A HYBRID LUNG NODULE DETECTION SCHEME ON CHEST X-RAY IMAGES

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I. Introduction

Lung cancer is one of the most common causes of cancer death. Many cures are only effective in the early and symptomless stage of the disease. Screening can help early diagnosis, but a sensitive[1], cheap and side effect-free method has to be used to enable mass usage. Standard chest radiography meets these requirements, except that current methods have moderate sensitivity. Efficiency can be improved by using a Computer Aided Detection (CADe) system. The most important problem of existing CADe systems is the low positive predictive value. In other words high sensitivity can only be reached at the cost of many false detections. Recently published systems can detect 60-70% of cancerous tumours, while they also mark approximately four false positive regions on each image [1], which allows them to be used only as a second reader.

Usability of CADe systems can be improved either by reducing the number of false detections – to give the examiner less extra work –, or by finding more nodules – to increase sensitivity –. The detections of CADe should be also complementary to the findings of radiologists, to better improve sensitivity when radiologists and CADe work in cooperation. Although this is true from the performance point of view, we observed that radiologists lose their faith in the system and ignore its results if it fails to detect some obvious cases. This remains true even if we explicitly specify what type of nodules the system searches for.

To overcome this issue, the current study focuses on enhancing the capabilities of an existing CADe scheme to find special types of nodules that were missed previously, but were frequently found by the radiologists. Therefore we introduce the Large Nodule Filter (LNF) targeting nodules larger than 30 mm diameter, having high contrast and usually overlapped by large structures for example the shadow of the heart or the spine. Finding these nodules have little utility in everyday screening, but may help the acceptance of CADe amongst radiologists. As a side effect we developed a framework that enables the simultaneous use of many nodule enhancing algorithms and the efficient integration of their results. This may help us in the near future to integrate more algorithms that complement our current algorithms by finding more subtle cases.

II. Materials and Methods

For our solution we used the following three-step scheme. The first step described in [2] segments the viewable area of the lung and frees the image from unnecessary objects and noise, thus making the nodule more visible. The next two steps can be seen in Figure 1. Nodule enhancement highlights round shaped objects like the target lung nodules by using image processing algorithms. After normalization and resizing the processing splits up based on the targeted nodule type. The Constrained Sliding Band Filter (CSBF) is used for the enhancement of smaller and subtle nodules and the recently developed LNF for large nodules with high contrast. The candidates collection algorithm is the same for the two threads. The last step reduces the number of false positive findings on the enhanced image with the help of a classifier. It begins with the calculation of features of candidates serving as an input for the

[1] Sensitivity is the fraction of correctly diagnosed positive cases and all positive cases.

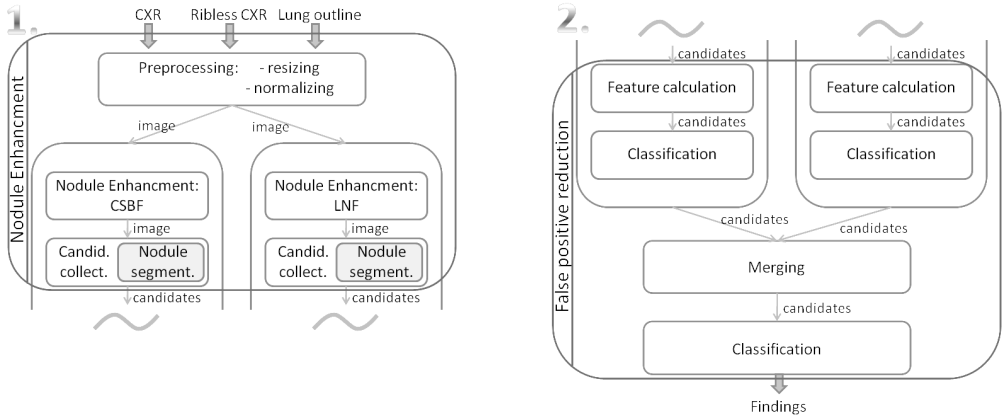

Figure 1: The nodule detection process. Arrow labels reveal the type of data flow.

classifier. Classification is done for each thread followed by a merging step that eliminates duplicate and highly overlapping results. A final classification is carried out on the merged set of candidates.

A. *Nodule Enhancement*

According to our observations different types of nodules may need completely different algorithms for efficient enhancement as they have different characteristic properties. A smaller nodule in the early stage is usually dimmer but has an approximately circular shape, thus the convergence of the gradient vectors can serve as an important clue. In large scales this can be computationally intensive, furthermore larger structures and intensity variations can alter gradient directions. On the other hand large nodules tend to have high contrast that can help detection. Hereinafter we will introduce the new LNF algorithm specialised for large nodules as the CSBF filter targeting smaller ones has been described in detail previously [3].

The LNF aims to enhance nodules with diameter between 30 mm and 75 mm and high contrast but allows them to lie almost completely outside the viewable lung. The basic idea behind the algorithm is a modified Local Contrast Enhancement (LCE) followed by a Top-hat filter. The LCE output is

$$G(x,y) = \frac{1}{1-\exp -(F(x,y)-\frac{1}{|R(x,y)|}\sum_{(u,v)\in R(x,y)}F(u,v))}, \quad (1)$$

$$R(x,y) = \begin{cases} \{(u,v)|(u-x)^2+(u-y)^2<2r^2\}\cap L & (x,y)\in L \\ \{(u,v)|(u-x)^2+(u-y)^2<2r^2\}\cap /L & \text{otherwise} \end{cases}, \quad (2)$$

where F is the original image, L is the viewable lung and r is the radius of the targeted nodule. The trimming of R with L ensures we have a homogeneous area completely inside or outside the lung. The rationale behind the logistic function is to get a result in between local normalization and local thresholding as it can be seen in Figure 2 (2nd).

Top-hat filtering is a simple convolution by a cylinder shaped kernel with radius r. The side of the cylinder is slightly tilted to allow circular shapes with little distortion or a small deviation of the nodule radius. This method besides nodules would also enhance other dark structures like remainders of rib shadows or areas filled with vessels like the mediastinum. To suppress these areas the filter output is weighted with the smoothness of the area. For smoothness the standard deviation of smoothed nodule pixels inside the viewable lung is calculated. An example is shown in Figure 2 (3rd). The method uses a multi-scale framework to detect different sized nodules.

To find nodules lying outside the viewable lung the Top-hat filter is run for the entire image. This would enhance structures like the vertebra so the filter output is kept only where both negative and

positive parts of the cylinder overlap with the viewable lung, and the area of intersection for both is greater than 15% of the filter part area. As a post processing step the areas where the predicted nodule would lie outside the whole lung are suppressed. This requires an overestimation of the whole lung area, for which we use the following algorithm. The binary masks of the left and right viewable lung parts are dilated towards the centre and then eroded with the estimated nodule radius. Then the union is taken for the two parts. The resulting mask is consistent with our assumption that nodules can reside under the shadow of the heart, aortic arth or hemidiaphragm but cannot hang out towards the side of the body. An example is shown in Figure 2 (4th and 5th).

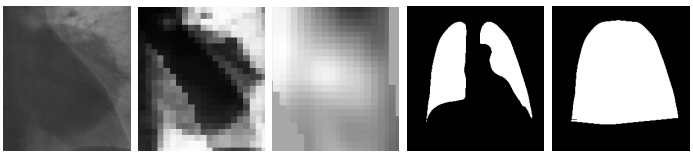

Figure 2: From left to right: a large nodule partly overlapped by the heart (1st), the LCE output (2nd), the final LNF output (3rd), the masks of the viewable lung area (4th) and the estimated area of the whole lung (5th).

B. Reduction of false positives

The candidate collector finds approximately 20-30 candidates on the enhanced image. For the reduction of false positive findings we use a Support Vector Machine (SVM). The training data comes from validated findings of radiologists. The most crucial design parameter of the SVM is the kernel function for which we use the isotropic Gaussian kernel. The input vector of the kernel consists of various features describing texture, geometry and location.

To eliminate irrelevant features, we ran a simple feature selection algorithm which observes the performance of the SVM while adding various features in a forward selection manner. As the relevant features turned out to be different for the output of the two nodule enhancing algorithms we decided to use separate classifier for each result set. Using one classifier requires the union of relevant features which would increase the number of dimensions reducing overall performance. Furthermore, tests showed that multiple classifiers can save run time.

The SVM with isotropic Gaussian kernel requires two hyperparameters to be chosen by the user. For this we use a gradient search with some modifications to make it robust against local maxima. For performance measurement cross validation is utilized.

III. Results

We tested the system on a private chest X-ray database containing images of 243 patients where 93 of the cases contained at least one malignant lung nodule. Nodule diameter ranged from 2 mm to 98 mm, the average was 24 mm. Most of the malignant cases were validated by CT. The images came from a digital X-ray machine working in daily practice at a Hungarian clinic.

As a testing method we used 4-fold cross validation with 100 iterations for each setup to reduce the variance introduced by the random permutation of images. The results can be seen on a free-response receiver operating characteristic (FROC) curve in Figure 3. The plot shows the fraction of malignant cases that can be found as a function of average number of false positives produced for each image. We ran the FROC analysis for a system using the CSBF or the LNF enhancers only and for the complete version using both algorithms. The poor performance of the LNF on its own is clear as the radiographs contained mostly small nodules; however integrating its results with the CSBF improves sensitivity without adding many false positives. The increase compared to the standard CSBF solution is obvious. At constant 70% sensitivity the number of false positives can be reduced from 2.3 to 1.7 per image.

Alternatively with a false positive rate of 3 the sensitivity can be increased from 73% to 77%.

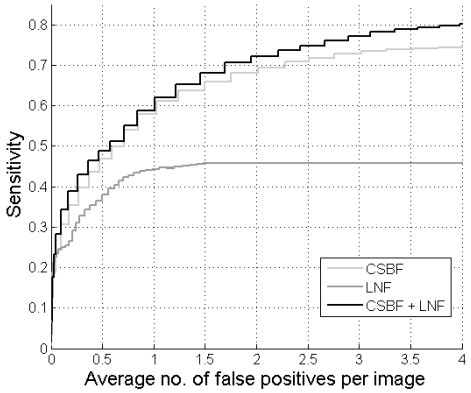

Figure 3: Comparison of systems using only CSBF or LNF and the complete (CSBF + LNF) version.

The final results are still good if we consider everyday applicability. 72% sensitivity with 2 false positives or 77% with 3 requires acceptable extra work from the examiner while it marks malignant areas the examiner may overlook otherwise. Of course the number of false positives should be reduced to further improve the usability of the system. However, the representativity of the used image database is not yet examined thus comparison of the results with other systems should be made carefully. Although we cannot be sure that system performance remains the same in everyday practice, we are optimistic as an in progress clinical study reported similar results based on the first 800 cases.

IV. Conclusion

In the current work we developed a new filter able to find larger nodules and integrated it to our existing CADe scheme. The main contribution to the CADe community is twofold. First, the introduced LNF can be a useful tool if the automated detection of mature tumours is needed. Second, the current case shows that a hybrid system involving specialized filters and proper synthesis can be more efficient than a system using one general-purpose filter. Furthermore the resulting CADe scheme turned out to be efficient for everyday clinical use. Future improvements should focus on the further reduction of false positive rate to ensure that CADe increases only the number of true positive diagnoses and not the number of unnecessary examinations.

References

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[2] S. Juhász, Á. Horváth, L. Nikházy, G. Horváth, and Á. Horváth, "Segmentation of Anatomical Structures on Chest Radiographs," in *XII Mediterranean Conference on Medical and Biological Engineering and Computing 2010*, R. Magjarevic, P. D. Bamidis, and N. Pallikarakis, Eds., vol. 29 of *IFMBE Proceedings*, pp. 359–362. Springer Berlin Heidelberg, 2010, 10.1007/978-3-642-13039-7_90.

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