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LUNG CAD SYSTEM

System overview:

The CAD system comprises at present four macro-steps [Riccardi06]:

1. Lung segmentation;
2. 2D nodule-like signals detection in slices: logical *AND* of
    a. Fast Radial filter;
    b. Scale Space filter;
3. Grouping of 2D signals into 3D candidate nodules;
4. False Positive Reduction (FPR):
    a. Coarse FPR (on the basis of a few geometrical features);
    b. Fine FPR:
        i. 2D Gray Level features and Support Vector Machine classifier;
        ii. 3D Ranklet-Based features and Support Vector Machine classifier;
        iii. 2D Support Vector Regression Filtering FPR.

    Steps i, ii, iii can be combined in different modalities.

1) Lung segmentation

Our segmentation algorithm is composed of six main steps: i) a smoothing algorithm is applied to the CT stack to reduce noise; ii) the lung region is extracted from the CT images by adaptive grey-level thresholding; iii) trachea region is eliminated from initial CT slices; iv) the left and right lungs are then separated to permit finer processing on each lung separately; v) some spurious regions, left over from the segmentation step based on region volume size, are eliminated; vi) lung contour is smoothed, in order to retain lung structures within the lung and include nodules attached to the lung wall. The overall segmentation process is described in Fig. 1, together with the type of data involved in each processing step.

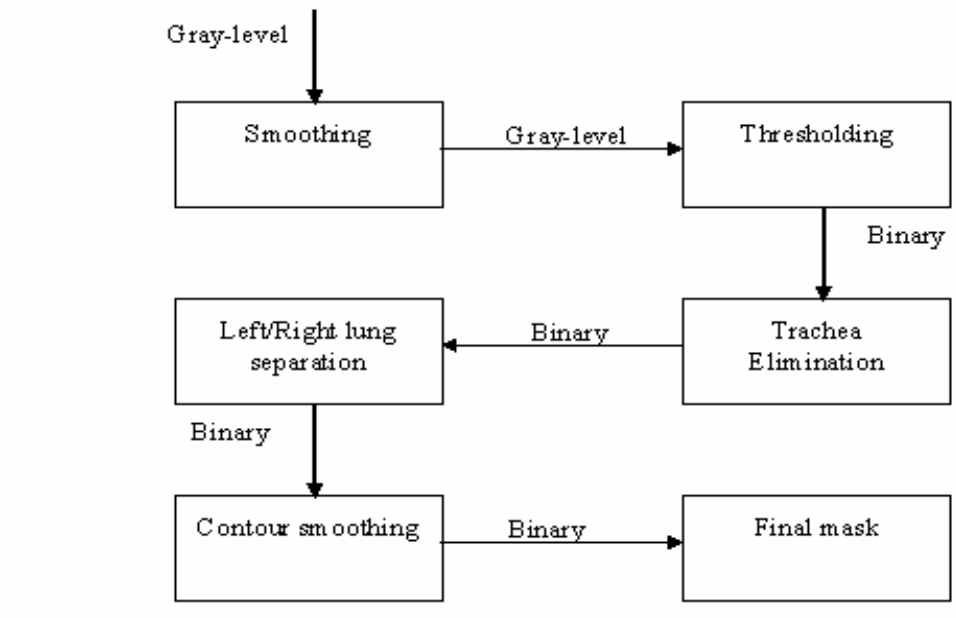

Figure 1: Overall segmentation algorithm. Arrows show direction of data flow.

2) 2D nodule-like signals detection in slices

Each slice in the segmented CT stack is processed in the following way:

i. Fast Radial filtering [Loy03]: it is a sort of non-linear and shape dependent Gray Level transformation. It enhances circular bright spots more than non-circular ones, hence it shows high specificity to nodule-like signals. This image undergoes a second identical
ii. Fast Radial filtering. Filtered image is then thresholded to find high peaks, corresponding to detected signals. Threshold is optimized with a Cross Validation procedure.
iii. All these signals are subsequently considered for the analysis with Scale Space techniques. According to Lindeberg [Lindeberg93] Scale Space extrema - points that are local extrema both in scale and space - of the Normalized Laplacian reflect a characteristic length of the objects in the image. Moreover, it has been found that there is a direct relationship between the sigma of the Normalized Laplacian employed for filtering and the radius of circular or quasi-circular bright objects (*sigma resonance*: $\sigma = \frac{r}{\sqrt{2}}$). By using this technique, it is possible to easily estimate the size of the detected objects, and to eliminate all those signals whose dimensions are out of the predefined detection range (usually, 4 to 20 mm diameter), without the need to determine the exact borders of the signals.

The logical AND with the Scale Space filter reduces the number of False Positives detected by the FR filtering step to 80÷90% of the initial value.

3) Grouping of 2D signals into 3D candidate nodules

After setting a proper spatial tolerance, 2D signals are matched across slices by simply comparing their positions, determined by means of the Scale Space procedure. Beginning from the first signal in the first slice, each signal is linked with each signal in the next slice, provided their spatial positions are within the chosen tolerance. The result of this operation is an ensemble of groups of 2D signals corresponding to objects extended across slices in the CT scan of patients: these objects are the candidate nodules that undergo a False Positive Reduction step.

4) False Positive Reduction

Coarse FPR

It is possible to cut all signals which are too short or too long, those which are too much inclined with respect to the z-axis (nodules are typically not inclined, vessels are very much inclined), and those whose volume is too large. In particular, too short means the signal is a singleton (it is linked with no other signals) and too long is related to the maximum size of searched nodules. Approximately 70% to 80% of false nodules are eliminated by this FPR step, and at the same time only 5÷10% of nodules are lost.

Fine FPR

This step includes three independent branches that can be combined in different ways, according to classifiers combination rules (see, for example, [Kittler98]).

i) 2D Gray Level features and Support Vector Machine classifier

Overview
This FPR branch comprises two sub-steps: one is the classification of each 2D signal; the other is the final labelling of each group of 2D signals. Eventually, only 3D objects judged as nodules will be prompted to the final CAD user.

Method: sub-step a
A training procedure is performed, based on SVM classifier. Square Regions of Interest (ROI) around candidate nodules are selected trough their *sigma resonance* values, without the need to determine their exact borders. Gray Level features are considered as discriminative features for classification. Each positive training sample is rotated multiple times with the aim to obtain a final classifier with a good degree of rotational invariance and to overcome the problem of small databases at disposal. Multiple rotations are considered also at time of classification of each 2D ROI: a percentage of these rotated views is set during a Cross Validation procedure as the minimum number of necessary positive classification to give the ROI a positive label

Method: sub-step b
A heuristic procedure is used, after a Cross Validation optimization step, to give each 3D group of 2D signals (ROIs) a final label: nodule or not-nodule. The positive label is given when a certain percentage of the ROIs of the group are classified as 2D nodules. This percentage depends on the number of ROIs of the group.

ii) 3D Ranklet-Based features and Support Vector Machine classifier

Overview
Contiguous 2D regions of interest found on segmented lung areas from sections of a CT scan are merged to form volumes of interest (VOIs). Feature vectors are then computed by submitting each VOI to the 3D Ranklet transform, a non-parametric orientation-selective and multi-resolution transform [Masotti06]. Finally, a Support Vector Machine (SVM) classifier is used to discriminate VOIs containing nodules from those containing normal tissue.

Method
Given a number of VOIs, also known as 3D nodule candidates, feature vectors are calculated by submitting each of them to the 3D ranklet transform. A 2D version of this transform was in fact successfully developed and evaluated by our group in the discrimination of breast tumoral mass from normal tissue.
By submitting VOIs to the 3D ranklet transform, a number of ranklet coefficients are produced. Ranklet coefficients are, for instance, non-parametric. As for the 2D case, in fact, the 3D ranklet transform deals with voxels' ranks rather than with their gray-level intensity values; i.e., given $(v_1,\ldots,v_N)$ voxels, the intensity value of each v_i is replaced with the value of its order among all the other voxels. Secondly, ranklet coefficients are multi-resolution and orientation-selective. Similarly to the bi-dimensional Haar wavelet transform, in fact, ranklet coefficients can be calculated at different resolutions and orientations (i.e., vertical, horizontal and diagonal) by means of a suitable stretch and shift of the oriented compact supports used for their computation.
As far as classification of the aforementioned feature vectors is concerned, an SVM classifier is adopted.

iii) 2D Support Vector Regression (SVR) Filtering FPR

Overview
Starting from two well-known facts:

- SVM-based classification and regression techniques, arisen from Statistical Learning Theory [Vapnik98], have widely demonstrated in recent years their superiority to conventional techniques, such as Multi-Layer Perceptron (MLP);
- MLPs are at the basis of the class of image filters known as Neural Filters, to which an interesting FPR method such as MTANN [Suzuki03] belongs;

we developed a modified version of MTANN employing SVR instead of Neural Networks. This SVR filtering approach was initially tested for FPR in a mass detection CAD for Mammography [Angelini05], giving interesting results.
This FPR branch is composed of two sub-steps: the first is the classification of each 2D signal by means of the SVR-based classification technique; the other is the final labelling of each group of 2D signals, similar to the *sub-step b* of point i) of Fine FPR.

Method: sub-step a
Each ROI holding a candidate-nodule is filtered with the SVR-based filtering technique: the result is an output image which is subsequently used to determine if the ROI image contains a nodule.
To obtain the filtered image, the SVR filter is applied to sub-regions in each ROI until the whole image is processed: each sub-region is associated by the SVR algorithm to a continuous output value ranging from 0 to 1, representing a measure of the presence of a portion of a nodule in the input sub-region. A weighted sum of the outputs over each image is used to accomplish the FPR task: a threshold is set on the base of a Cross-Validation procedure.

Method: sub-step b
It is a heuristic procedure similar to that introduced in point i) of Fine FPR.

Conclusion

The system was initially trained on a small 34 nodule database (slice thickness 5 mm and slice spacing 3 mm), reaching these results: each of the three fine FPR branches alone made the system detect approximately 80% of nodules at 34 FP/Patient, or 65% at 6 FP/Patient, in a Multi-Fold Cross-Validation procedure. It must be noted that nodules in the database are in the range 3 ÷ 10 mm, and that their detectability is negatively affected by slice thickness and spacing, respectively 5 and 3 mm; moreover, the 3D Ranklet-Based FPR method is even more influenced by the relationship between nodule size and slice thickness and by high voxels anisotropy.
In conclusion, taking into account all the disadvantages of our initial database, we consider the system obtained very promising results, and we believe it will strongly improve its performances when trained on a better database, which will also consent to properly validate the FPR combination step, which we highly value and have already successfully tested in our previous works. For “better database” we intend a larger one with proper (fine) slice thickness and spacing. Indeed, at present we are working on the LIDC public database, and we have also begun creating a database of fine CT scans of patients examined at the local University Hospital (slice thickness 1.25 mm and slice spacing 1.25 mm).

References

[Angelini05]: E. Angelini, R. Campanini and A. Riccardi, “Support vector regression filtering for reduction of false positives in a mass detection cad scheme: preliminary result”, University of Bologna Preprint, 2005. *Available at: http://amsacta.cib.unibo.it/archive/00000912/*

[Kittler98]: J. Kittler, M. Hatef, R. P. W. Duin and J. Matas, “On Combining Classifiers”, *IEEE TPAAMI*, 20, 3:226-239, 1998
[Lindeberg93]: T. Lindeberg, “On Scale Selection for Differential Operators”, *Proc.8th Scandinavian Conference on Image Analysis*, May 1993, 857-866
[Loy03]: G. L. Loy and A. Zelinsky, “Fast Radial Symmetry for Detecting Points of Interest”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25, 8, 2003
[Masotti06]: M. Masotti, A ranklet-based image representation for mass classification in digital mammograms, *Medical Physics*, 33(10) (2006) 3951-3961
[Riccardi06]: A. Riccardi, A new computer aided system for the detection of nodules in lung CT exams, PhD Thesis, University of Bologna, Department of Physics, July 2006
[Suzuki03]: K. Suzuki, S. G. Armato III, F. Li, S. Sone, and K. Doi, “Massive training artificial neural network (MTANN) for reduction of false positives in computerized detection of lung nodules in low-dose computed tomography”, *Med. Phys.* 30 (7), 1602-1617, July 2003
[Vapnik98]: V. N. Vapnik, “Statistical Learning Theory”, J. Wiley 1998