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Suppression of Translucent Elongated Structures: Applications in Chest Radiography
Laurens Hogeweg*, Clara I. Sánchez, and Bram van Ginneken, Member, IEEE

Abstract—Projection images, such as those routinely acquired in radiological practice, are difficult to analyze because multiple 3-D structures superimpose at a single point in the 2-D image. Removal of particular superimposed structures may improve interpretation of these images, both by humans and by computers. This work therefore presents a general method to isolate and suppress structures in 2-D projection images. The focus is on elongated structures, which allows an intensity model of a structure of interest to be extracted using local information only. The model is created from profiles sampled perpendicular to the structure. Profiles containing other structures are detected and removed to reduce the influence on the model. Subspace filtering, using blind source separation techniques, is applied to separate the structure to be suppressed from other structures. By subtracting the modeled structure from the original image a structure suppressed image is created. The method is evaluated in four experiments. In the first experiment ribs are suppressed in 20 artificial radiographs simulated from 3-D lung computed tomography (CT) images. The proposed method with blind source separation and outlier detection shows superior suppression of ribs in simulated radiographs, compared to a simplified approach without these techniques. Additionally, the ability of three observers to discriminate between patches containing ribs and containing no ribs, as measured by the area under the receiver operating characteristic curve (AUC), reduced from 0.99–1.00 on original images to 0.75–0.84 on suppressed images. In the second experiment clavicles are suppressed in 253 chest radiographs. The effect of suppression on clavicle visibility is evaluated using the clavicle contrast and border response, showing a reduction of 78% and 34%, respectively. In the third experiment nodules extracted from CT were simulated close to the clavicles in 100 chest radiographs. It was found that after suppression contrast of the nodules was higher than of the clavicles (1.35 and 0.55, respectively) than on original images (1.83 and 2.46, respectively). In the fourth experiment catheters were suppressed in chest radiographs. The ability of three observers to discriminate between patches originating from 36 images with and 21 images without catheters, as measured by the AUC, reduced from 0.98–0.99 on original images to 0.64–0.74 on suppressed images. We conclude that the presented method can markedly reduce the visibility of elongated structures in chest radiographs and shows potential to enhance diagnosis.

Index Terms—Artifact removal, chest radiography, suppression.

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I. INTRODUCTION

TWO-DIMENSIONAL projection images are commonly made for a multitude of purposes and are daily acquired in large quantities in clinical radiology. Fig. 1 shows some examples of commonly acquired 2-D projection images. An identifying property of these images is that multiple 3-D structures are superimposed at a single point in the 2-D image. This overlapping effect might partially obscure regions of interest in the image, reducing their visibility and making correct interpretation challenging for both humans and automated systems. Therefore, image processing methods aimed at identifying and removing the effect of superimposed structures in 2-D projection images have the potential to reduce manual and computer-based interpretation errors.

Among medical projection images, the chest radiograph is the most commonly performed diagnostic exam in the world [1]. Chest radiography is widely applied to diagnose diseases such as tuberculosis, pneumonia, and lung cancer. These and other chest diseases are an important cause of mortality, leading to 10 million deaths annually [2]. A major difficulty in the manual and automatic reading of chest radiographs is the presence of superimposed normal structures such as ribs, clavicles, catheters, and vessels. These structures confuse interpretation and hide abnormalities, causing important decision-making errors [3], [4].

Several studies have addressed the problem of analyzing chest radiographs where the lung fields are obscured by overlapping normal anatomy. Giger et al. [5] proposed a method to improve the detectability of nodules by suppressing the normal background using an image difference technique, in which a nodule-suppressed image is subtracted from a nodule-enhanced image. A similar filtering method that suppresses elongated objects (ribs) and enhances sphere-like objects (nodules) before classifying nodule candidates was used by Kersirci and Yoshida [6]. In both studies the individual effect of the filtering method on the performance was not reported. Chen et al. [7] classified automatically selected square regions in the lung using power spectrum based texture measures. Regions containing high gradient edges with an orientation corresponding to ribs were removed. A high classification performance of images affected by interstitial lung disease was reported. Loog and van Ginneken [8] presented a general filter framework based on regression, which has been applied to the suppression of bony structures on chest radiographs. The method gave promising results but was not further evaluated on a clinical problem. Suzuki et al. [9], [10] suppressed ribs using an artificial neural network and showed that this technique increased the visibility of nodules [11] and improved the
quality of temporal subtraction images [12]. Simkó et al. [13] suppressed clavicles by creating a bone model from a gradient map smoothed along the clavicle border direction, after which a clavicle free image was created by subtraction of the model. They showed promising results of clavicle suppression on reducing false positives in a nodule detection task. Recently it has been shown that suppression of bony structures in the chest radiograph can improve the radiologist’s performance to detect nodules [14]–[16].

In this paper, we propose a method to remove unwanted structures on 2-D projection images, particularly elongated structures. Elongated structures, like bones or tubes, are common in natural images, such as those acquired in medical imaging. The proposed method uses blind source separation techniques together with outlier identification to estimate an intensity model of the unwanted structures and subsequently remove it from the original image. Common artifact removal techniques [17]–[19] estimate the structure model by extracting information from image areas where the artifact is not present. In contrast, the proposed method does not require the presence of unaffected areas to remove the structure; our model is estimated using only the intrinsic properties of projected structures, such as elongated shape and translucency. The main goal of this study was to establish a general algorithm for suppressing elongated structures. We thoroughly evaluate the method in experiments where three different elongated structures commonly found in chest radiographs are suppressed, namely ribs, clavicles, and catheters.

The paper is organized as follows. Section II describes isolation and suppression of elongated structures. Experiments and results are provided in Section III. Discussion and conclusion are presented in Sections IV and V.

II. METHODS

In this section, we describe a general algorithm for the isolation and removal of an elongated structure of interest S in a 2-D projection image from a background with other structures present. The goal is to estimate a projected image that is similar to the projection of the 3-D scene in which the structure of interest was not present. To achieve this goal the image is decomposed into an image containing only the structure and one containing the background.

We assume that the 2-D projected image $L(x, y)$ can be linearly decomposed into independent components as follows:

$$L(x, y) = \sum_i L_i(x, y)$$

where $L_i(x, y)$ is the 2-D image of one component, a structure of interest in the image. For a case with only one structure of interest $S$, (1) can be written as

$$L(x, y) = L_S(x, y) + L_{BG\setminus S}(x, y)$$

where $L_S(x, y)$ is the projection image of the structure $S$ only and $L_{BG\setminus S}(x, y)$ is the projection image of the 3-D scene projected in $L(x, y)$ but without the presence of $S$. To perform this decomposition two conditions are assumed to be fulfilled: 1) the structure $S$ can be modeled in a 2-D projection and 2) the structure is translucent. The algorithm focuses on modeling of elongated structures. The specific appearance of these structures makes it possible to derive a model for $S$ from the local intensity information only. The condition of translucency is expressed by the linearity of the composition, i.e., a fully translucent structure has no nonlinear interactions with other structures in the imaging process.

To remove translucent elongated structures from natural images we propose two steps: 1) modeling and reconstruction of the elongated structure using subspace filtering and 2) suppression of the identified structure from the original image. The next two sections describe these steps for one instance of an elongated structure $S$. If multiple instances of elongated structures are present they can be modeled and removed in succession in order to obtain a final estimate $\hat{L}_{BG\setminus S}(x, y)$ of $L_{BG\setminus S}(x, y)$.

A. Modeling and Reconstruction of the Structure

The purpose of this step is to isolate/reconstruct the image response of $S$ by filtering out the superimposed responses from other structures. Assuming that an observed intensity in the image is a mixture of unknown independent sources, we can use blind source separation (BSS) techniques to filter out the unwanted responses. Such an approach has been widely used, for example in wireless communication [20], speech processing [21], and EEG analysis [22].

Given a group of observations $X = [x_i \ x_{i+1} \ \ldots \ x_n]$, composed of a mixture of underlying independent sources $Z$,
BSS techniques allow to recover an estimate of the sources $\tilde{Z}$ by identifying a demixing matrix $W$:

$$\tilde{Z} = XW^{-1}.$$  

Reducing the rank of $\tilde{Z}$, in such a manner that unwanted or uninteresting sources are removed, subspace filtering can be performed [22], [23] and a filtered version $X_F$ of the observations $X$ is reconstructed

$$X_F = \tilde{Z}_rW.$$  

The components in $\tilde{Z}_r$ form a local model of the structure, which is used to separate it from the background structures. In order to apply BSS to reconstruct the image response of the structure $S$, we perform the following steps: 1) definition of the observed structure responses; 2) outlier detection; and 3) subspace filtering by means of BSS.

1) Observed Structure Responses: Given a curve segment $\gamma$, aligned with the structure $S$, let $p_i = \{p_{i1}, p_{i2}, \ldots, p_{iM}\}$ be an observed profile with length $M$, sampled through the point $s_i = (x_i, y_i)$ on $\gamma$ and perpendicular to its direction $s_i^\perp$ (Fig. 2). Intensity values of the profile are determined by linear interpolation from the original image. We represent the observed structure responses $P$ as a group of $N$ profiles evenly spaced along $\gamma$

$$P = [p_1, p_2, \ldots, p_N].$$  

$P$ can be interpreted as an image patch, with dimensions $N \times M$, of the structure that has been straightened so that the cross sections of the structure align. To separate elongated structures in 2-D projection images from their background, $M$ and $N$ must be set to values appropriate for the type of structure being suppressed. To ensure good subtraction the sampling must be dense enough and the spacing of $s_i$ and individual profile points needs to be on the order of the pixel spacing or smaller. The length of the profile is taken greater than the width of the structure to 1) provide sufficient background area to accurately estimate the background values and 2) account for variations in the width of the structure. The profile extends distances $d_{x}$ and $d_{y}$, which do not have to be equal, to both sides [Fig. 3(a)]. Fig. 3(b) and (c) shows, respectively, the sample locations and the resulting patch $P$.

To determine the right amount to subtract later on, $P$ is preprocessed to have uniform and zero average background intensity values. The preprocessing is performed first on the whole image and then per structure patch. Global low frequency variations, not associated with $S$, are eliminated by subtracting a low pass filtered version of the input image. In the case of chest radiographs this removes intensity gradients across the lung that originate from projection of the elliptical shape of the lung in the caudo-cranial direction.

At the patch level the global correction for low frequency variations does not guarantee zero average background values. Therefore, a normalization procedure is performed on $P$ which provides approximate zero intensity values at the borders of the structure patch, i.e., the endpoints of the sampled profiles. A thin plate spline [24] (TPS) surface is fitted through the border points and subtracted from the structure patch. To prevent crossing structures disturbing the TPS plane excessively, border points with outlying intensity values (>0.95 times the average intensity value of all the border points) were excluded in the fitting process.

2) Outlier Detection: Many of the common decomposition techniques that can be used to reconstruct $S$ are sensitive to outliers. In our context, outliers are other structures crossing $S$ corrupting the profiles in $P$. The presence of a significant number of outliers that dominate over $S$ leads to inclusion of unwanted sources in $\tilde{Z}$, and consequently in $X_F$. To avoid the effect of these unwanted sources, outlier profiles are detected and removed before performing subspace filtering. Profiles in $P$ are clustered into two sets $\{P_1, P_2\}$ using $k$-means clustering [Fig. 3(d)]. As it is impossible for any (unsupervised) method to recover from more than 50% of outliers in a dataset, the set with the largest number of elements, defined as $P_1$, is assumed to contain the uncorrupted profiles.

3) Subspace Filtering by BSS: A number of techniques have been developed to perform BSS. The most commonly known are principal component analysis (PCA) [25], singular value decomposition (SVD), and independent component analysis (ICA) [26]. PCA and SVD are closely related techniques which give linearly uncorrelated sources. ICA imposes a stronger constraint and produces components which are statistically independent. Non-negative matrix factorization is another technique for BSS where the condition is enforced that the input and the components are non-negative [27]. We assume that the largest variance in $P$ is caused by $S$ and therefore use PCA to perform the BSS.

Letting $P_1$ assume the role of $X$, the observations from which the sources are computed, (3) is rewritten as

$$\tilde{Z} = P_1W^{-1}.$$  

PCA determines $\tilde{Z}$ by finding components in the data which are linearly uncorrelated. These principal components are sorted according to their variance. Principal components can be computed by performing an eigenvector decomposition of the covariance matrix $C = P_1^T P_1$. Assuming the largest variability in $P_1$ is caused by $S$, the first principal components contain this...
Fig. 3. Visual overview of method, exemplified by segmentation and suppression of one rib in a simulated chest radiograph. (a) Original image with structure $S$ and aligned elongated curve segment $\gamma$. One profile is indicated, extending respectively a distance of $d_1$ and $d_2$ to both sides. (b) Sample locations of all profiles. (c) Sampled profiles arranged in a straightened image patch, $\mathbf{P}$. (d) Map indicating corrupted profiles (shown in black). Only the uncorrupted white profiles ($\mathbf{P}_{\text{white}}$) are used to construct the PCA model. (e) Subspace filtered patch. The filtering is performed using the PCA model. (f) Final structure estimation created by applying smoothing to (f) to further reduce noise. (g) Result $\{\mathbf{U}\}$ of suppression at the patch level. (h) Estimated intensity model of the rib $\hat{L}_S$. (i) Final image $\hat{L}_{P, S}$ after the suppression of the estimated rib model.

Information and $\hat{\mathbf{Z}}_r$ is created by selecting the first $n_\mathbf{Z}$ columns of $\mathbf{Z}$. $n_\mathbf{Z}$ can be set to a fixed quantity or be determined by setting a fixed percentage of the variance $f_\mathbf{Z}$ that should be explained by the model.

Filtered profiles can be computed using (4) rewritten as

$$\mathbf{P}_S = \hat{\mathbf{Z}}_r \mathbf{W}$$

(7)

where $\mathbf{P}_S$ is a filtered version of $\mathbf{P}$, i.e., an estimate of the projection patch containing only the structure $S$ [Fig. 3(e)]. The weights for the profiles in $\mathbf{P}$ are computed by least squares projection

$$\mathbf{W} = \hat{\mathbf{Z}}_r^T \mathbf{P}.$$  

(8)

Unrealistically small or large intensity values in profiles can occur in $\mathbf{P}_S$ when elements of $\mathbf{W}$ have large magnitudes. Therefore the weights are constrained by truncation to a fixed absolute maximum magnitude before applying (7)

$$w_{ij} = \begin{cases} w_{ij}, & \text{if } |w_{ij}| < \beta \\ \text{sign}(w_{ij})\beta, & \text{if } |w_{ij}| \geq \beta \end{cases}$$

(9)

where $\beta$ is the maximum value. We refer to $\beta$ as the PCA model bound, which can be interpreted as the maximum number of standard deviations that each fitted component is allowed to deviate from the mean value.

### B. Suppression

After subspace filtering all profiles in $\mathbf{P}_S$ are assumed to contain mainly intensities originating from $S$. To remove any noise remaining after subspace filtering the filtered structure patch is smoothed in the $s$ direction using a moving average with a
kernel size of $\sigma$ pixels [Fig. 3(f)]. The suppression of the structure is then performed at the patch level to create a suppressed patch

$$U = P - P_S^+$$

(10)

where $P_S^+$ is a positive matrix which is created from $P_S$ by setting all element values $<0$ to 0 [Fig. 3(g)]. The clipping of the negative values prevents the physically impossible increase of intensity values in $U$.

$U$ is projected back into the coordinate system of the original image. In curved structures the sampled profiles typically do not cover all the positions of the whole structure in the original image as the ends of the profiles can be more than one pixel apart in the original image space [Fig. 3(b)]. This undefined space between the profiles is filled using iterated nearest neighbor interpolation. In this procedure the intensity of undefined pixels, that are four-connected to defined pixels, are set to the average of their four-connected defined neighboring pixels. The procedure is repeated until all undefined pixels have been filled.

The intensity values of the suppressed patch in the original image space are used to replace the values in the original image [Fig. 3(i)]. A fluent transition between the patch and its surroundings is needed to prevent boundary artifacts and is ensured by multiplying it with a Gaussian blurred mask. The mask is created from a binary map indicating the sample locations of the profiles [Fig. 3(b)].

### C. Suppression of Multiple Instances

By repeated application of the algorithm, multiple individual instances of $S$ can be removed. The resulting suppressed image after removal of the first instance is the input for the removal of the second instance and so on. After removal of all the instances a solution to (2) has been approximated and two estimates of the components of the original image are available: $L_{R1\setminus S}$ containing the background structures and $\hat{L}_S = L - L_{R1\setminus S}$ which contains all the instances of $S$.

## III. EXPERIMENTS AND RESULTS

Four sets of experiments were performed to determine the effectiveness of the algorithm and to analyze the effect of parameter changes. In the first experiment ribs are suppressed on chest radiographs simulated from computed tomography (CT) images and compared to simulated rib-free chest radiographs. Additionally the suppression quality was visually evaluated by observers. In the second experiment the effect of suppression is shown on clavicle visibility. In the third experiment the effect of suppression on the visibility of nodules simulated near the clavicles is shown. In the fourth experiment catheters are suppressed in chest radiographs and the quality was visually evaluated by observers.

### A. Rib Suppression in Chest Radiographs Simulated From CT

Ribs are the most common projected structure in chest radiographs, and cause a disturbance over whole the image, which makes the detection and analysis of abnormalities and other structures difficult. In this experiment radiographs were simulated from CT images to provide a direct estimate of the suppression quality. The suppression algorithm was run on simulated chest radiographs containing only posterior ribs. The resulting images were compared with simulated rib-free chest radiographs. The effect of applying subspace filtering, outlier detection and several parameters was evaluated.

1) **Data**: From the publicly available ANODE09 database [28] 20 chest CT scans were selected. All scans in the ANODE09 database originate from the NELSON study, the largest CT lung cancer screening trial in Europe. Current and former heavy smokers, mainly men, aged 50–75 years were included in this study. Axial images have a size of $512 \times 512$ voxels with a resolution of 0.59–0.83 mm and spacing between axial images 0.7 mm. More details can be found in [29]. The images for this study were selected to contain no gross abnormalities and to be without major rotation of the chest cage.

2) **Segmentation and Suppression**: Ribs were segmented from chest CT images using the following procedure. Bony structures were selected based on the CT intensity values measured in HU. To prevent artifacts at the transition from bone to other tissue to every voxel a bone probability $p_b(HU)$ was assigned

$$p_b(HU) = \begin{cases} 0, & \text{if } HU \leq 100 \\ (HU - 100)/900, & \text{if } 100 < HU < 1000 \\ 1, & \text{if } HU \geq 1000. \end{cases}$$

An automatic lung segmentation [30] was dilated to encompass the chest cage containing the ribs. The ribs were segmented by selecting voxels with $p_b = 1$ inside the dilated lung mask. This selection will also include parts of the spinal column and the sternum. Individual ribs were segmented by disconnecting them from the sternum and the spine using a manually placed 3-D box. Ribs were then divided in their posterior and anterior sections by manually defining a vertical plane running through the widest part of the chest cage.

Simulated chest radiographs were created by an orthogonal projection over the anterior-posterior axis. Only the volume inside the bounding box of the dilated lung mask was projected. Chest radiographs without ribs were created by replacing the segmented ribs with a soft tissue equivalent ($HU = 40$) in the volume. Partial volume rib voxels ($0 < p_r < 1$) were assigned the same intensity value of 40 HU. Two simulated radiographs per CT case were created: 1) one containing no ribs which was used as reference (Fig. 4; second row) and 2) one containing only posterior ribs on which the suppression algorithm was run (Fig. 4; first row). After projection, image dimensions were in the range of 346–503 for the $x$-dimension and 381–498 for the $y$-dimension.

The segmentation of the ribs in the 2-D simulated chest radiograph was performed semi-automatically based on the 3-D CT. Individually segmented 3-D ribs were projected onto the coronal plane. The centerline of the 2-D rib segmentation was determined using the convex sets algorithm described in Staal [31]. The curve segment and the simulated radiograph form the input of the suppression algorithm. Ribs were processed sequentially, i.e., the output image of the suppression of the first rib is used as input for the suppression of the second rib, etc. No particular ordering was present in the segmented ribs. $d_1$ and $d_2$ were visually

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Fig. 4. Three examples of rib suppression in simulated chest radiographs. On the first row the input of the algorithm, a simulated chest radiograph with only posterior ribs, is shown. Second row shows the reference, a chest radiograph simulated without ribs and other bony structures. Third row shows the rib suppressed image obtained using subspace filtering and outlier detection. Fourth row shows the centerlines that were used as input for the algorithm.

The amount of suppression was quantified using the sum of squared differences (SSD) between the processed image and the rib-free image by

$$r = \frac{\text{SSD}(I_R, I_{NR}) - \text{SSD}(I_S, I_{NR})}{\text{SSD}(I_R, I_{NR})}$$  (11)

determined from the simulated radiographs and set to 11.25 mm (15 pixels) at both sides, resulting in $M = 22.5$ mm (31 pixels). $f_Z$ was set to 99%. Optimal values for $\beta$ and $\sigma$ were determined experimentally (as explained in the evaluation section).

3) Evaluation: The suppression was evaluated in two subexperiments: 1) by quantifying differences between images before and after suppression and 2) in a observer experiment.
TABLE I
CONFIGURATIONS EVALUATED FOR THE RIB SUPPRESSION EXPERIMENT

<table>
<thead>
<tr>
<th>Name</th>
<th>Outlier detection</th>
<th>BSS modeling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full system</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>No outlier detection</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Only smoothing</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

TABLE II
PARAMETERS EVALUATED FOR THE RIB SUPPRESSION EXPERIMENT

<table>
<thead>
<tr>
<th>Name</th>
<th>Values</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smoothing scale $\sigma$</td>
<td>16, 32, 48</td>
<td>pixels</td>
</tr>
<tr>
<td>PCA model bound $\beta$</td>
<td>0.2, 0.5, 1.0, 2.0, 5.0</td>
<td>-</td>
</tr>
</tbody>
</table>

where \( SSD(\cdot, \cdot) \) is the sum of squared differences between two images, \( I_R \) the image with only posterior ribs, \( I_{R|S} \) the rib-free image, and \( I_S \) the result of the suppression algorithm run on \( I_R \). A value of \( r = 1 \) indicates perfect suppression and \( r = 0 \) no change. The calculation of \( r \) was limited to an area in the upper half of the lung fields with pixels close to the lung border excluded. The reason for excluding this area is that outside this area the segmentation of the ribs fails in some cases.

Different algorithm configurations, shown in Table I, were evaluated: Full system includes subspace filtering and outlier detection, No outlier detection system uses subspace filtering but no outlier detection, Only smoothing does not perform subspace filtering. Optimal parameter values of the free parameters \( \beta \) and \( \sigma \) for each system were determined using a grid search procedure. The optimization was performed in a leave-one-case out crossvalidation setup where optimal parameters were determined on 19 cases and applied to one case. Table II shows the tested parameters and their tested values. In total \( 3 \times 5 = 15 \) combination of settings were tested. Differences between optimized configurations were determined by a Wilcoxon signed rank test for the 20 cases.

Additionally, the suppression was evaluated in an observer experiment by three observers: one medical doctor with experience in reading chest radiographs and two certified chest radiograph readers. The observers’ ability to discriminate between patches from images simulated without ribs and from images containing ribs was determined before and after suppression. Square patches of \( 40 \times 40 \) mm were sampled from inside the unobscured lung fields. Four patches were sampled from the three types of source images derived from 20 cases, giving a total of 240 patches. These patches were presented randomized in one session to each observer who gave a score on the presence of a rib in the patch on a scale of 0–100: 0 and 100, respectively, indicating definitely not present and definitely present. Receiver operator characteristic (ROC) analysis was performed to determine the observer’s performance. The area under the ROC curve (AUC) of the two experiment modes was compared using case-based bootstrapping [32].

4) Results: Fig. 4 shows a number of examples of rib suppression on simulated chest radiographs. Visually, most ribs were successfully removed from the simulated radiograph. Table III compares the amount of suppression \( r \) achieved by the tested configurations. Full system shows the highest overall improvement and is significantly better than the configurations Only smoothing and No outlier detection. No outlier detection performs worse than Full system but significantly better than Only smoothing. Table IV shows the parameters that were most selected in crossvalidation for the tested configurations. For subspace filtering \( \beta = 1.0 \) was most selected in both Full system and No outlier detection. This value of \( \beta \) limits the model’s components to within 1.0 standard deviation of the mean and limits the appearance of crossing structures after filtering. For all three configurations \( \sigma = 32 \) pixels (±22 mm) was most selected. This scale is approximately the width of a rib and will remove any remaining small structures, but not smooth away the evolution of the shape of the rib’s cross section along the curve segment.

Fig. 5 shows the ROC curves for the three observers for judging the presence of ribs in patches extracted from rib free, rib containing, and rib suppressed images. The AUC of the ROC was significantly reduced from very high values on original images to moderate values on suppressed images, respectively from 1.0 to 0.81, 0.99 to 0.75, and 0.99 to 0.84 for observers 1, 2, and 3 with significant differences for all observers (case-based bootstrapping; \( p < 0.001 \)). Before suppression ribs were detected almost without error by the observers. After suppression observers can detect ribs or the remnants in about half of the patches (±50%; initial steep part of the ROC curve) before starting to confuse patches with and without ribs.

B. Suppression of Clavicles in Chest Radiographs

The lung tops are a difficult area to analyze in chest radiographs. Clavicles, ribs, vessels, and mediastinal structures overlap and create a complicated pattern in which abnormalities are more difficult to discriminate. The suppression algorithm is used to remove automatically segmented clavicles and evaluate using measures for interior and border conspicuity.

1) Data: A set of 253 consecutively obtained posterior–anterior chest radiographs were selected from a database containing images acquired at two sites in sub-Saharan Africa with a high tuberculosis incidence. The data was previously used to evaluate our clavicle segmentation algorithm [33] and is publicly available on crass12.grand-challenge.org. The data comes from a larger database used for the CAD4TB project, which is aimed at
automatically detecting tuberculosis in chest radiographs [34].
All subjects were 15 years or older. Images from digital chest radiography units were used (Delft Imaging Systems, Delft, The Netherlands) of varying resolutions, with a typical resolution of 1800 × 2000 pixels, the pixel size was 250 μm isotropic. The set consisted of both normal and abnormal chest radiographs.

2) Segmentation and Suppression: Clavicle segmentation is performed using the algorithm described in Hogeweg et al. [33]. In this method, supervised pixel classifiers are constructed to segment the interior, the head and the border of the clavicle. Active shape model segmentation based on the interior segmentation is performed to generate an initial outline. The outline is refined using dynamic programming. The result of the algorithm is an outline with known points corresponding to anatomical positions on the clavicle.

The outline of the clavicle is taken as basis for the suppression algorithm. The outline is divided into three sections: 1) the lower border: running from the edge of the lung field to the start of the head, 2) the head: running from the medial end of the lower border to the medial end of the upper border and 3) the upper border: running from the superior end of the head section to the edge of the lung field. The number of sampled profile points is different on each side of the sections. For the upper and lower border 35 mm (140 pixels), the profiles are extended d_1 = 25 mm and d_2 = 10 mm towards respectively the inside and outside of the clavicle making sure that the profiles reach over the other border. For the head section M = 5 mm (20 pixels), with respectively d_1 = 4 mm and d_2 = 1 mm towards the inside and the outside. The other algorithm parameters were set as n = 11 pixels, f_Z = 99%, and β = 0.5.

3) Evaluation: The visibility of the clavicle before and after suppression was measured with the Weber contrast of the clavicle and with the line response on the border of the clavicles. The two measures reflect the conspicuity of the low frequency interior of the clavicle and the high-frequency borders, respectively. The Weber contrast is defined as

\[ C' = \frac{I_F - I_h}{I_h} \]  

(12)

where \( I_F \) is the average intensity on the clavicle and \( I_h \) the average background intensity. \( I_h \) is measured in a band around the clavicle with a width of 10 mm. The contrast was measured only inside the unobscured lung field, which was manually outlined.

The line response is derived from the Hessian matrix [35] calculated at a scale of 0.5 mm. Given the two eigenvalues of the Hessian matrix \( \lambda_1, \lambda_2 \) with \( |\lambda_1| > |\lambda_2| \), the line response is defined as

\[ r_l = \begin{cases} 0, & \text{if } \lambda_1 < 0 \\ \frac{1}{\sqrt{\lambda_1^2 - \lambda_2^2}}, & \text{if } \lambda_1 \geq 0 \end{cases} \]  

(13)

where the condition \( \lambda_1 < 0 \) ensures that only positive contrast is determined. \( r_l \) is measured in a 10-mm-wide band centered around the border of the clavicle segmentation and was only computed inside the unobscured lung fields. The measures were computed on original and clavicle suppressed images, with higher values indicating higher conspicuity of the clavicle.

4) Results: Fig. 6 shows examples of original and suppressed clavicles. The interior of the clavicle is mostly suppressed in all cases, while remnants of the clavicle border can still be observed in some cases. The first three cases are sorted according to their relative contrast reduction \( (C_{\text{org}} - C_{\text{sup}})/C_{\text{org}} \), where \( C_{\text{org}} \) and \( C_{\text{sup}} \) are, respectively, the contrast in the original and suppressed image. Analogously the second three cases are sorted according to the relative line response reduction. Over the whole dataset of 253 cases both the contrast of the clavicle body with respect to the surroundings \( C \) and the line response \( r_l \) of the clavicle border were reduced significantly (Table V).

C. Suppression of Clavicles in Chest Radiographs—Effect on Simulated Nodules

Nodules were simulated close to the difficult area around the clavicles and the effect of suppression on nodule conspicuity characteristics was determined. The simulation of nodules enables evaluation on a large set of cases.

1) Data: Normal chest radiographs were selected from the dataset described in Section III-B and out of the in total 253 cases 116 contained no abnormalities.

Fig. 5. Observers’ ability to discriminate between rib free patches and patches containing ribs on original and suppressed images. The AUC of the ROC is significantly reduced for all observers comparing original images to suppressed images (case-based bootstrapping; \( p < 0.01 \)). (a) Observer 1. (b) Observer 2. (c) Observer 3.
2) Simulation of Nodules: Nodules were simulated in the chest radiograph by projecting CT-derived templates on the clavicle. The procedure was previously described in [36] and is summarized here. Five nodules were obtained from a lung cancer screening database [37]. To provide good templates nodules with diameter > 20 mm and which were not connected to the lung wall or large blood vessels were extracted. Nodules were segmented using the smart opening algorithm [38] and extracted as a bounding box. Two-dimensional nodule templates were then created by orthogonal ray casting. By scaling and rotation the 3-D templates before projection a single 3-D template can be used to create multiple 2-D templates. To achieve realistic simulation of the nodules a conversion function was used to transform CT units to X-ray units.

Simulated nodules were added to chest radiographs, one per radiograph, with a random nodule template and rotation. The location of the nodules was chosen so that the nodule overlapped with the clavicle, ranging from a slight to full overlap. The contrast of the simulates nodules was set heuristically to a value so that it does not give unrealistically bright nodules but they were still visible for a human observer with knowledge of the location of the nodule. Clavicle suppression was performed with the same settings as in Section III-B.

3) Evaluation: Nodule contrast is measured similarly as for the clavicles using the Weber contrast (12), where $I_f$ is the average gray level in the nodule region and $I_b$ in the background region. The simulation of the nodules provides an exact location and direct determination of background and nodule regions. The nodule region is defined as the projected nodule outline. The background region was defined as a 5 mm band around the nodule region. Another aspect of nodule visibility is its heterogeneity. On a uniform background the intensity values of nodules are more homogeneous than when other structures overlap, making them more difficult to detect. The heterogeneity $H$ was defined as the standard deviation of the intensity values in the nodule region.

4) Results: Fig. 7 shows examples of cases with simulated nodules in original images and with suppressed clavicles. It can be observed that the clavicles are substantially suppressed, while the nodules remain visible. Over the whole dataset of 116 cases the contrast of the nodule with respect to the surroundings $C$ was slightly reduced, but the homogeneity of the nodule increased, as indicated by a decrease of heterogeneity (Table V). Before suppression average clavicle contrast was higher than average nodule contrast, but after suppression nodule contrast was more than twice as high. A further analysis of the nodule contrast showed that in the group with an initial high contrast (defined as 50% of cases with highest contrast before suppression) $C$ decreased from $2.04 \cdot 10^{-2}$ to $1.76 \cdot 10^{-2}$ ($p < 0.001$), but in the remaining cases with initial low contrast it slightly increased from $1.69 \cdot 10^{-2}$ to $1.13 \cdot 10^{-2}$ ($p = 0.06$).
TABLE V

<table>
<thead>
<tr>
<th>Measure</th>
<th>Original Mean ± std</th>
<th>Suppressed Mean ± std</th>
<th>Significance</th>
<th>Original Mean ± std</th>
<th>Suppressed Mean ± std</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weber Contrast</td>
<td>2.46 ± 1.11</td>
<td>0.55 ± 0.66</td>
<td>p &lt; 0.001</td>
<td>1.83 ± 0.90</td>
<td>1.35 ± 0.68</td>
<td>p &lt; 0.001</td>
</tr>
<tr>
<td>Line response</td>
<td>1.95 ± 0.57</td>
<td>1.29 ± 0.39</td>
<td>p &lt; 0.001</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td>1.52 ± 0.51</td>
<td>1.24 ± 0.43</td>
<td>p &lt; 0.001</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

**Fig. 7.** Effect of clavicle suppression on nodule contrast for three selected cases. Top row shows the original image with simulated nodule, middle row shows the clavicle suppressed image, bottom row indicates the location of the nodule (inner outline) and the background region for measuring contrast (band between inner and outer outline). Cases are ranked on the relative nodule contrast change from high to low.

### D. Suppression of Catheters in Chest Radiographs

Catheters commonly occur in chest radiographs acquired in a hospital setting and their presence complicates the reading of the images. Catheters were manually segmented and then suppressed using the algorithm. The quality of the suppression was judged by three readers in an observer experiment where they had to discriminate between square patches containing no catheters and patches containing either catheters or containing suppressed catheters.

#### 1) Data

From the clinical archives of Radboud University Nijmegen Medical Centre, The Netherlands, 36 chest radiographs containing catheters overlapping the unobscured lung fields and 21 chest radiographs without catheters were randomly selected and anonymized. Images were acquired with digital chest radiography units (Siemens Healthcare, The Netherlands) of varying resolutions, with a typical resolution of 2700 x 2700 pixels and a pixel size of 143 μm isotropic. Suppression was performed on images downsampled to a fixed width of 1024 pixels.

#### 2) Segmentation and Suppression

Catheters were manually indicated by drawing the centerline along its whole length. The centerline was used as input to the suppression algorithm. The settings for the algorithm were determined in a pilot experiment by visual inspection of the suppressed images: \( \sigma = 21 \) pixels, \( M = 10.5 \) mm (28 pixels), \( d_1 = d_2 = 5.25 \) mm, \( n_Z = 12 \) and \( \beta = 0.5 \).

#### 3) Evaluation

The suppression was evaluated in an observer experiment by three observers: one medical doctor with experience in reading chest radiographs and two certified chest radiograph readers. The observers’ ability to discriminate between patches with and without catheters was examined in two sessions. In session I patches without catheters and original patches with catheters were presented, in session II patches without catheters and patches with suppressed catheters were shown. Square patches of 30 x 30 mm were sampled. In chest radiographs containing no catheters patches were randomly sampled from inside the unobscured lung fields. In images containing catheters square patches were sampled along the trajectory of the catheter inside the lung fields, ensuring that the center pixel of the patch coincides with the centerline of the catheter. Three and five patches were sampled from images with and without catheters, respectively, with a total of 213 patches. These patches were presented randomized to each observer who gave a score on the presence of a catheter in the patch on a scale of 0–100: 0 and 100, respectively, indicating definitely not present and definitely present. The observers were not aware of the proportion of patches containing catheters in the study. ROC analysis was performed to determine the observer’s ability to discriminate between patches with and without a catheter. The AUC was compared between session I and II using case-based bootstrapping [32].
Fig. 8. Examples of catheter suppression inside the lung fields for two cases. Only the part of the catheter inside the lung fields is suppressed.

Fig. 9. Example of four patches with catheters and one without used in the observer experiment. The catheter patches are sorted on average score for presence of catheter in the suppressed patch of the three observers. The fifth example does not contain a catheter but shows the highest rated normal patch.

4) Results: Fig. 8 shows two examples of catheter suppression inside the lung fields. Visually, the catheter was removed successfully by the suppression over the majority of its length. Fig. 9 shows five examples of patches used in the observer study. The first four patches contained catheters and are sorted on average rating by the three observers. The last example (rating = 77) contained no catheter but was rated on average highest on presence of catheters.

Fig. 10 shows the ROC curves for the three observers for judging the presence of catheters in patches extracted from catheter free and catheter suppressed images. The AUC of the ROC was significantly reduced from very high values on original images to moderate values on suppressed images, respectively, 0.98 to 0.64, 0.99 to 0.74, and 0.99 to 0.74 for observers 1, 2, and 3 with significant differences for all observers (case-based bootstrapping; $p < 0.01$). Before suppression catheters were detected almost without error by the observers. After suppression observers can detect catheters or the remnants thereof only in a minority of patches ($< \pm 35\%$; initial steep part of the ROC curve) before starting to confuse patches with and without catheters.

IV. DISCUSSION

A method to suppress translucent elongated structures in 2-D images has been presented. Key elements of the method are subspace filtering of the structure and outlier rejection. The method was evaluated in four experiments on rib, clavicle, and catheter suppression in chest radiographs. In this section we first discuss the results of the four experiments, we subsequently critically evaluate the merits of the subspace filtering approach and the determination of the background, finally we discuss other applications of the method and consider possible improvements.

In the first experiment it was shown that subspace filtering using PCA improved suppression of ribs in simulated chest ra-
diagrams, compared to a method using only smoothing. The use of simulated radiographs allowed us to measure exactly the amount of suppression, showing a large reduction of the intensity values of the ribs after suppression. In addition an observer experiment was performed were it was found that the ability of human observers to detect ribs in patches after suppression was markedly reduced. Rib centerlines were not automatically segmented in the project radiograph, but instead derived from the CT segmentation. This allowed us to determine the suppression quality without the influence of errors that typically occur in automatic segmentation techniques. Automatic segmentation of ribs in radiographs has not been fully solved, but a number of systems have been proposed in the literature [39]–[44]. Recent other work on suppression of ribs in chest radiographs is based on statistical regression techniques [10], [8], [45]. In these methods patches with bony structures are replaced with boneless patches by using either massively trained artificial neural networks [10], [45] or k-nearest-neighbor [8] regression. Both methods require the availability of dual-energy (DE) bone images as training material. These types of images are not routinely acquired in most settings. Our algorithm does not require the availability of DE images to remove the bony structures. Instead, the information needed to suppress the bone is obtained under only the assumption of the presence of a common profile pattern along the ribs and the clavicles. This property makes the method more easily applicable to other domains where removal of elongated structures is useful.

In the second experiment clavicles were suppressed in chest radiographs. Clavicle suppression reduced clavicle conspicuity as measured by the contrast of the whole clavicle with respect to the background and by the line response on the border of the clavicle. The contrast of the body was reduced to a large extent. The line response gives a measure of the ability of the method to suppress high frequency structures. While the line response is clearly reduced, visual examination shows remaining clavicle borders in some cases. A possible reason for this is that PCA, although in principle able to model any structure up to the Nyquist frequency, has not modeled the border fully. An improvement of the method would be to modify the modeling and the subspace filtering to place extra focus on the border of structures, for example using weighted PCA. For this experiment a fully automatic segmentation was used providing accurate outlines of the clavicles [33]. Other segmentation methods for the clavicles are available as well [46]–[48], [13]. Two other methods to suppress clavicles have been published [13], [45]. In Chen et al. [45] a location specific massively trained artificial neural network was used to suppress the clavicles and good (visually examined) suppression of clavicle body and edges was achieved. As discussed before, a disadvantage of this algorithm is the need for DE images as training material. In Simkó et al. [13] a bone model was created by smoothing along the automatically segmented clavicle border, after which the bone model is subtracted. Such a method, which only uses smoothing to identify the structure, will not be able to cope with larger disturbances: in our first experiment on rib suppression we have shown that outlier detection and subspace filtering, which deal with larger disturbances, significantly contribute to a more accurate suppression.

In the third experiment nodules were simulated in the neighborhood of the clavicles in real chest radiographs. The use of simulated nodules allows for the exact determination of the location of nodules and for creating a larger dataset than would have been possible using public datasets. Nodule contrast decreased slightly after suppression, a similar finding was made by Suzuki et al. [10], who also found a slight degrading of the contrast after suppression. Interestingly, we found that nodules with an initial low contrast showed a slight increase of contrast after suppression. This observation can be explained by the finding that on average the contrast per nodule increased by 15%; the overall slight reduction in absolute contrast is thus mainly caused by large nodules. For detection purposes not only the contrast of the nodule itself, but also the value relative to the overlapping and surrounding structures is important. We found that before suppression the contrast of the clavicle, which is the most conspicuous structure in the upper lung fields, was considerably higher than that of the nodule, but after suppression nodules had on average a higher contrast than the clavicle. Additionally we found that the appearance of the nodule was more homogeneous after suppression. Both the increase of contrast with respect to other structures and the increased homogeneity may aid detection by automatic methods or humans. To achieve these beneficiary effects a perfect visual suppression of bony structures is not required. Instead, the suppressed image pro-

Fig. 10. Observers’ ability to discriminate between unaffected patches and patches containing catheters on original and suppressed images. The AUC of the ROC is significantly reduced for all observers comparing original images to suppressed images (case-based bootstrapping; p < 0.001). (a) Observer 1. (b) Observer 2. (c) Observer 3.
vides extra information compared to the original. Providing both original and bone suppressed images to the radiologist is the common mode of operation [14]–[16] and may help automatic methods as well.

In the fourth experiment human observers judged the quality of the suppression of catheters in chest radiographs. It was found that the observers’ ability to identify a catheter was markedly reduced after suppression. In about one third of the patches, originally containing catheters, the observers could still identify (remnants) of the catheter. Readers rarely take such a close-up look at the radiograph as in this experiment, and the overall suppression of the catheter might be sufficient for practical purposes. The reduction in the observers’ ability to detect suppressed structures was higher for the catheters than for the ribs, and this suggests that the proposed algorithm should be extended to improve rib suppression, as is discussed below. Suppression of catheters is a new research area; we are not aware of any previously published method that addresses this topic. In this experiment we used manual segmentations of the catheters, but automatic catheter (tip) detection methods in chest radiographs have been developed [49], [50] and could be combined with the presented algorithm to achieve fully automatic catheter removal in chest radiographs. The removal of foreign objects, such as catheters, is also important for automatic processing by computer aided detection algorithms to prevent false positives [51].

In the experiments both real and simulated data were used. In the rib suppression experiment, chest radiographs simulated from CT provided a reference standard which allowed to exactly determine the amount of suppression. Simulation of the clavicles from CT is not possible because the position of the arms in a CT scanner is different from the position in chest radiography, leading to the clavicles being rotated and not overlapping anymore with the lung fields on a posterior–anterior simulation. Instead highly realistic nodules extracted from CT were simulated in the clavicle region to provide an accurate measure of the effect of clavicle suppression on the conspicuity of these lesions, and provide insight into characteristics relevant to their detection in a diagnostic task. As an alternative to simulated data, DE images could be employed. They have as disadvantage that they are not commonly used in clinical practice and that DE images acquired using a dual-exposure technique can contain bony structure artifacts as a result of the misaligned subtraction in the imaging procedure [52] and are therefore less suited as reference standard. Another option is to use a digital phantom of known composition, which would allow to exactly measure the amount of suppression achieved. A realistic digital phantom of the chest is difficult to create due to the complexity of the lung structure and to the best of our knowledge none have been described in literature. Instead, a simpler phantom could be constructed, but this makes it difficult to judge the algorithm’s merit in a real radiograph.

Subspace filtering, i.e., the use of decomposition techniques to remove the noise subspace of a signal, has been done before using PCA [53], singular value decomposition [54], independent component analysis [22], and non-negative matrix factorization (NMF) [27]. A critical step in these methods is to determine which and how many components belong to the signal and which to the noise. Under the assumption that most of the variance in the patch originates from the structure of interest, PCA can directly provide the relevant model by selecting the linear components with the highest variance. ICA and NMF do not provide an automatic way to determine the components representing the structure and need an extra step to identify the relevance of each component [22], [55].

In certain situations it might be difficult to extract a model which gives a good segmentation of the structure of interest based on only the intensity values in the image patch. An example of such a situation is the presence of many crossing structures, such as ribs crossing another rib, or ribs intersecting the clavicle. In that case a low model dimensionality might not be sufficient to accurately model the structure, as the first few components are used to model the crossing structures. Increasing the dimensionality can partially solve this problem, but will lead to an inclusion of a larger amount of crossing structures in the model. The performance of outlier detection will also be reduced as it will be more difficult to decide which profiles are outliers when their frequency approaches 50% of the dataset. At 50% outlier frequency any (unsupervised) outlier detection technique will reach its breakdown point [56]. Potentially this limitation can be remedied by incorporating a priori information about the structure of interest, such as by inclusion of a model derived from a larger number of instances. Another situation where the algorithm worked less successfully is when there is a significant change in the appearance of one structure over the course of its centerline. This happens to the part of the ribs close to the chest wall, resulting in a reduced suppression quality. A solution could be to divide the centerline of the structure into multiple segments, so that for each segment a separate model is used.

Estimating the structure of interest through modeling and outlier removal performs significantly better than through smoothing alone, as was shown in the first experiment. We hypothesize that this higher performance was achieved because the noise that disturbs the structure of interest is not purely Gaussian. In a Gaussian noise setting positive and negative disturbances of the structure of interest would cancel out by an appropriate smoothing procedure. High-frequency variations in background tissue density from small vessels and parenchyma can be considered Gaussian and are removed by smoothing. When larger disturbances, such as big vessels and other ribs, cross the structure, smoothing will not cancel out the disturbance but will only distribute it over a larger part of the structure. This is where modeling of the structure provides a better estimation. Larger disturbances cannot be fitted by the model and are not segmented. To ensure limiting the model to the structure of interest, larger disturbances are excluded from modeling by rejecting them as outliers.

A key aspect of a method that suppresses structures by subtraction is to determine accurately the amount of intensity to subtract. This requires the background values to be known. The presented method determines this value from the assumption that the background values have an average of zero. In reality background values are not zero and the patch must first be normalized. The background values are obtained from pixels outside the structure of interest. If a segmentation of the structure
of interest is available, the background locations can be easily found. When an accurate segmentation is not available and only a centerline is used as input, the background values are found by sampling profiles that extend well over the expected width of the structure of interest. Care must be taken to not extend so far that other instances of the same structure are included in the patch as this introduces an offset in the background values.

Multiple instances of one type of structure are removed by successive application of the algorithm. The order of removal is not important, provided that in each application only the instance and not other structures are removed. In practice this is not always true and slight differences between different orderings can be observed. An example of this successive application is the suppression of clavicles where first the lower, and later the upper border are used to guide the suppression. This choice was made to focus the suppression on the conspicuous borders.

The proposed method presents a general framework that can be applied to any projection image and to any structure which meets the assumption of translucency and the presence of a common pattern along a curve. It is not necessary for the curve to be located at the center of the structure. As illustrated by the clavicle suppression, the structure can also be decomposed in multiple curve segments to meet the working conditions for the algorithm. Likewise a radial curve can be used to suppress elliptical structures.

The resulting structure suppressed images can be used as an additional image to aid human reading or as input for subsequent processing steps, such as computer aided detection. Clavicle and rib suppression have been shown to improve radiologist’s performance in the detection of nodules [15], [16]. Rib suppression has been shown to improve the measured visibility of nodules [10], but so far the effect on a fully automatic nodule system has not been determined yet. Another detection task in chest radiographs—and showed a marked reduction of the contrast of rib shadows in chest radiographs by means of massive training artificial neural network (MTANN), IEEE Trans. Med. Imag., vol. 25, no. 4, pp. 406–416, Apr. 2006.


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