An Approach for Resolving Conflicts in Automatic Medical Objects Classification

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Abstract. We describe a new approach for resolving conflicts for automatic identifying human organs from a medical CT images. The main premise of this approach is the use of classifier created with using two-level classifier and domain knowledge advisers decisions. We test our approach on multiple CT images of chest organs (trachea, lungs, bronchus) and demonstrate usefulness and effectiveness of the resulting classifications. The presented approach can be used to assist in solving more complex medical problems.

Key words: CT images, conflicts resolving, concept approximation, classifiers, decision trees, medical object recognition, object classification, domain knowledge, organs identifying, medical system

1 Introduction

A design of human–machine interface is the most important aspect of computer aided interpretation of medical image exams. Assists include decision support, reminder and navigation techniques to help avoid diagnosis errors, content-based data mining capabilities, and access to reference libraries. Human–machine systems should take advantage of computer capabilities to increase physicians interpretation capabilities [11].

An automatic identification of medical objects visualized by Computed Tomography (CT) imagery (e.g., organs, blood vessels, bones, etc.), without any doubt, could be useful, to support solving many complex medical problems using computer tools. Our approach is based on a two-level classifier. On the lower level, our approach uses a classical classifier based on a decision tree that is calculated on the basis of the local discretization (see, *e.g.*, [7, 2]). This classifier is constructed and based on the features extracted from images using methods known from literature (see [6, 3] for more details). At a higher level of our two-level classifier, a collection of advisers works that is able to verify actions performed earlier by the lower-level classifier. This is possible by using domain knowledge injected to advisers. Each of the adviser is constructed as a simple algorithm based on a logical formula, that on input receives selected information extracted from a tested image and a decision returned by the lower-level classifier, and the output returns confirmation or negation for the suggestion generated by the lower-level classifier. It consists in the fact, that in a situation where the decision taken by the lower-level classifier, is clearly incompatible with domain knowledge, the advisers suggestions and classifier decision are used to create conflict resolving classifier. Thanks to this, increases the accuracy of such the two-level classifier. To illustrate the method and to verify the effectiveness of presented classifiers, we have performed several experiments with the data sets obtained from Second Department of Internal Medicine, Collegium Medicum, Jagiellonian University, Krakow, Poland.

In the Section 2, we describe the problem of medical image understanding. Second section present conception of design a system for automatic medical objects classification. Finally, we present the complete structure of two-level classifier with method for resolving conflicts for the automatic classification of chest organs (see Section 4).

Table 1. "Low-Level" Features

Name	Description
DT	Distance to the first image in the series (mm)
SIZE	Object size
WIDTH	Object width
HEIGHT	Object heihgt
DFL	The distance from the object to the left edge of the image
DFT	The distance from the object to the top edge of the image
R1	Size of the object located in the region R1
R2	Size of the object located in the region R2
R3	Size of the object located in the region R3
R4	Size of the object located in the region R4
R5	Size of the object located in the region R5
R6	Size of the object located in the region R6
R7	Size of the object located in the region R7
R8	Size of the object located in the region R8
R9	Size of the object located in the region R9
CIRCUIT	Object circuit
TFACTOR	Object thickness factor
SFACTOR	Object shape factor

2 Medical Image Understanding

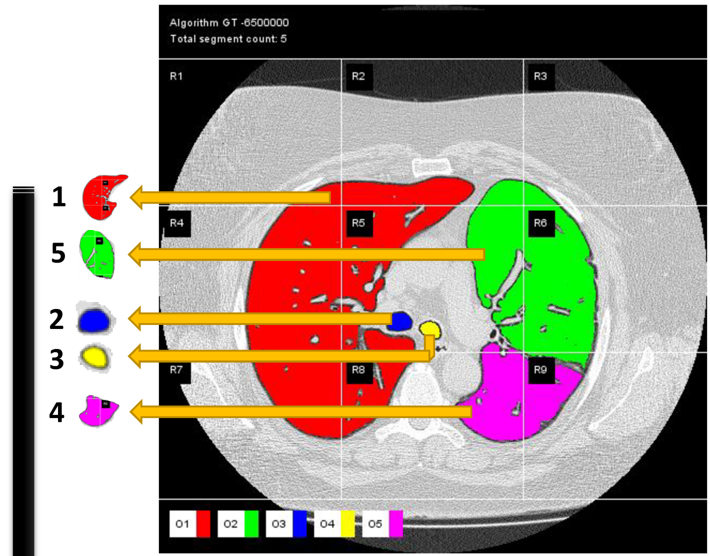
A process of radiological interpretation generally includes the understanding of medical image content resulting in recognition of possible pathology symptoms, most often called detection, and assessment of comprehensive image information in a context of current clinical case-knowledge. It involves image-based detection of disease, defining disease extent, determining etiology of the disease process, assisting in designing of the clinical management plans for the patient, based on imaging findings, and following response to the therapy [12].

Table 2. ”Domain Knowledge” Features

Name	Description
CENTER	Center of the object region (*e.g.*R1, R2 ...)
OIL	The number of objects on the right side
OIR	The number of objects on the left side
OIA	The number of objects above
OIB	The number of objects below
DTNLO	Distance to the nearest object on the left side
DTNRO	Distance to the nearest object on the right side
DTNAO	Distance to the nearest object above
DTNBO	Distance to the nearest object below
SNLO	The size of the nearest object on the left side
SNRO	The size of the nearest object on the right side
SNAO	The size of the nearest object above
SNBO	The size of the nearest object below

The other area of application of the automatic image understanding technique is deep and requires a detailed analysis of particularly difficult images, especially in case of doubts and difficulties in deciding on final diagnosis. A very important difference between all traditional methods of automatic image processing (or recognition) and the new paradigm for image understanding is that there is one directional scheme of the data flow in the traditional methods; there are two-directional interactions between signals (features) extracted from the image analysis and expectations resulting from the knowledge of image contents, as given by experts (physicians). The results of all analyses of medical image characteristics and objects visible in them, generated by computers, allow the physician to base his/her reasoning on much more reliable and quantifiable premises than just a visual assessment of that image, improving both the effectiveness of his/her activities, and the feeling of reliability and security. Finally, the increasing acceptance of techniques for the automatic recognition and classification of biological objects distinguished in medical images can help the doctor make the right diagnostic decisions, although these techniques sometimes require the doctor to be able to critically assess the automatically suggested categories, as every recognition technique carries some level of error, while nothing excuses the doctor’s personal responsibility for his/her decisions [9].

Medical image analysis is one of the areas of computer vision where domain knowledge plays a very important role, because localized pixel information obtained from CT images is often ambiguous and unreliable [5]. The history of knowledge-based medical image analysis is older than the history of practical usage of CT imaging. One of the early studies in knowledge based medical image analysis was done by Harlow and Eisenbeisc [4] on radiographic image segmentation, when CT imaging was not yet available in hospitals. They proposed a top-down control system using a trees structured model description containing knowledge about locations and spatial relations of parts/organs of the human body. In his thesis work, Selfridge [13] discussed image understanding systems in general and divided the causes of difficulties into problems of model selection, segmentation techniques, and parameter setting [5].



	OIL	OIR	...	DTNLO	DTNRO	...	SNLO	SNRO	...	CENTER	DECISION
1	0	4	...	0	4	...	0	134	...	R5	RL
2	1	3	...	70	40	...	1256	120	...	R5	RB
3	2	2	...	40	90	...	134	540	...	R5	LB
4	3	1	...	90	20	...	120	678	...	R8	LL
5	4	0	...	20	0	...	540	0	...	R6	LL

Fig. 1. Examples of "domain knowledge" features extraction

We conclude that the automatic detection of organs is the first step to understand medical images and it is necessary to begin the process of proper medical diagnosis support. To understand the CT image correctly, a computer should detect and recognize all medical objects located on the image by using domain knowledge. The knowledge about objects located in the medical image, allows the correct identification of areas related to various medical problems. To understand medical image correctly, a computer should detect and recognize quite correctly all medical objects located on the image by using domain knowledge (extremely challenging task even for a man).

3 Conception of Design a System for Automatic Medical Objects Classification

3.1 A General Description

In order to understand the medical images, it is important to create a tool for understanding the interior of the human body on different levels of abstraction and tracking of interaction between the observed medical objects. The main issues to be addressed include problems with the quality of the medical image data, problems with domain knowledge descriptions and problems with modeling and exploration of the human body, which is very complex. The system should include the assumptions, such that the system should support work of doctors (not replace), expert always decide, system should allow for future sharing of knowledge and should naturally communicate in order to exchange knowledge (speech).

Table 3. Object classes

Class	Object	Number
TR	Trachea	671 (8,96%)
RL	Right lunge	1621 (21,64%)
LL	Left lunge	1616 (21,57%)
RB	Right main bronchi	190 (2,54%)
LB	Left main bronchi	211 (2,82%)
LL+RL	Object by gluing the left and right lungs	55 (0,73%)
OT	Other objects	3127 (41,74%)

3.2 ”Low-Level” Features (LLF)

There is no ”*ideal set of features*” which characterize the object. Features are selected individually depending on the recognized objects. In the computer analysis of the images, extracted features from the image, can be assigned to one of the categories, such as non-transformed structural characteristics (*e.g.*moments, power, amplitude information, energy, etc.),transformed structural characteristics (*e.g.*frequency and amplitude spectra, subspace transformation methods, etc.), structural descriptions (formal languages and their grammars, parsing techniques, and string matching techniques) and graph descriptors (*e.g.*attributed graphs, relational graphs, and semantic networks) described in detail in [6] and [3]. In this publication we call these features as Low-Level Features (LLF). In total, for the purposes of the experiments we define 18 LLF features (see Table 1).

3.3 ”Domain Knowledge” Features (DKF)

To understand the image, it is also necessary to define the additional features that will define the acquired domain knowledge from experts. We call these features Domain Knowledge Features (DKF). DKF can be assigned to one of the categories, such as:

- features used to describe domain knowledge about the number of objects that surround an analyzed object,
- features used to describe domain knowledge about the distance from analyzed object to surrounding objects,
- features used to describe domain knowledge about the size of objects that surround an analyzed object,
- features used to describe domain knowledge about position of an object.

In total, for the purposes of the experiments we define 13 DKF features (see Table 2).

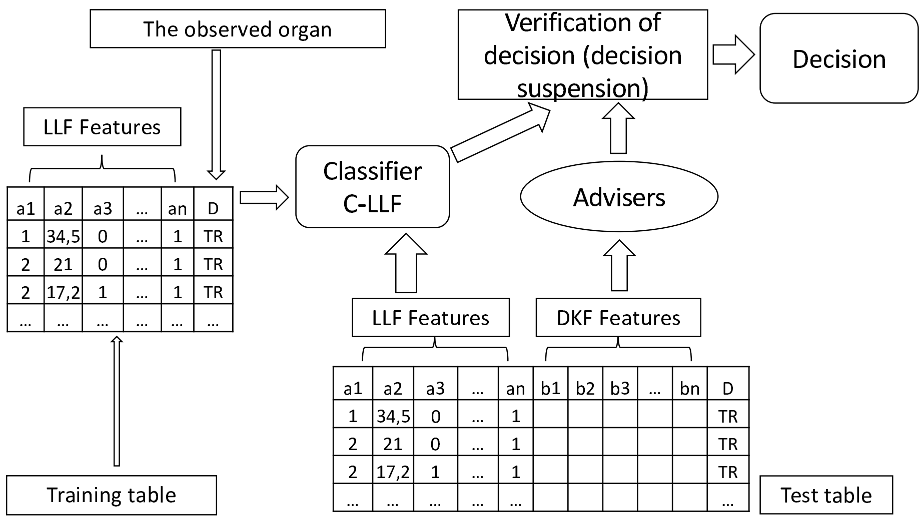


Fig. 2. Diagram of method 4: Two-level Classifier with ”advisers”

3.4 Medical Data

Our experiments were carried out on the data obtained from the clinical hospital Jagiellonian University Medical College in Kraków (the patients were diagnosed with asthma). The entire data set counted 26 patients (19 woman, 7 man). The average age of patients was 58.12 years (st.dev. 6.78 years, age range from 47 to 70 years). In all patients, volumetric CT torso scans were performed at both full inspiration and expiration with using 16-channel multi-detector CT scanner Toshiba (manufacturer’s model name:

Aquilion). The acquired data were reconstructed using a kernel (FC86) with 1 mm increments. Images were stored in the Digital Imaging and Communications in Medicine (DICOM) format. For each patient was taken 300 to 400 images (full inspiration) with a resolution of 512x512 pixels. The total size of the data set for the experiment count 9655 CT images.

From all images we select every fifth image (20% of all images, 5mm increments) to pre-processing. As a result of the segmentation process, we acquired 7491 objects for experiments. For all the objects we set LLF and DKF features, further all objects are classified by an expert to one of the 7 classes (chest organs) presented in the Table 3.

Table 4. Comparison of the results Train&Test (Methods 1,2,3 and 4)

	Method 1		**Method 2**	
Object	Acc	St.Dev.	Acc	St.Dev.
TR	**94,00%**	3,61%	93,97%	4,99%
RL	**97,31%**	0,98%	97,56%	0,83%
LL	**97,64%**	0,92%	97,56%	1,11%
RB	**78,55%**	6,04%	78,12%	4,97%
LB	**76,77%**	6,00%	75,74%	8,80%
LL+RL	**87,95%**	24,01%	86,82%	23,94%
OT	**94,73%**	1,76%	94,76%	1,23%

	Method 3		**Method 4**		
Object	Acc	St.Dev.	Acc	St.Dev.	Coverage
TR	79,61%	6,45%	**99,90%**	1,02%	94,58%
RL	81,66%	2,89%	**98,32%**	0,61%	99,27%
LL	80,73%	3,96%	**98,44%**	0,50%	98,82%
RB	60,77%	11,65%	**88,19%**	4,06%	85,52%
LB	49,33%	7,63%	**85,04%**	5,06%	88,76%
LL+RL	22,38%	23,03%	**97,92%**	3,50%	94,09%
OT	75,12%	2,07%	**96,40%**	1,27%	97,57%

The entire data set was divided 20 times randomly into two sets - a set with training data and a set with test data (around 70% of the data getting into a training set - 18 patients, other (around 30%) into test set - 8 patients). Experiments 1,2,3 and 4 we conducted on these datasets. In 5-th experiment the entire data set was divided 20 times randomly into three sets - a set with training data and a set with test data (9 patients of the data getting into a training set, 9 patients into valid set and other 8 patients into test set).

4 Methods and Experiments

To verify the effectiveness of classification we prepare five methods. In methods one to four with using training data we built a classifier, which has been tested on test data. In method five with using training data we built a two-level classifier. Decision from this classifier has been used with advisers decisions to create second classifier on valid data. This classifier is used to resolve conflicts between domain knowledge advisers and two-level classifier.

We designed a classifier to the automatic classification of chest organs. In all methods we have implemented classifiers in the IMPLA (Image Processing Laboratory), which is a continuation of the RSES-lib library (forming the kernel of the RSES system [1]), in the field of image processing. The IMPLA has developed recently in Interdisciplinary Centre for Computational Modelling, University of Rzeszów, Poland.

4.1 Method 1

Method 1 is a method based on the decision tree with local discretization (LLF features, the quality of a given cut is computed as a number of objects pairs discerned by this cut and belonging to different decision classes, see, *e.g.*, [7, 2]). The method gave good results (see Table 4).

4.2 Method 2

The second method was similar to the method 1 and based on the decision tree with local discretization. This method has used both LLF and DKF features (see Table 4).

4.3 Method 3

Method 3 was similar to the method 1 and based on the decision tree with local discretization. This method has used only DKF features (see Table 4).

4.4 Method 4: Two-level Classifier with ”advisers”

Method 4 is a method based on two-level classifier with ”advisers” (Figure 2). In this approach classification decision is dependent on suggestions of domain knowledge advisers. DKA suggest decisions based on domain knowledge *e.g.*”*Left lung is located on the right side of medical image*”, ”*Object located on the left side of medical image is probably not a left lunge*”. We prepare 15 DKA for all chest organs. Advisers are divided into two groups:

- YES advisers - Advisers to advise on YES *e.g.*”*yes, this is probably the left lung*” (6 DKA),
- NO advisers - Advisers to advise on NO *e.g.*”*no, this is probably not the left lung*” (9 DKA).

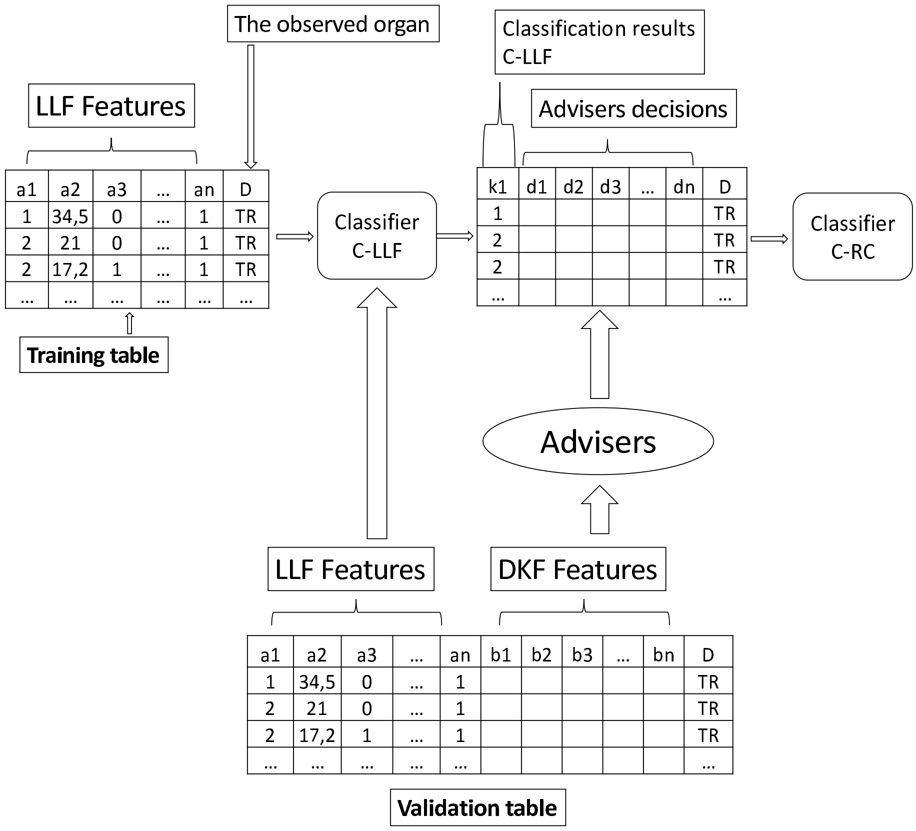


Fig. 3. Diagram of method 5: Two-level Classifier with ”advisers” and conflicts resolving - classifier creation

Verification was followed on the basis of the DKF features *e.g.*if object center is located in region R3, R6 or R9 then YES adviser for right lunge take *false* decision. Advisers suggest what should be a decision (YES advisers) or suggested what should not be a decision (NO advisers). If any of the advisors suggested otherwise than the classifier (in some sense, the low-level classifier), decision was suspended (see [10]). All the decisions taken by the DKA pause the classifier decision where decisions are different. This is the direct reason for the decline coverage of the analyzed objects. By using domain knowledge we have obtained an improvement in the automatic classification of each chest organ. We presented the results of the experiments in the Table 4.

4.5 Method 5: Two-level Classifier with conflicts resolving

This method was similar to the method 4. In this experiment the entire data set was divided 20 times randomly into three sets - a set with training data, a set with validation

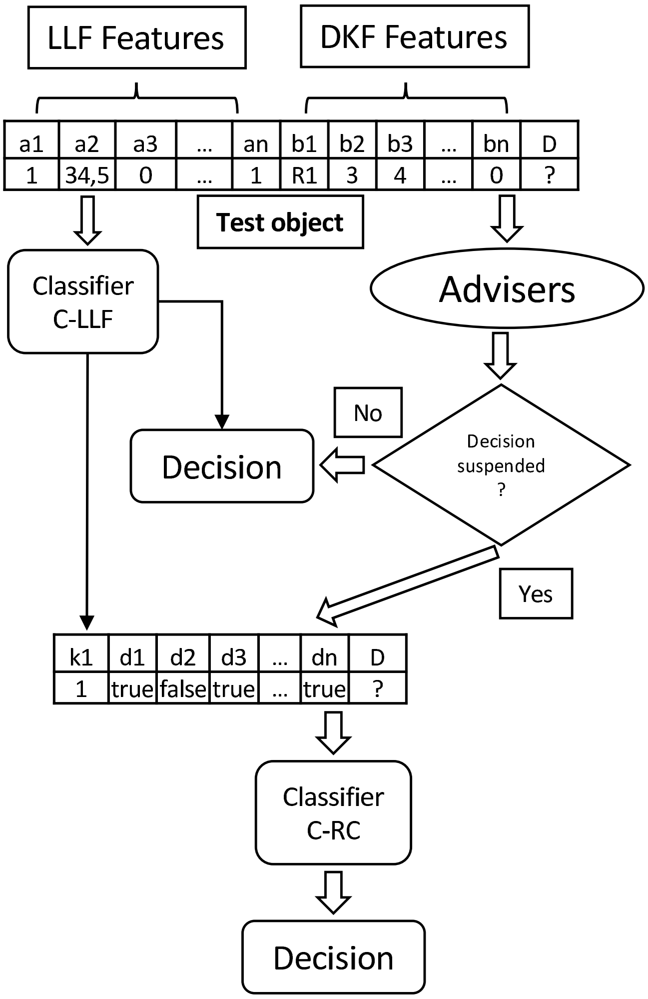


Fig. 4. Diagram of method 5: Two-level Classifier with "advisers" and conflicts resolving - testing data process

data and a set with test data (9 patients of the data getting into a training set, 9 patients into valid set and other 8 patients into test set). All the experiments (experiment with method 1 and 4 was prepared on merged training and validation data sets) we conducted on these datasets. Classification decision is dependent on suggestions of domain knowledge advisers (see [10]). Advisers decisions and classifier decisions has been used to create second classifier (conflict resolving classifier, C-RC) on valid data. This classifier is used to resolve conflicts between domain knowledge advisers and two-level classifier (Figure 3). The classifier C-RC is computed as a set of all decision rules with minimal number of descriptors (see, *e.g.*, [2]). If any of the advisors suggested otherwise than

Table 5. Comparison of the results Train&Valid&Test (Methods 1,4 and 5)

	Method 1		**Method 4**			**Method 5**	
Object	Acc	St.Dev.	Acc	St.Dev.	Coverage	Acc	St.Dev.
TR	91,44%	6,20%	97,59%	1,48%	92,92%	**95,54%**	3,77%
RL	97,46%	0,87%	98,29%	0,64%	99,14%	**97,40%**	0,82%
LL	97,42%	0,97%	98,43%	0,63%	98,95%	**97,65%**	0,90%
RB	77,02%	9,44%	89,71%	5,48%	84,53%	**80,02%**	5,17%
LB	**76,67%**	6,77%	83,19%	7,14%	89,99%	74,16%	5,32%
LL+RL	77,82%	23,58%	98,68%	2,69%	76,30%	**95,74%**	6,95%
OT	95,05%	1,47%	96,50%	1,36%	97,88%	**95,80%**	1,00%

the classifier, decision is taken with using conflict resolving classifier (Figure 4). By using conflict resolving classifier we have obtained an improvement in the automatic classification of almost each chest organ (except left bronchi) and coverage of the analyzed objects 100% and we improved classification stability. We presented the results of the experiments in the Table 5.

5 Conclusions and Further Works

The results of experiments performed on medical data sets indicate that the presented approach seems to be promising. The use of domain knowledge and the addition of a classifier resolving conflicts between advisers significantly improved the quality of the medical object identification. The next steps will focus on the use of time dependencies between medical images (object tracking in time).

The presented approach can be used in the future to support solving more complex medical problems. We plan to use the results of research, among other things, to treatment of an asthmatic airway remodeling (see, *e.g.*, [8] for more details) and develop more advanced methods of using domain knowledge to construct more effective classifiers.

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