P, 2003, Incremental learning of retrieval knowledge in a case-based reasoning system. In Ashley, KD and Bridge, DG (eds) *Case-Based Reasoning—Research and Development (Lecture Notes in Artificial Intelligence, 2689)*. Berlin: Springer, pp. 422–436.
- Perner, P and Bühring, A, 2004, Case-based object recognition. In Funk, P and González Calero, PA (eds) *Advances in Case-Based Reasoning (Lecture Notes in Artificial Intelligence, 3155)*. Berlin: Springer, pp. 375–388.
- Perner, P, Günther, TH, Perner, H, Fiss, G and Ernst, R, 2003, Health monitoring by an image interpretation system—a system for airborne fungi identification. In Perner, P, Brause, R and Holzhütter, H-G (eds) *Medical Data Analysis (Lecture Notes in Computer Science, 2868)*. Berlin: Springer, pp. 64–77.
- Perner, P and Jähnichen, S, 2004, Case acquisition and case mining for case-based object recognition. In Funk, P and González Calero, PA (eds) *Advances in Case-Based Reasoning (Lecture Notes in Artificial Intelligence, 3155)*. Berlin: Springer, pp. 616–629.
- Perner, P, Perner, H and Müller, B, 2002, Similarity guided learning of the case description and improvement of the system performance in an image classification system. In Craw, S. and Preece, A (eds) *Advances in Case-Based Reasoning (ECCBR2002) (Lecture Notes in Artificial Intelligence, 2416)*. Berlin: Springer, pp. 604–612.