Cognition Network Technology for Automated Holistic Analysis in Mammography

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Abstract. Digital mammography and comprehensive breast cancer screening approaches have led to the generation of a vast amount of image data. Since the visual inspection of a large set of images is expensive and to some extend also subjective, new methods for fully automated mammography image analysis are needed. The Definiens Cognition Network Technology (CNT) solves the image analysis problem by simulating human cognition processes using knowledge based and context dependent processing. It represents processed image data, image processing methods, and image objects and their definitions in a unified model which incorporates elements from semantic networks, description logics and functional programming. We present first steps towards a successful application of this technology on automated detection of masses and calcifications according to the ACR BI-RADS$^{\text{TM}}$ standard.

1 Introduction

The Definiens Cognition Network Technology (CNT) has revolutionized automated image analysis for complex scenes. Since its invention in 1996 it has been applied with great success to a variety of image analysis tasks based on data from very different kind of sensors ranging from satellites equipped with radar or optical sensors, over electron or optical microscopes to three-dimensional computer tomographs [1, 2, 3].

CNT generates automatically a semantic object network from unstructured data such as images and database tables. This object network represents explicitly all user-relevant information about real world objects (e.g. breasts, nipples, and lesions) which was initially hidden in the input data. CNT is based on three pillars:

First, the automatic analysis of the data can be formulated in a knowledge-driven fashion. Knowledge about real world objects is explicitly specified in a semantic network of class objects. Each class object contains a fuzzy or a nearest neighbour classifier which is able to calculate the class membership of a data object. The fuzzy classifier may use any logical combination of object properties to calculate the membership according to user-defined fuzzy sets.

Second, based on the semantic network of class objects, a hierarchical object network is generated by iteratively segmenting and classifying the image and segments of it. In CNT data understanding in general and image understanding in particular is an iterative local and context depended process which uses the class network to generate in several steps a network of objects of interest on the basis of the input data. The resulting object network is a semantic network which consists of classified nodes and links carrying high-level properties. The classification connects the object network with the class network and provides the objects with a meaning. The object's properties characterize an object by calculating statistical properties from the underlying input data or by aggregating properties of connected objects. Frequently used image object properties represent spectral, texture, shape and relational information.

Third, the object network generation and processing is defined by process objects which are embedded in a processing hierarchy. Process objects modify the elements of the object network according to an algorithm and a process domain. The process domain specifies which subset of the object network will be used for algorithm execution or for further downstream processing. The domain specification uses the classification, the properties and the link information of objects. Through the links a meaningful navigation from those objects that are already identified as relevant to objects or regions that have to be processed in the next step becomes possible. The three most basic process algorithms in CNT are context-dependent classification, segmentation and information bundling. Each segmentation step creates a new data object from a set of objects and links this new object with each object in the set using a given link type. This enables the system to build dynamically image object hierarchies to analyze an image simultaneously on several scales to generate context for further processing. The information bundling updates automatically object properties such as pixel statistics if there are any changes in the semantic object network. This ensures the consistency of structure and information content at each time step. As the result of the CNT processing, all relevant image objects and their mutual relations are available for further analysis.

We applied this technology in the context of mammography to the holistic processing of complete patient records, including four mammogram images (cranio-caudal and medio lateral views of both breasts) and including patient metadata such as weight, age, medication, number of children and family history. The knowledge base comprise in depth anatomical and diagnosis-related information as provided by mammography experts and as specified in the ACR BI-RADS standard [4].

2 State of the art and new contribution

Since 1972 there are numerous approaches to automate mammography image analysis. These approaches can be categorized in the specific task and the methods used. Common tasks are the detection of breasts and nipples, the registration of views, the detection of masses and the detections of calcifications [5, 6]. There are pixel- and region-based methods used for detection of abnormal regions (masses, calcifications). In pixel-based approaches, several filters such as edge detection, Law's texture, Gaussian smoothing, adaptive thresholding and others generate a feature vector per pixel. This feature vector is then classified into "normal" and "abnormal" using nearest neighbour, fuzzy, neural network or Bayesian classifiers. Region-based methods generate simply connected regions using a segmentation of the pixel filter responses. For those regions features are calculated which form the bases for classification.

Our approach extends and unifies pixel- and region-based methods. The image analysis task is modelled by an iterative segmentation and classification. All knowledge about the objects (regions) to detect is stored in an explicit semantic class network. The filtering, segmentation and classification processes are context-dependent and utilise the information gained in previous analysis steps. The generated object network enables us to analyse all four images simultaneously so that findings in one image may be supported by findings in other views.

3 Methods

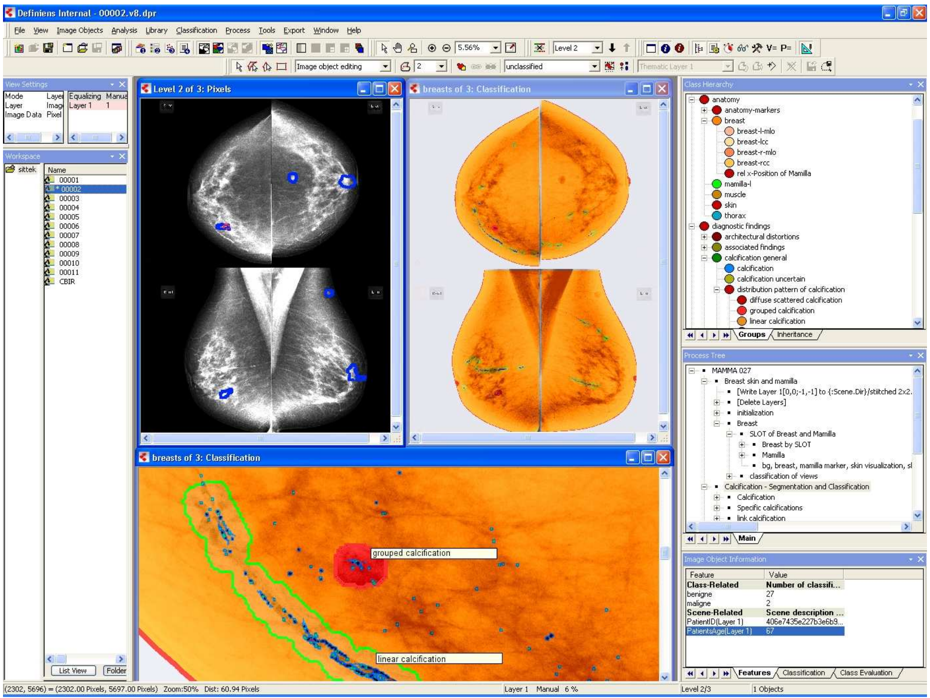
We obtain 200 complete patient data sets from the Diagnostic Mammazentrum Munich and the Institute for Diagnostic Radiology of the University Erlangen. Each data set consists of a cranio-caudal (cc) and a medio-lateral (ml) mammogram of one or two breasts. The data sets are manually annotated using a BI-RADS compatible software tool developed at the Fraunhofer-Institute for Integrated Circuits IIS. For data sets with BI-RADS category 4 and 5 a breast biopsy is performed to validate the findings.

To automate mammography image analysis, we develop a Cognition Network Language (CNL) script using the Definiens Developer software. CNL is a concrete implementation of the Cognition Network Technology featuring rapid script prototyping and a graphical user-interface for visual script development. The mammography CNL script comprises a class network which describes the breast anatomy and BI-RADS related categories for findings (Fig 1). To describe the anatomy, classes for breast, nipple, skin, pectoral muscle, duct, mass and calcification are defined. Each class includes several attributes to allow its more specific classification. For example, the breast is described by a relative gray value range within the image histogram and by a given minimal size. The nipple is described as a local object boundary feature in breast shape (protruding part of specific size) or a texture feature when segmenting breast tissue in a stripe near skin. The calcifications are classified using a combination of edge filter response, contrast and area. The CNL script uses these class descriptions to segment and identify the objects simultaneously in all available images of one patient data set. The implemented strategy is to find first breasts, then skin and nipples, pectoral muscle, calcifications and finally masses. For the final classification of objects we utilise object linking. This generic concept enables CNL processes to establish and retrieve semantic (named) links between objects in a set of images. To link objects between the two views of one breast, the position of the nipple provides a reference coordinate. Since two two-dimensional views are registered, we further use the fact that one object dimension must be the same in both views. This registration enables the system to identify corresponding, similar objects (masses and calcifications) in both views (cc/ml). If an object was found in both views, we increase its detection probability. Furthermore, the intra-view linking of calcifications enables their classification according to group properties such as *linear*, *branched*, *segmented* and *pleomorphic*. We intend to use linking between objects found in the left and right breast to enhance the detection accuracy of masses. All findings are classified according to BI-RADS standard. Each patient record is automatically classified in BI-RADS category 1 to 5. To evaluate the quality of the automated analysis, we compare the detection results with the manual annotations provided by the medical experts. To calculate the number of true positive findings, we determine for each visual annotation its relative pixel overlap with each automatically found segment bearing the same classification. If the relative pixel overlap and the segment's classification probability are greater than predefined thresholds, then the annotation is counted as true positive (hit). The number of false negatives (misses) is determined by subtracting the number of hits from the number of annotations. The number of false positives (false alarms) is determined by counting all segments bearing a finding and having a relative overlap to a visual annotation of the same class less than a predefined threshold.

4 Results

In a first experiment we developed a CNL script which is able to extract breast, nipples nd calcifications reliably in a data set from 11 patients (see Figure 1). The script automatically detects the view orientation and classifies the extracted breast object according to that view e.g. right breast cranio-caudal. The nipples were found in all images at the correct location, although the exact position is sometimes difficult to determine even for a human expert. Individual calcifications were detected and grouped using the links to create a basis for benign/malign classification. The found malign calcifications in 11 patient cases indicate a true positive rate of 100% (no masses detected yet). We are therefore very confident to implement a prototype system in the next months which will deliver a true positive rate of greater than 99% on the full dataset of 200 patients while keeping false alarms and misses less than 1%.

Fig. 1. Screenshot of Definiens Developer software with a preliminary CNL script. The left-top window shows the raw data of one patient, the manual annotated regions (blue) and one selected, automatically found, potentially malign group of calcifications (red). The right-top window shows the segmentation results for breasts (orange), nipples (red), calcifications (blue) and malign/benign calcification markers (red/green). The bottom window shows a detail of two found groups of calcifications, one malign (red) and one benign (green). The small frames at right shows sections of the class and process hierarchies



5 Summary

Already the first preliminary results of the knowledge driven approach for automated image analysis of mammograms described in this paper demonstrate the potential for the development of an analysis system with a very high degree of robustness and flexibility. The explicitly specified anatomical knowledge in the class network enables continuous improvement by medical experts and a transparency of decisions which are not achievable with other solutions such as neural networks. Based on Definiens platform technology "classical" concepts such as using various pixel image filters were embraces while the depth of analysis was extended by using a semantic (classified) object network. Moreover, the CNT implementation comprises an interactive scripting language, so that rapid solution development is possible. This enabled the detection of breasts, nipples and calcifications with high accuracy.

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