Towards a clinical chest workstation

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Abstract. Finding similar images, or *reference cases*, is one way to aid a radiologist during daily clinical practice. Attracting his attention to possible sites of lesions is another one, and directly providing a diagnosis would be the most useful, but in most cases unattainable form of assistance. However, all of these types of support require a set of computer analysis methods that needs to be developed or adapted for each clinical problem. In this work I outline a set of methods for automatic analysis of standard chest radiographs. The focus is on texture analysis and the method is applied to mass chest screening for tuberculosis and to the detection interstitial disease. I discuss various ways to use this method in practice, as part of a clinical chest workstation and hint on the role of CBIR in such workstations.

1 CAD ≈ CBIR

Content-based image retrieval (CBIR) is the common term for systems that retrieve "similar" images from a database. But CBIR is not the most apt name for medical applications; when radiologists have difficulties in interpreting an image they are interested in *reference cases*, that is, patients with the same disease in the same stage. Often this will be an image with similar content, but that is not the prime requirement. In some cases the lesion may have a completely different location, scar tissue in the lung top of one patient may be similar to scar tissue in the lower lung fields of another patient, while in other cases the location needs to be the same. A CBIR system should take this into account and is therefore closely related to computer-aided diagnosis (CAD). A perfect CBIR system would immediately give a diagnosis, and a CAD system that yields a sufficiently detailed diagnosis can be used to retrieve a similar image. This is not only true in theory but also in practice: sophisticated CAD systems all use large image databases for training their segmentation and classification components and retrieving similar cases from that database once the analysis is completed can be done in a straightforward manner.

Having made this point, we can now turn our attention towards CAD in an important clinical task, namely interpreting chest radiographs. Even with the wide variety of 3D medical imaging techniques available, about one third of all radiological examinations is a chest exam, a 2D projection radiograph. Reading chest images is one of the most difficult tasks for a radiologist, because a wide variety of diseases can give rise to a wide range of often very subtle signs. In this work, the focus will be on mass chest screening for tuberculosis and on the detection interstitial disease in clinical chest films. Only an outline of the method is given here, the reader is referred to [1] for further details. In the last section we will return to the relation between CAD and CBIR in chest radiography.

2 The task

Our goal is to estimate the probability that a chest radiograph is normal or abnormal. Two databases are used:

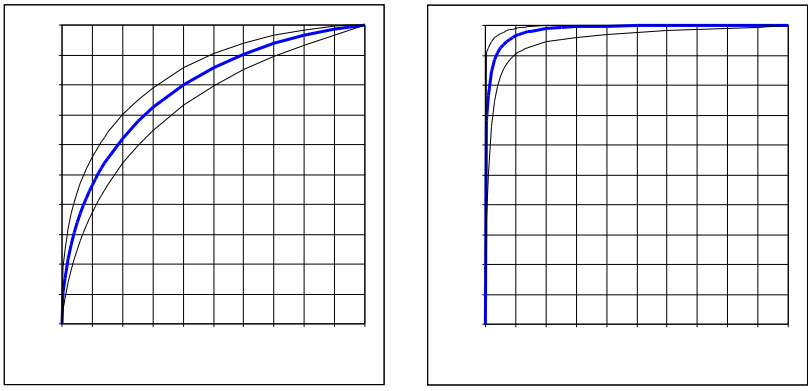
- the **TB database** contains 279 abnormal and 290 normal posterior-anterior (PA) chest radiographs collected from a tuberculosis screening program for people seeking political asylum in The Netherlands.
- the **ID database** contains 100 normal and 100 abnormal PA chest radiographs with interstitial disease obtained at the University of Chicago Hospitals.

3 Segmentation

The purpose of segmentation is to find corresponding regions within the lung fields. We used a standard knowledge-based algorithm for segmentation, namely Active Shape Models (ASM), developed by Cootes and Taylor [2]. After segmentation, the lung fields are subdivided into 12 smaller regions, that can be grouped together to form larger regions. These regions are warped to the segmentation result. Examples are shown in Figure 2.

4 Texture analysis

The segmented regions are classified as normal or abnormal by a radiologist. Texture features are computed for each region, and are used to train k-nearest-neighbor classifiers. The performance of these classifiers varies substantially from region to region, which can be attributed for a large part to the fact that the number of abnormal regions in the databases is small for many regions (for instance tuberculosis is most



(a) (b)

Fig. 1. ROC curves for both databases. The thin lines below and above the curve denote the asymmetric 95% confidence intervals. (a) The TB database. The area under the curve is 0.820. (b) The ID database. The area under the curve is 0.986.

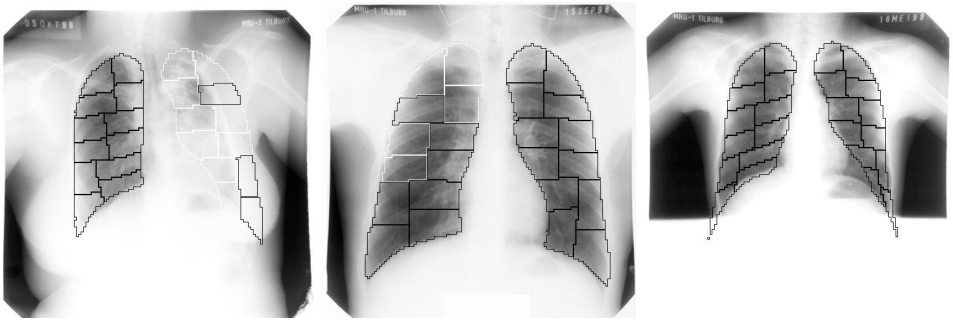


Fig. 2. Some results for the TB database. Segmentations are produced by the system, actually abnormal areas have white outlines. Left: the most abnormal case in the TB database, according to the computer system. This case is indeed abnormal. Middle: the most normal case, according to the computer system, that is actually abnormal. Right: the most abnormal case, according to the computer system, that is actually normal.

often located in the lung tops, so there are only a few examples of abnormal lower lung regions in the TB database). The performance of each classifier is measured in terms of its A_z-value (the area under the ROC curve). The score for a complete image is constructed from a weighted average of the scores of individual regions, in which areas with high classifier performance are weighted more heavily.

The texture features are moments of histograms of responses of the region to a set of filters. Such texture analysis systems have been shown to perform well in practice (see e.g. [3] or [1]). The filter bank is a set of image derivatives at multiple scales.

Comparisons between left and right lung fields yield important clues for radiologists when reading chest images. Therefore we added the difference between corresponding features for corresponding areas to the feature set.

5 Results

The results of the system depended (although not heavily) on the set of filters and texture features used. For both databases a suitable set of features was selected, using leave-one-out experiments. ROC curves for these feature sets for both databases are shown in Figure 1 and a few results from the TB database are given in Figure 2. For the TB database, the results are encouraging. For the ID database, the result is near-perfect.

6 The future: chest workstations and the role of CBIR

The analysis system described here has not been tested in clinical practice. There are several ways in which such a system could be used in practice: (a) As a stand-alone filtering stage in which each image in a mass chest screening is processed and only sent to a radiologist if it is possibly abnormal; (b) As a computer-aided diagnosis module that the radiologist can use as a second opinion; (c) to highlight possibly

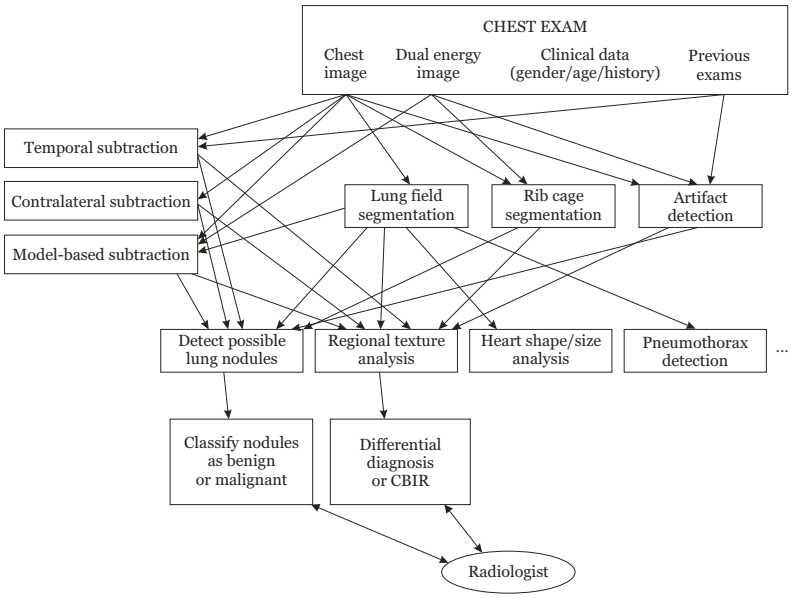


Fig. 3. Tentative architecture of a computer analysis system for chest radiography.

abnormal areas during reading; (d) to retrieve images with similar textural appearance in abnormal regions as reference cases. This enumeration is by no means exhaustive.

The system described is based on texture analysis, performed on local regions with sizes varying from one third to one twelfth of a lung field and may therefore be rather insensitive to very small abnormalities. For other types of abnormalities, other analysis methods have been, or need to be developed. Some of them will be very specific, for example the detection of pneumothorax. I foresee that "chest workstations" will be developed which contain a range of analysis modules. These modules can benefit from the result of other modules, or from extra information, such as previous exams or dual energy images. All these modules need large training databases to achieve optimal performance and these databases could be used in CBIR. A possible architecture of a clinical chest workstation is given in Figure 3. A detailed discussion of the components of this (tentative and incomplete) scheme is beyond the scope of this paper. I believe that CBIR may be valuable in the interpretation of interstitial disease, but other areas may be more suitable. In conclusion, CBIR in chest radiography is not an isolated subject, it is intricately linked to other forms of CAD.

References

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