Local noise reduction for emphysema scoring in low-dose CT images

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ABSTRACT

Computed Tomography (CT) has become the new reference standard for quantification of emphysema. The most popular measure for emphysema derived from CT is the Pixel Index (PI), which expresses the fraction of the lung volume with abnormally low intensity values. As PI is calculated from a single, fixed threshold on intensity, this measure is strongly influenced by noise. This effect shows up clearly when comparing the PI score for a high-dose scan to the PI score for a low-dose (i.e. noisy) scan of the same subject. This paper presents a class of noise filters that make use of a local noise estimate to specify the filtering strength: Local Noise Variance Weighted Averaging (LNVWA). The performance of the filter is assessed by comparing high-dose and low-dose PI scores for 11 subjects. LNVWA improves the reproducibility of high-dose PI scores: For an emphysema threshold of -910 HU, the root-mean-square difference in PI score drops from 10% of the lung volume to 3.3% of the lung volume if LNVWA is used.

Keywords: noise reduction, emphysema quantification, low-dose CT

1. INTRODUCTION

Emphysema is a pathology of the lung, characterized by the destruction of lung tissue. This deficiency can be measured by aberrations of pulmonary function tests (PF), in which the performance of the lungs (e.g. total lung capacity and diffusion of CO) is compared to the expected performance. However, these pulmonary function test are not very sensitive, and can only make a rough distinction of emphysema stages: normal, mild, or severe. A more sensitive method for in vivo quantification of emphysema can be obtained using Computed Tomography (CT) images.

Since emphysema shows up on CT as areas with abnormally low attenuation coefficients (close to that of air, i.e. -1000 Hounsfield Units (HU)), visual CT scoring of emphysema is feasible. Because visual scoring is rather subjective, a variety of automatic methods for emphysema quantification have been proposed in literature (for an overview see Madani et al.[1] and Müller and Coxson[2]). Indeed these automatic methods offer quantifications that are more sensitive than PF and more objective than visual scoring.

As emphysema is identified by air-like voxels in the lungs, thresholding is the most straightforward way to automatically obtain a measure for the extent of emphysema. Indeed the most popular emphysema quantifier, the Pixel Index PI(T) (introduced by Kalender et al.[3]), is just the percentage of lung volume with intensities below a threshold T. Commonly this threshold is picked between -960 HU and -910 HU.

CT images exhibit strongly non-uniform noise. The noise becomes more apparent when the radiation dose is lowered. When emphysema is calculated from a fixed threshold on CT value, noise can greatly influence the visual and PI scores: See the difference between emphysema content of a high-dose and a low-dose image of the same person in Fig. 5. Although noise greatly hampers the accuracy of emphysema quantification, few studies on automatic emphysema scoring consider noise reduction. Tylén et al.[4] use Gaussian blurring to reduce noise, and Kostis et al.[5] use averaging over 5 slices for noise reduction.

To reduce the health risk from exposure to radiation while making a CT scan, it is desirable to use a radiation dose that is as low as possible. This is especially true for screening studies, for which asymptomatic people volunteer. By applying a simple averaging filter prior to emphysema scoring, the achieved accuracy is

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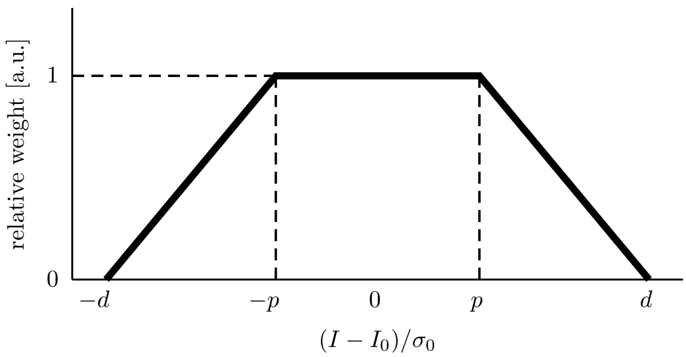


Figure 1. The weighting function for the local noise variance weighted averaging filter. The contribution of the intensity I in a point in the averaging window to the filtered intensity in the central pixel, is determined by the difference between I and the intensity in the central pixel I_0, and the standard deviation of the noise at the location of the central pixel σ_0.

already greatly improved (compare Fig. 5 to the top row of Fig. 6). However, for accurate scoring of emphysema in low-dose CT images, an improved noise filter is needed. This filter should have the following characteristics: *(i)* Filtering should bring the PI score of a low-dose image closer to the score obtained for a high-dose scan of the same subject. *(ii)* Preservation of small image structures and edges; and *(iii)* Large three-dimensional images should be processed sufficiently fast for intensive use. For visual scoring an additional requirement is that the processed images should look realistic (e.g. no quantization-like artifacts).

Since the application of an averaging filter substantially improved the image quality, we looked for a way to extend the averaging filter to enhance its effectiveness. As a starting point the Moving Average (MA) filter was used, which is the simplest noise reduction filter and can be found in any textbook on signal processing. The MA filter replaces a pixel value with the average of the pixel values in a window around that pixel. It is separable and extremely fast when implemented in a recursive manner. The largest drawback of MA filtering is the amount of blur it introduces into an image, wiping out small structures and sharp edges. This blurring can be prevented if averaging only takes place over intensities that are close to the value of the pixel to be replaced. The intensity deviation allowed should be related to the noise in the image. This idea can be incorporated into the MA filter by adding a weighting function $W(I - I_0)$ to the averaging, which is a function of the intensity of the pixel to be replaced I_0, and the intensity of a pixel in the averaging window I. The usage of W breaks the separability of the filter. Lee[6] used this concept to build the sigma filter, using $W = 1$ for $|I - I_0| < 2\sigma_N$ and $W = 0$ for other intensities, where σ_N expresses the standard deviation of the noise throughout the image. The SUSAN noise filter[7] is in fact also a type of intensity weighted MA filter, using $W = \exp\left[-(I - I_0)^2/\sigma_N\right]$.

The noise removal filter proposed in this paper is actually a class of filters and can be regarded as a generalization of the sigma filter. This new filter class will be termed Local Noise Variance Weighted Averaging (LNVWA) filter in the remainder of this article. The main difference with the plain sigma filter is the usage of a standard deviation σ which is a measure of the local noise (the so-called 'noise map'), and that it uses a trapezoidal weighting function instead of a box.

This paper proceeds as follows: In Section 2 the construction of the LNVWA filter is discussed and an iterative scheme is proposed to filter an image and obtain the noise map needed for the filtering; the experimental data and setup is described in Section 3; the performance of the filter with respect to emphysema quantification is evaluated in Section 4; conclusions are drawn in Section 5.

2. LOCAL NOISE VARIANCE WEIGHTED AVERAGING

The LNVWA filter is basically a moving average filter with an added weighting function W. For the LNVWA filter, the weighting function should make pixels within the averaging window contribute less if they are likely to belong to a different structure than the central pixel. To reflect that idea, the LNVWA weighting function is a decreasing function of $(I - I_0)/\sigma_0$, with I_0 and σ_0 the intensity and the local standard deviation of the noise at the filtered pixel position, and I the intensity of a pixel in the averaging window.

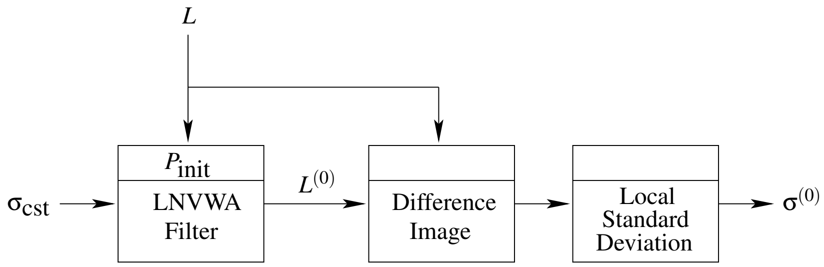


Figure 2. The initialization step to determine an initial noise map $\sigma^{(0)}$ from the input image L and a uniform noise map σ_{cst}.

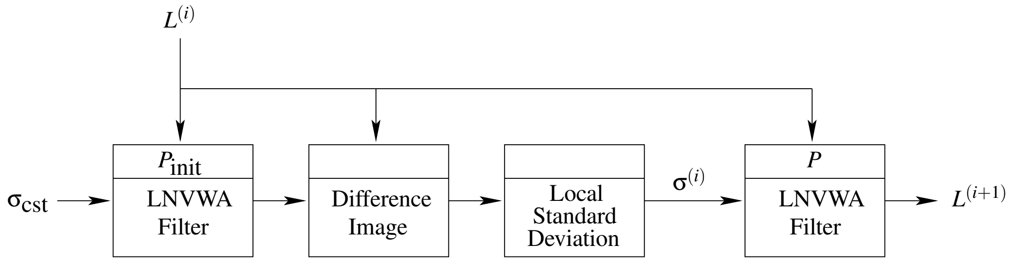


Figure 3. Iterative calculation of the noise filtered image $L^{(i+1)}$ from the previous estimate $L^{(i)}$.

For LNVWA, W is a trapezoid (see Fig. 1), with the extents of the platform and the filter denoted p and d, respectively, giving a relative weight as a function of the intensity difference and the local standard deviation of the noise. For each averaging window the weights are normalized. With $p = d = 2$ and a uniform σ, the LNVWA filter is a sigma filter.[6]

If a description of the 3D noise is available (e.g. an approximation might be derived from the raw scanner data[8]), the localized standard deviation of the noise (the 'noise map') can be calculated straightforwardly. The filtered image L' is then obtained from the original image L by a convolution with the LNVWA filter:

$$L' = \mathcal{F}_{\mathrm{LNVWA}}\left\{P;\sigma\right\} \circledast L; \tag{1}$$

here P denotes a list of parameters defining the shape of the weighting function and the spatial extent of the averaging window.

2.1. Iterative Implementation of LNVWA

In absence of an external noise map, the noise can be estimated iteratively from the image, using the idea that $L - L' \equiv$ noise. The iterative implementation of LNVWA can be done in several ways. For this paper we choose a scheme that incrementally changes the input image. Alternative schemes that focus on estimating the true noise map of an image can be derived, but these will not be discussed in this paper.

For the initial step of the iteration scheme LNVWA filtering is applied with a uniform noise map σ_{cst}, followed by calculating an improved noise map $\sigma^{(0)}$ from the difference image (see Figure 2):

$$\begin{aligned} L^{(0)} &= \mathcal{F}_{\mathrm{LNVWA}}\left\{P_{\mathrm{init}};\sigma_{\mathrm{cst}}\right\} \circledast L \\ \sigma^{(0)} &= \mathcal{S}_{\mathrm{3D}} \circledast [L - L^{(0)}], \end{aligned} \tag{2}$$

with $\mathcal{S}_{\mathrm{3D}}$ indicating the operator used for calculating the noise map.

In each iteration step (see Fig. 3) this initialization step is performed on the previously filtered result. This iteration scheme is aggressive in the sense that in each step the previous image is discarded as inferior.

As to the practical implementation of the LNVWA filter, we apply the filter in a separable manner. Although this is definitely not correct, the decrease in computational cost was used to justify this action. A disadvantage of this approach is that the end result will depend on the ordering of the filtering directions.

All ingredients considered, the LNVWA filter has a list of parameters that are summarized in Table 1. Note that the parameters listed in this table can be specified separately for each direction x, y, and z. Furthermore, for the iterative implementation this whole set of parameters can be specified differently for both the initialization step and the filter iterations. In addition, the number of iterations, the value of σ_{cst}, and the order of filter directions should be chosen. In the most diverse set up, this amounts to $3 + 2 \times 3 \times 4 = 27$ parameters.

Table 1. Parameters of the LNVWA filter.

Parameter	Meaning
N_A	width of the averaging window
N_S	width of the neighborhood for $\mathcal{S}_{3\text{D}}$
d	width of the weighting function
p	platform extent of the weighting function

3. MATERIALS AND EXPERIMENT

Eleven patients of the University Medical Center Utrecht that were scheduled for a clinical high-dose CT scan, agreed to undergo an additional low-dose scan immediately after the high-dose scan. All CT images were acquired with a Phillips MX8000 IDT 16-slice CT scanner. The scanning conditions were kept as similar as possible, reducing only the radiation dose by a factor of ten. The images were reconstructed on a 512×512 matrix. The spacing between slices was between 0.65 and 1.0 mm.

The experiment in this paper investigates whether emphysema scoring in low-dose CT images can be improvement by applying noise filters to the low-dose scans. Under the assumption that in high-dose images PI gives a reliable quantification for emphysema, the performance of a filter is measured by how closely the emphysema scores of the filtered low-dose images resemble the PIs of the corresponding high-dose scans. For this experiment the performances of the iterative LNVWA filter and the MA filter are compared.

For calculation of PI the lung volumes are automatically segmented from the scans, using a technique similar to the one of Hu et al.[9] Restricted to these volumes, PI is calculated for thresholds of -950, -930, -910, and -900 HU.

3.1. Parameter Settings

As stated in Section 1, filtering should preserve small image structures and edges. Because the iterative LNVWA filter is aggressive, it seems best to use a small number of iterations. In fact, to shorten the computational time we decided to use only one iteration.

For our experiments we resolved to use $N_A = N_S \equiv N$ and to pick the same parameters for each direction, since we do not want to prefer one direction over another. With these setting, using a different ordering of filter directions did not have a large effect. That leaves three parameters to be determined for the LNVWA filter: N, d, and p.

The window width should not be too big, for the averaging should be local. On the other hand, if N is too small, the number of candidates for averaging will be very limited. We tried $N = 3, 5, 7, 9, 11$ and picked the smallest number that resulted in filtered images clearly different from the originals: $N = 5$.

We assume that on a local scale the noise can be considered Gaussian, so the standard deviation is a good measure of the local noise. As a consequence, the probability that a pixel has a noise component of more than three noise standard deviations is close to zero. Therefore we set $d = 3$.

As the initialization step is only meant to give a rough estimate of the local noise, we decided to use a kernel with $p = d = 1$ (unweighted averaging within one σ_{cst} intensity difference) and $N_{A,\text{init}} = 9$, and $N_{S,\text{init}} = N = 5$.

From a small pilot study using low-dose images that are not part of the test set of 11 images used in the experiment of this paper, we observed that a higher p mostly resulted in a more blurred image, so we fixed $p = 0$.

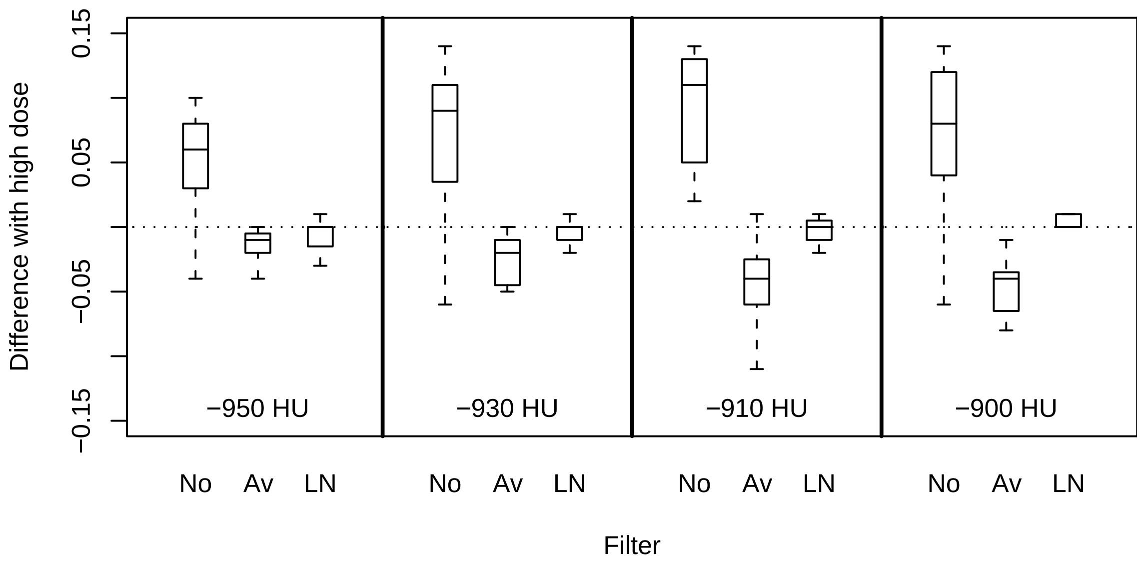


Figure 4. Signed difference between (un)filtered low-dose and high-dose score for the fraction of lung volume below four different attenuation thresholds: 'NO'=unfiltered low-dose image, 'Av'=averaged low-dose image, 'LN'=LNVWA filtered low-dose image. The used threshold is indicated in each panel.

Using a high value of σ_{cst} induced more blur too; filtered low-dose images with σ_{cst} between 50 and 100 HU looked acceptable, so we set $\sigma_{\text{cst}} = 70\,\text{HU}$.

With the parameters thus chosen, filtering a CT image of 350 slices of 512×512 pixels takes about 10 minutes on a modern, standard PC.

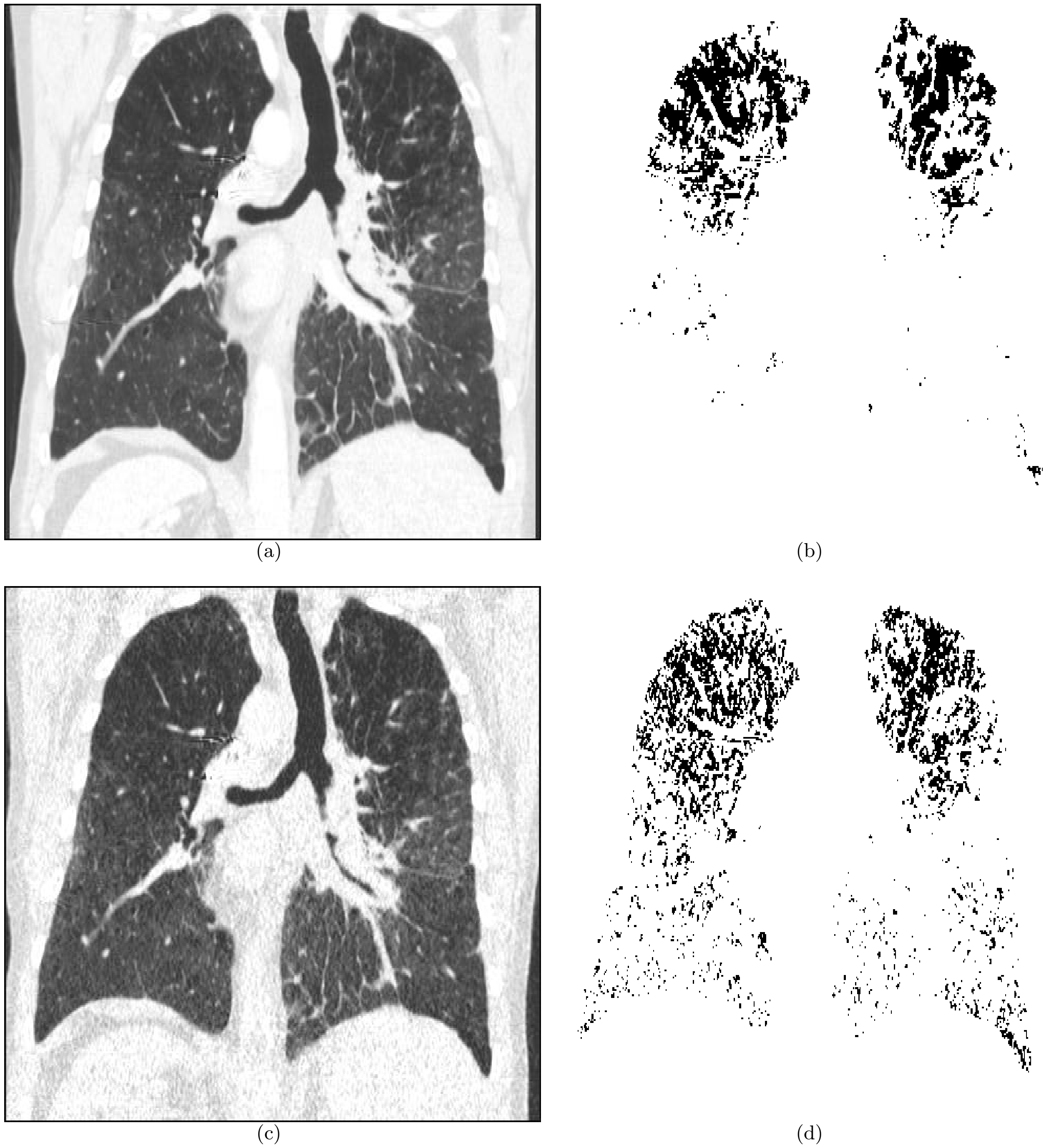
In the noise filtering experiment, we compared the performance of LNVWA to MA filtering. For MA filtering we took the same window width of 5 pixels.

4. RESULTS

Figure 4 shows in boxplots the effect of applying the MA and the LNVWA filters to low-dose images for emphysema quantification. It shows the difference in PI scores of filtered and unfiltered low-dose images as compared to the scores obtained for the corresponding high-dose images. The PIs are calculated for four different intensity thresholds. It is seen that without filtering, the PI value might be off by 15 percentage points or more.

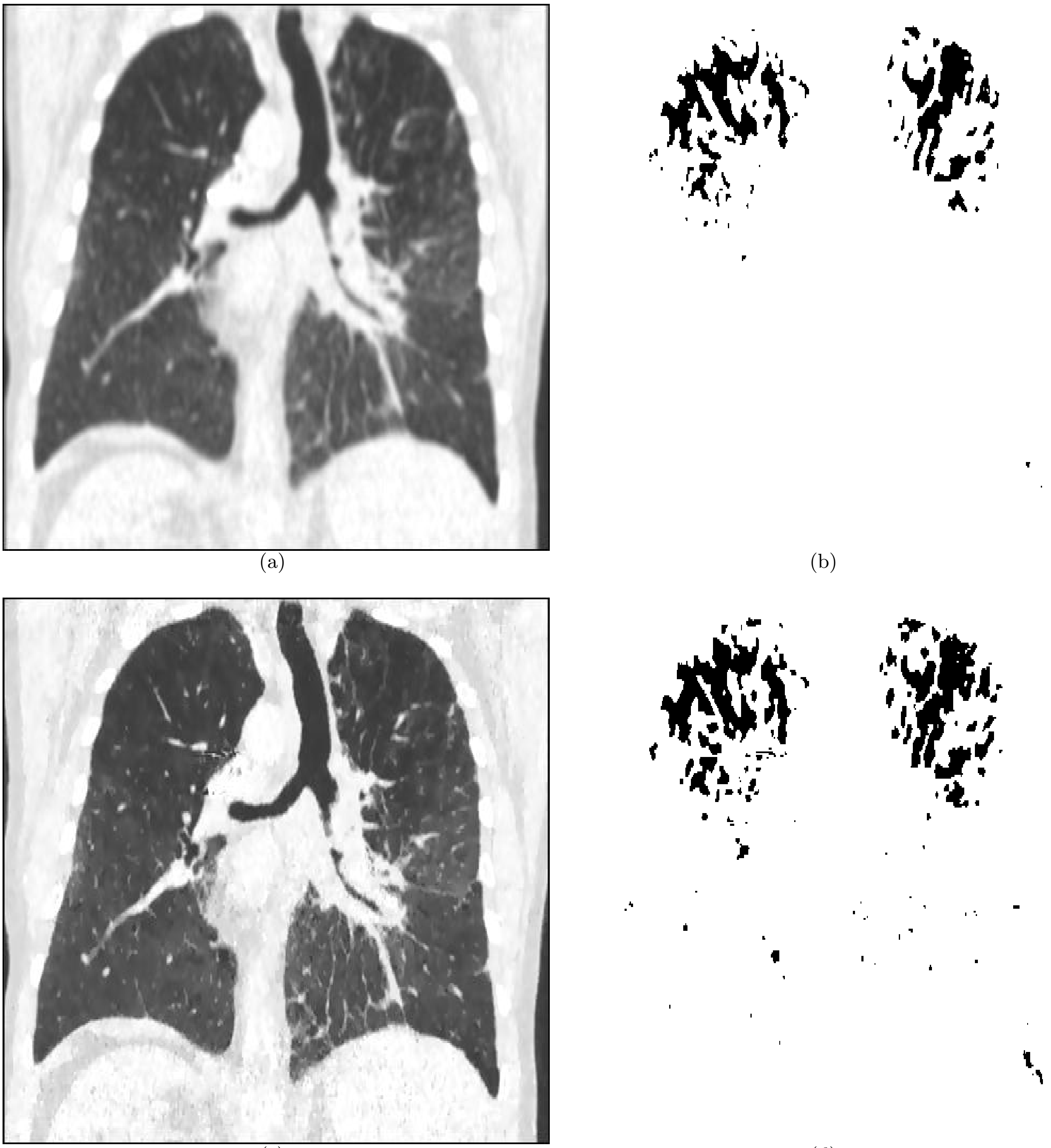
Figure 5 highlights the effect of noise on emphysema scoring by comparing a coronal slice of a high-dose image and its emphysema map, to the corresponding low-dose image and its map. Note that the high-dose and low-dose slices do not display exactly the same anatomical structures; the low-dose slice was hand-picked to match the position of the high-dose slice best. For these image the emphysema threshold is set to -930 HU, giving PI=13.90% for the high-dose scan, and PI=16.32% for the low-dose case. Although both images show that emphysema is concentrated upper half of the lungs, the low-dose image would suggest quite some diffuse emphysema in the lower half of the lungs as well.

The top row of Figure 6 shows the same low-dose slice and corresponding emphysema map as in Fig. 5 (bottom row), but after MA filtering has been used. Although the MA emphysema map does not show the diffuse emphysema in the lower half of the lungs as seen on the low-dose map, it seems to have overshot the mark: The emphysema in the top half of the lungs is less pronounced than in the high-dose image. This overshooting shows up too when comparing the PI(-930) scores for the high-dose and MA filtered image: PI=13.90% versus PI=8.85%. Looking at the coronal slices a similar description holds: MA filtering makes the scan cleaner, but it also wipes out some of the small structures.



(a) (b) (c) (d)

Figure 5. A coronal slice and its accompanying emphysema map calculated for a threshold of -930 HU. (a) and (b): high-dose scan (PI=13.90%); (c) and (d): the corresponding low-dose slice (PI=16.32%).



(a) (b)

(c) (d)

Figure 6. A coronal slice and its accompanying emphysema map for the filtered low-dose scan in Fig.5. (a) and (b): the MA filtered slice (PI=8.85%); (c) and (d): the LNVWA filtered slice (PI=12.48%).

The bottom row of Figure 6 shows the same low-dose slice and corresponding emphysema map as in Fig. 5 (bottom row), but after LNVWA filtering of the scan. The spurious emphysema seen in the low-dose emphysema map has disappeared, and the LNVWA emphysema map resembles the high-dose one more closely than the low-dose or the MA filtered ones do. Indeed, comparing the PI scores of the four images, it turns out that the LNVWA value is closest to the high-dose score. From Figs. 5 and 6 it is also appreciated that LNVWA does clean up the image considerably, without producing a blurred image like MA does.

In Table 2 the improvement by noise filtering is summarized as the root-mean-square (rms) values of the deviations of low-dose PI from high-dose PI for the four different thresholds. The rms values are taken over all eleven pairs of high-dose and low-dose scans. Paired t-tests show that LNVWA filtering gives a significant improvement (p-value < 0.05) over plain averaging for all threshold values except -950 HU (see Table 2 for p-values).

Table 2. The rms values of differences (expressed in percentage points (%pt)) between PIs of (un)filtered low-dose images and high-dose images, for different intensity threshold values, using eleven pairs of low-dose and high-dose scans. The p-value is indicative of the significance of the difference between averaging and LNVWA.

	rms difference from high dose PI in %pt			
Threshold	Unfiltered	Average	LNVWA	p-value
Below -950 HU	6.4	4.5	1.5	0.196
Below -930 HU	9.2	4.3	1.5	0.047
Below -910 HU	10.0	5.6	3.3	0.042
Below -900 HU	9.2	6.6	4.5	0.039

5. CONCLUSIONS

In conclusion an advanced noise filtering scheme has been presented, which adheres to the wanted characteristics: *(i)* After filtering the PI scores of low-dose images are closer to the scores obtained for corresponding high-dose scans of the same subject; *(ii)* Small image structures and edges are preserved; *(iii)* Large three-dimensional images can be processed sufficiently fast for intensive use; *(iv)* The processed images look realistic. Using this filter indeed gives a better agreement between low-dose and high-dose emphysema scores. This implies that with LNVWA filtering, accurate emphysema scoring of low-dose images is possible. The increased accuracy due to LNVWA filtering is significantly larger than can be obtained by simple averaging.

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