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ROTATION–COVARIANT TEXTURE ANALYSIS OF 4D DUAL–ENERGY CT AS AN INDICATOR OF LOCAL PULMONARY PERFUSION

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ABSTRACT

We propose rotation–covariant texture analysis of 4D dual–energy computed tomography (DECT) as a diagnosis aid tool for acute pulmonary embolism in emergency radiology. The cornerstone of the proposed approach is to align 3D Riesz directional filters along bronchovascular structures to enable rotation–covariant comparisons of the parenchymal texture. The latter is enabled using the steerability property of Riesz filterbanks. Blockwise classification of the parenchyma from all pulmonary lobes allowed a mean area under the receiver operating characteristic (ROC) curve of 0.85, which suggests that the proposed approach can be successfully used to assist radiologists in DECT data interpretation.

***Index Terms*—** 3D texture analysis, steerability, Riesz transform, dual–energy CT, acute pulmonary embolism.

1. INTRODUCTION

Acute pulmonary embolism (APE) is a common and often fatal condition. It refers to the obstruction of pulmonary arteries leading to cardiac dysfunction, hypoxia and the necrosis of the pulmonary parenchyma. Untreated APE is associated with a mortality rate of 30 percent [1]. A prompt diagnosis and therapy (e.g., anticoagulation) are essential to avoid fatality. Unfortunately, APE symptoms are not specific and an accurate diagnosis workup is often difficult. Increased diagnosis accuracy is obtained with the visualization of the arterial irrigation in injected computed tomography (CT). However, it remains very difficult to assess the impact of arterial obstruction on the parenchyma function, the latter being associated with mortality prognosis [2]. Studies reported that APE was related to the presence of oligemia, ground glass, mosaic perfusion and other texture–related patterns in CT [3, 4]. Regional alterations of the pulmonary blood flow result in important changes of the lung regional density [5], which create texture patterns with strong directional information that can be hardly assessed by human observers.

Dual–energy CT (DECT) is a recent, promising imaging technique to quantify parenchymal perfusion in APE [6, 7]. DECT yields 4D data; i.e., a 3D image series is obtained for every X–ray energy level between 40 and 140keV. Multi–energy attenuation curves differ among materials in DECT, which allows separating iodine components from materials with similar appearance in classical CT. A current limitation of the use of DECT imaging in clinical routine is the complexity of 4D data interpretation, where the energy level is little intuitive. It is very difficult to have an accurate mental representation of 4D texture appearance of the lung parenchyma. As a result, clinicians often discard the wealth of 4D DECT data while using one single–energy image at 70keV for the diagnosis workup in clinical routine. Computerized analysis of DECT data allows for an exhaustive characterization of the underlying 4D data and has been little investigated so far. Some studies proposed computerized detection of pulmonary embolism in CT [8] and DECT [7] while focusing on shape analysis of the arterial tree and without exploiting the parenchymal texture properties associated with APE [3, 4, 5]. In [9], Ganeshan *et al.* showed that 3D texture analysis using multiscale isotropic Laplacian of Gaussian filters correlates with altered vascularity in injected CT. We used similar isotropic filters combined with the bags of visual words approach in [10], which demonstrated the feasibility of characterizing texture patterns from APE in DECT data. However, isotropic filters may discard important directional information defined by bronchovascular structures in 3D.

In this work, we propose a computerized multiscale directional texture analysis of DECT data for local pulmonary perfusion assessment. 3D multiscale steerable Riesz filterbanks yield rotation–covariant texture descriptors allowing subtle characterization of directional vascular morphological changes associated with APE in CT imaging (e.g., oligemia). Rotation covariance is obtained by locally aligning the Riesz templates, which is done analytically using steerability. Local orientation estimations are obtained using a Riesz–based regularized structure tensor proposed by Chenouard *et al.* [11].

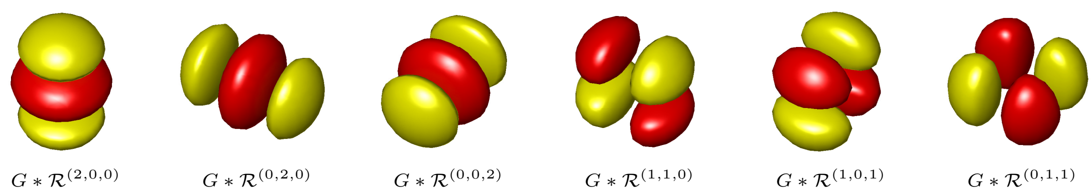

Fig. 1. Second–order Riesz kernels $\mathcal{R}^{(n_1,n_2,n_3)}$ convolved with isotropic Gaussian kernels $G(\boldsymbol{x})$.

Support vector machines (SVM) are then used to classify between 9,347 normal and embolic cubic instances of lung parenchyma from 19 patients with APE and 8 control cases.

2. MATERIAL AND METHODS

2.1. Rotation–covariant texture analysis

3D multiscale Riesz filterbanks are used to characterize the texture of the lung parenchyma in 3D at a given CT energy level. The N–th order Riesz transform $\boldsymbol{\mathcal{R}}^{(N)}$ of a three–dimensional signal $f(\boldsymbol{x})$ is defined in the Fourier domain as:

$$\widehat{\mathcal{R}^{(n_1,n_2,n_3)}f}(\boldsymbol{\omega}) = \sqrt{\frac{n_1+n_2+n_3}{n_1!n_2!n_3!}} \frac{(-j\omega_1)^{n_1}(-j\omega_2)^{n_2}(-j\omega_3)^{n_3}}{||\boldsymbol{\omega}||^{n_1+n_2+n_3}}\hat{f}(\boldsymbol{\omega}), \quad (1)$$

for all combinations of (n_1, n_2, n_3) with $n_1 + n_2 + n_3 = N$ and $n_{1,2,3} \in \mathbb{N}$. Eq. (1) yields $\binom{N+2}{2}$ templates $\mathcal{R}^{(n_1,n_2,n_3)}$ and forms multiscale steerable filterbanks when coupled with a multi–resolution framework based on isotropic band–limited wavelets (e.g., Simoncelli) [12]. The second–order Riesz filterbank is depicted in Fig. 1. Rotation–covariance is obtained by locally aligning the Riesz components $\mathcal{R}^{(n_1,n_2,n_3)}$ of all scales based on the local prevailing orientation [13]. The steerability property allows synthesizing the responses of the templates at any orientation based on a linear combination of themselves. It therefore does not require additional convolutions of oriented filters [12]. Locally prevailing orientations based on the three Euler angles parameterizing $SO(3)$ are estimated using a regularized version of the structure tensor, where the latter is computed over a 3D Gaussian window. The variance σ_t of this Gaussian window determines the scale for the local orientation estimation. We use the implementation of the regularized structure tensor by Chenouard *et al.* [11]. Locally aligned multiscale Riesz features are denoted as $\widetilde{\boldsymbol{\mathcal{R}}}^{(N)}$ in the next sections.

2.2. Experimental setup

19 patients with APE and 8 control cases are used to evaluate the proposed approach. All 27 cases underwent a DECT scanner[1] at the Department of Radiology of the University Hospitals of Geneva with an inter–slice distance of 1mm, a slice thickness of 1.25mm, and a sub–millimetric resolution in the axial plane. 11 energy levels are used from 40keV to 140keV with a step of 10keV. All five lobes of each patient have been manually segmented using the OsiriX software[2]. The perfusion levels of each lobe were quantified using the Qanadli index (QI) on a lobe basis [14]. The QI is defined as the sum of the scores of all arteries as: 0 if no occlusion is visible, 1 if partially occluded, and 2 if totally obstructed.

DECT data of all energy levels are preprocessed to have an isotropic voxel resolution, which is obtained by dividing samples along the z axis. All lobes are divided into 32^3 overlapping blocks to constitute a local instance of the lung parenchyma. A block is considered as valid when at least 95% of its voxels belong to it. To obtain a sufficient number of blocks for the middle right lobe, this rule was changed to 90% due to its smaller size when compared to the other lobes. A total of 9,347 blocks are obtained for all lobes of all patients. The classes of all blocks from a given lobe are defined as embolism if QI>0. Only blocks from control cases are used to represent the healthy class, as the redistribution of the blood flow in healthy lobes of embolism patients may alter parenchymal texture properties. Since the visual appearance of the healthy parenchyma may vary from upper and lower lobes due to gravity effects and anatomy, each lobe type (i.e., left, right, lower, middle, upper) is analyzed separately. Grey–level histograms (GLH) in Hounsfield Units (HU) of the extended lung window $[-1000; 512]$ HU with N_{bins}=50 bins are used to characterize X–ray attenuations. GLH are providing essential information to characterize hypo– and hyper–attenuated regions which respectively result from under–perfused oligemic areas of the lung or from shunting of blood to irrigated parenchyma. The feature space is composed of the concatenation of the HU histogram bins and the energies of the Riesz coefficients for all 11 DECT energy levels with a total dimensionality of $11 \times (N_{bins} + \binom{N+2}{2})$. SVMs with a Gaussian kernel are used to learn from the multi–energy features. Several parameters are exhaustively optimized for each lobe: N, σ_t, the cost C of the errors of SVMs and the variance σ_K of the associated Gaussian kernel $K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(\frac{-||\boldsymbol{x}_i - \boldsymbol{x}_j||_1^2}{2\sigma^2})$ as: $N \in [1; 4]$, $\sigma_t = 0.75, 1.5, 3$, $C \in [10^0; 10^{18}]$ and $\sigma_K \in [10^0; 10^{-13}]$. A leave–one–patient–out cross–validation is used to estimate the generalization performance of the proposed approach.

[1] GE Discovery CT750 HD with two X–ray tubes and rapid peak kilovoltage switching (gemstone spectral imaging, GSI).

[2] http://www.osirix-viewer.com/, as of 31 October 2012.

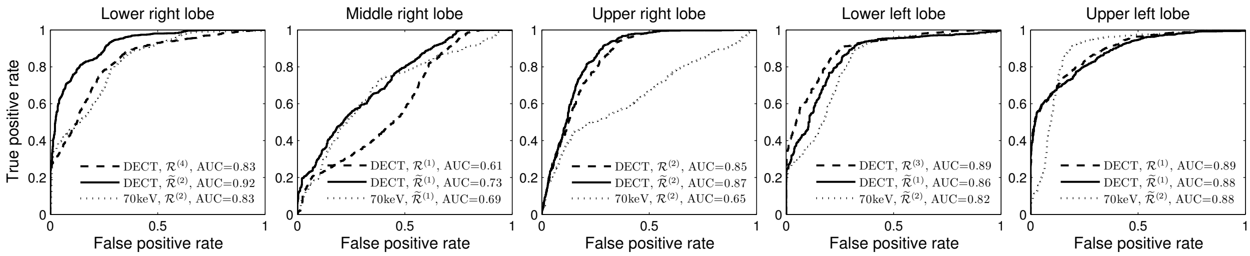

Fig. 2. ROC curves of the classification between normal and lung tissue with APE for each lobe Aligned $\widetilde{\mathcal{R}}$ and non–aligned $\mathcal{R}$ Riesz components using all 4D DECT data are compared with using only the 70keV 3D image series.

3. RESULTS

Receiver operating characteristic (ROC) curves of the classification between normal and lung tissue with APE are shown in Fig. 2 for each lobe. ROC curves are obtained by varying the decision threshold between the minimum and the maximum of the kernelized decision function of SVMs $d(\boldsymbol{x}_i) = K(\boldsymbol{w}, \boldsymbol{x}_i) - b$, where $\boldsymbol{x}_i$ is an instance, $\boldsymbol{w}$ is the separating hyperplane and b its offset. The performance of the aligned Riesz descriptors $\widetilde{\mathcal{R}}$ in DECT data are compared both with the performance of non–aligned Riesz $\mathcal{R}$ in DECT and the best configuration (either $\mathcal{R}$ or $\widetilde{\mathcal{R}}$) using only the 70keV image series that is commonly used by the clinicians for the diagnosis workup. Mean area under ROC curves (AUC) for $\widetilde{\mathcal{R}}$ in DECT, $\mathcal{R}$ in DECT and best configuration in 70keV are 0.85, 0.81 and 0.77, respectively.

4. DISCUSSIONS AND CONCLUSIONS

Multiscale rotation–covariant texture analysis of 4D DECT data is proposed to assess local pulmonary perfusion changes induced by APE. The proposed approach allows local orientation characterization and compensation by aligning the Riesz templates along locally prevailing orientations, which is obtained analytically through steerability. With the number of directions increasing drastically from 2D to 3D, classical texture analysis approaches (e.g., grey–level co–occurrence matrices (GLCM), non–steerable filterbanks) would not enable accurate characterizations of the local scale and orientation properties of the vascular structure. The latter is however required to detect subtle APE–related morphological changes.

Results shown in Fig. 2 suggest that the proposed approach can be valuable to assess the impact of clots on the lung parenchyma function in emergency radiology and therefore enables better prognosis. AUC ranges between 0.73 and 0.92, which shows a promising trade–off between true and false positive rates, and allows appropriate tuning of the operating point for a clinical usage of the system. It is important to note that the classification task is difficult for two main reasons. First, all blocks from lobes with QI>1 are considered as embolism, whereas only sub–parts of the lobes are affected in lobes with low QI. Moreover, partial occlu-

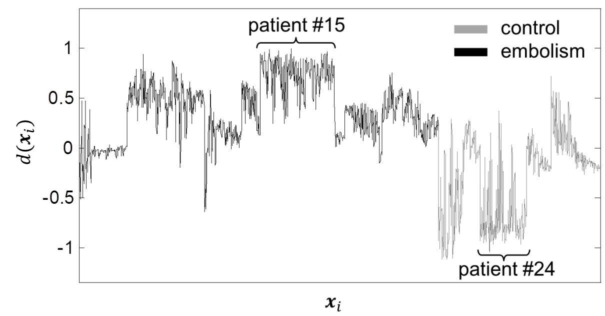

Fig. 3. Patient–specific texture properties are highlighted by the decision function $d(\boldsymbol{x}_i)$ for the lower right lobe using $\widetilde{\mathcal{R}}$.

sions of pulmonary arteries may have little or no impact on the perfusion of the associated parenchyma. Support vector regression will be used in future work to investigate the ability of the proposed texture features to predict QI values. The lowest performance was observed for the middle right lobe, which can be explained by the fact that the rule for block inclusion was less strict than for other lobes (i.e., 90% of the voxels in the lobe instead of 95%). Aligned Riesz templates $\widetilde{\mathcal{R}}$ allowed increased overall AUC when compared to $\mathcal{R}$ ($p = 2.19 \times 10^{-16}$ based on a one–tailed paired T–test), although both approaches allowed similar performance in the left lung. For all lobes, DECT data allowed increased or equivalent performance when compared to 70keV, which demonstrates the richness of DECT data when compared to classical injected CT ($p = 1.3 \times 10^{-7}$). An accurate tuning of σ_t was found to be critical to allow for an adequate alignment of the Riesz components on small oligemic arteries. Normal artery size is patient–specific and a normalization of σ_t using patterns from healthy lobes will be investigated in future work. Clear patient–specific texture properties are highlighted by SVM's decision function $d(\boldsymbol{x}_i)$ for the lower right lobe using $\widetilde{\mathcal{R}}$ in Fig. 3. Future work will include SVM–based feature weighting to select and foster discriminative combinations of the various energy levels. It also allows building texture signatures [15] to learn the important scales of arteries and orientations of the branching configurations related to embolized lung parenchyma. This will foster relevant combinations of multiscale Riesz components to better exploit the richness of higher–order Riesz filterbanks.

The proposed work opens a new direction for DECT data analysis allowing prompt diagnoses of APE in an emergency setting. 3D perfusion maps resulting from blockwise classifications of the entire lung parenchyma will be built to enable human-understandable local quantification of the local perfusion. Ultimately, objective and reproducible diagnosis workup should contribute to quickly orient adequate treatment of APE and reduce mortality.

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