QUANTITATIVE LUNG NODULE ANALYSIS SYSTEM (NAS) FROM CHEST CT

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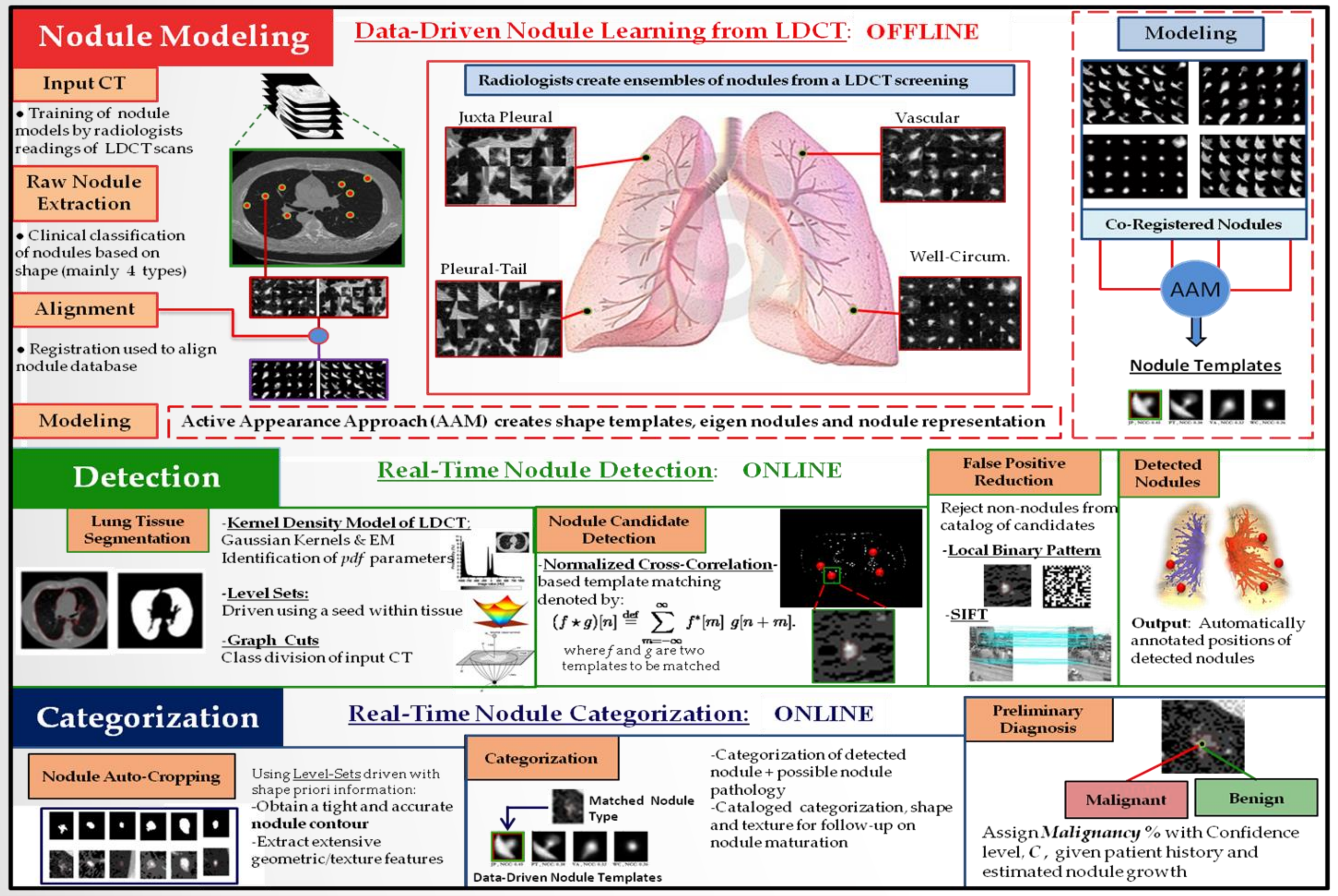
I. Big Picture –Data-Driven System for Lung Nodule Analysis

System Components, as illustrated below:

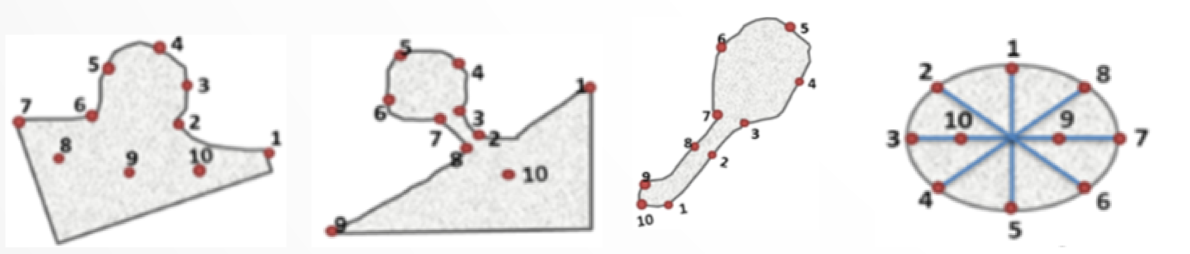
1) Lung Tissue Segmentation – To isolate the lungs from the other tissues in the chest
2) Nodule Detection
3) Nodule Segmentation
4) Nodule Categorization

These steps (2–4) require proper nodule models



II. Main Purpose and Contribution

- This work devises an automatic approach for creating elastic deformable nodule templates using the AAM approach and biomarkers on the nodule contours
- New templates were used in the detection process resulting in simultaneous improvement in sensitivity and specificity
- Framework presented that conducts feature extraction and classification using cascaded SVM in a CNN architecture to identify non-nodules, malignant and benign nodules.



- Critical points for annotation (left to right): juxta-pleural, pleural-tail, vascularized and well-circumscribed

III. Deformable Active Appearance Modeling

- ❑ Given location x, in the nodule's spatial support, $C = \{ c_i , i \in [1, L]\}$ represents a single set of realizations (e.g., shapes or appearances or both). The combined AAM approach represents the shape $\boldsymbol{S}(x)$ and appearance $\boldsymbol{A}(x)$ such that :

$$\boldsymbol{S}(x) = \boldsymbol{S_o}(x) + \sum_{i=0}^{L} c_i\, S_i(x) \text{ and } \boldsymbol{A}(x) = \boldsymbol{A_o}(x) + \sum_{i=0}^{L} c_i\, A_i(x)$$

$\boldsymbol{S_o}(\cdot)$ and $\boldsymbol{A_o}(\cdot)$ ~ Average shape and appearance realizations

Novel Automatic Nodule Annotation and Alignment:

- ❑ Generate nodule models using 24 manually annotated nodules per category
- ❑ Extract feature points for each nodule image per types using high and low curvature regions
- ❑ Register the nodule samples using the maximum or minimal curvature points as reference
- ❑ Modified Iterative Closest Point computes the transformation matrix by exploiting the curvature information
- ❑ Construct updated AAM Models

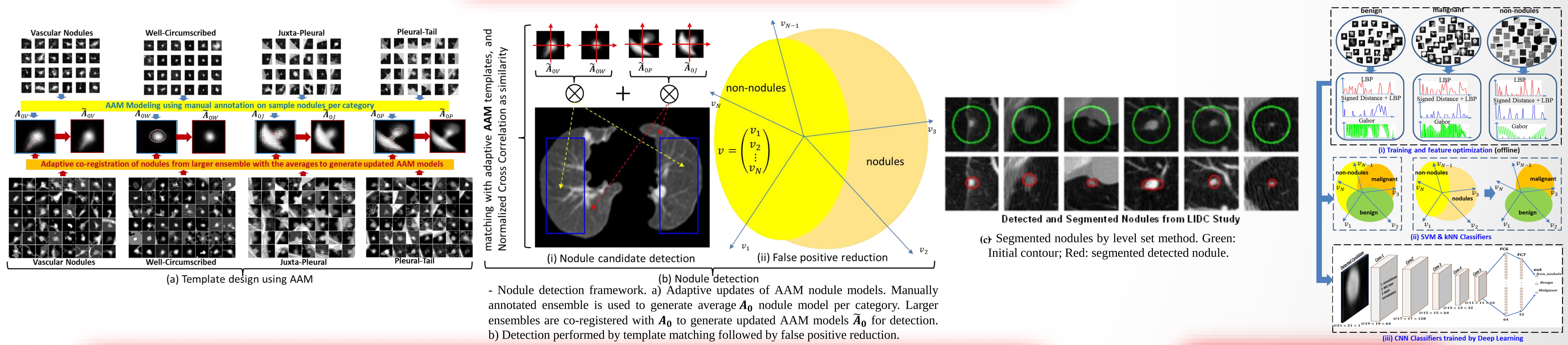
Main issues in developing AAM:

- ❑ Shape definition – shape representation as contours, signed-distance, histograms, etc.
- ❑ Shape annotations – which features to select
- ❑ Uncertainties – with deformations, imaging errors, and size

Lung Nodules suffer from:

- ❑ Inconsistency of shape definitions among clinicians
- ❑ Resolution of CT scans
- ❑ Size makes it worse

IV. NAS Data Driven System



(a) Template design using AAM

(b) Nodule detection

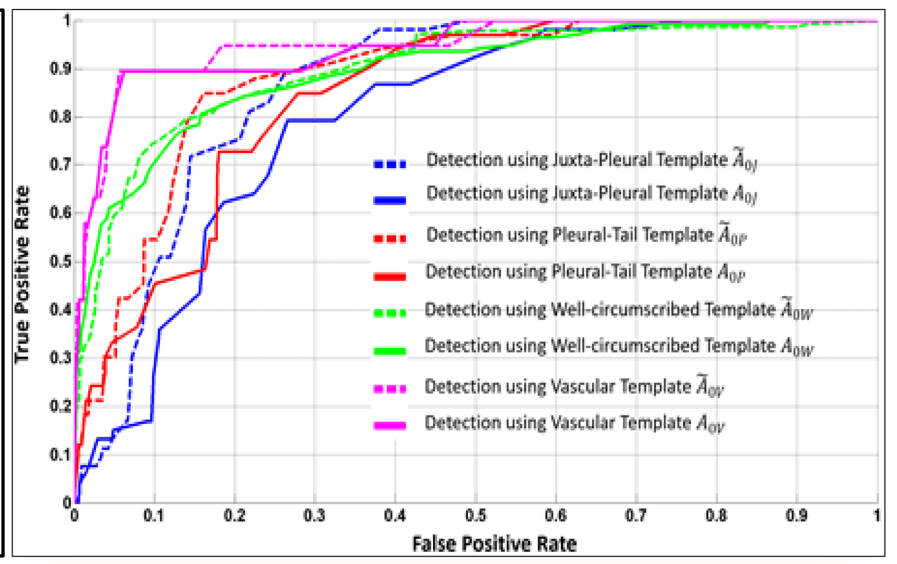
- Nodule detection framework. a) Adaptive updates of AAM nodule models. Manually annotated ensemble is used to generate average $\boldsymbol{A_0}$ nodule model per category. Larger ensembles are co-registered with $\boldsymbol{A_0}$ to generate updated AAM models $\tilde{A}_0$ for detection. b) Detection performed by template matching followed by false positive reduction.

(c) Segmented nodules by level set method. Green: Initial contour; Red: segmented detected nodule.

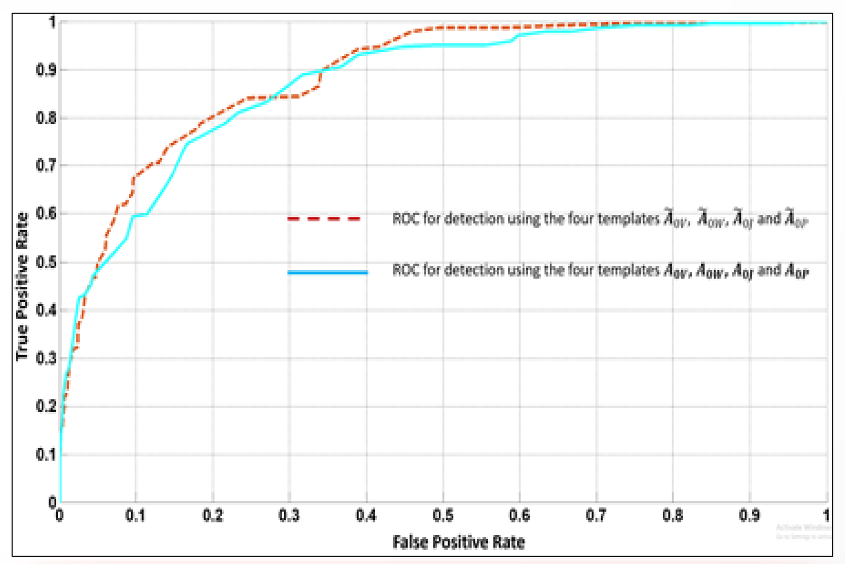
V. Performance of AAM vs. Parametric Templates for Nodule Detection

1. **Early Lung Cancer Action Program** (ELCAP)
   - 50 scans. 1.25 mm thickness
   - 397 total nodules with sizes ranging from 2mm to 5mm
2. **Lung Image Database Consortium**(LIDC)
   - 1010 Patient scans
   - Low and High dose CT images with varying nodule diameter sizes

Datasets used in the analysis



ROC for detection by updated AAM templates



ROC for detection by average AAM templates

VI. Conclusions

- ❑ A general fully automatic approach has been developed to create deformable templates from an ensemble of lung nodules
- ❑ A fully model-based mechanism to detect, authenticate (reduce false positives) and segment/crop the nodules for the last step in the CAD system, classification, is presented

VII. Sample References

1. Amal Farag, Asem Ali, Salwa Elshazly and Aly Farag, "Feature fusion for lung nodule classification". Int. J Comput Assist Radiol Surg. 2017 Jun 16. doi: 10.1007/s11548-017-1626-1.
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