Automated interpretation of ventilation-perfusion lung scintigrams for the diagnosis of pulmonary embolism using Support Vector Machines

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Abstract. The purpose of this study was to develop a new completely automated method for the interpretation of ventilation-perfusion (V-P) lung scintigrams for the diagnosis of pulmonary embolism. A new way of extracting features, characteristic for pulmonary embolism is presented. These features are then used as input to a Support Vector Machine, which discriminates between pulmonary embolism or no embolism. Using a material of 509 training cases and 104 test cases, the performance of the system, measured as the area under the ROC curve, was 0.86 in the test group. It is concluded that a completely automatic method can be used for interpretation of V-P scintigrams. It is faster and more robust than a previously presented method [4, 5] and the accuracy is at the same level as the the previous method. It also handles abnormalities in the lungs.

1 Introduction

Pulmonary embolism is an acute disease caused by blood clots obstructing the blood vessels of the lungs. It can be a life threatening disease and early treatment may be life saving. On the other hand treatment of patients not suffering from pulmonary embolism may cause serious complications.

Blood has an ability to form clots, which is necessary for stopping bleedings from for example skin wounds and nose bleedings. Blood clots form on the walls of injured blood vessels to prevent blood from leaking until the natural repair process is finished. Large blood clots may, however, be washed away by the blood flow. Pieces of blood clots then follow the blood flow until they get stuck in the thin vessels of the lungs. Extensive obstruction of blood vessels in the lungs can lead to failure of the right ventricle of the heart, which may be life threatening.

A rapid decision regarding the diagnosis and treatment of pulmonary embolism is of great importance. Lung scintigraphy is a common method to diagnose pulmonary embolism. It is a simple and safe method to visualize the blood flow of the lung. In addition to perfusion scintigraphy showing the distribution of blood flow in the lungs, ventilation scintigraphy is performed, which shows the distribution of air flow to different parts of the lung during inspiration. A region of pulmonary embolism is characterized by impaired perfusion but normal ventilation. Images from young and healthy patients are usually easy to interpret, but images from patients, who are old, smokers or have certain lung diseases are far more difficult to interpret.

The physician has to rely on the lung scintigrams for the diagnosis. A reliable computer-aided interpretation would be of great value. Computer-aided interpretation of lung scintigrams was first presented in 1993 by Tourassi [3] and Scott [6]. They used artificial neural networks to classify manually obtained inputs from scintigrams. No computerized image processing was used. Today, 10 years later, manually obtained features are still the most common way to obtain the inputs used for classification. The approach to use manually obtained inputs has two important disadvantages. First, the physician requiring advice from the computer must read the scintigram and report whether a number of features relevant to pulmonary embolism are present or not. This information must then be entered manually into the computer. Second, there is also a variability between different physicians in the way features are found and in the importance attached to them [7]. In order to eliminate the time-consuming manual feature extraction and to receive good reproducibility of the inputs, the inputs should be obtained using computerized image processing. Our group has presented and evaluated a completely automated method for the interpretation of lung scintigrams [4, 5]. The performance of the method was as good as experienced physicians. A disadvantage with the method, however, was that it had difficulties to handle lung images with extensive abnormalities.

The purpose of this study was to develop a method that is more robust than in [4, 5]. It should handle cases with extensive abnormalities, e.g. blood flow to only one lung or one half of the lung.

2 Data

2.1 Training and test set

The same training and test sets were used in this study as have been used in our previous study [4]. Both the training and test set consisted of ventilation and perfusion (V-P) lung scintigrams from patients, who had undergone an examination with six projections, see Figure 1. The training set consisted of 509 patients and the test set of 104 patients, see Table 1. Two experienced physicians classified all cases of the training set into either "no pulmonary embolism" or "pulmonary embolism" and this classification was used as the gold standard. The result of a pulmonary angiography was used as the gold standard in the test group.

2.2 Imaging protocol

Images were obtained using a gamma camera and stored digitally as 128×128 matrices. They were obtained in 6 different projections: anterior, posterior, left posterior oblique (LPO), right posterior oblique (RPO), left and right lateral.

	Training set	Test set
Nr. of patients	509	104
Females (%)	62	58
Mean age, (range)	63 (16-93)	58 (17-93)
Embolism (%)	15	55

Table 1. Composition of the training and test sets.

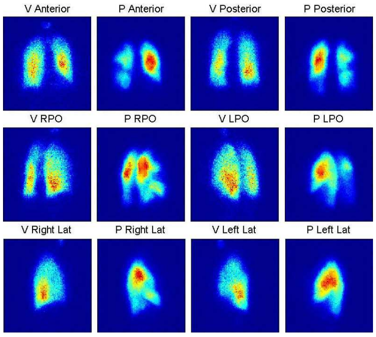

Fig. 1. A typical emboli case: it can be seen that the perfusion (P) is impaired in parts of the lungs but the ventilation (V) is normal.

3 Method

3.1 Segmenting out lungs from projection images

Figure 1 shows a lung scintigram of a typical case of pulmonary embolism. In healthy subjects the corresponding ventilation and perfusion images should be very similar. It is typical for cases of pulmonary embolism that visible lung tissue in the ventilation image is missing in the perfusion image, due to the vessels that have been obstructed by blood clots. To discriminate between pulmonary embolism and no embolism a comparison between corresponding six projections, i.e. 12 images must be done. In lung scintigrams it is common that parts of the trachea, stomach, and kidney are visualized. Before the comparison can be made, it is necessary to separate the regions of interest, i.e. to segment out the lungs in all projections.

To remove parts of the images that do not belong to the lungs, the horizontal profile of the image is used. By horizontal profile it is meant the sum of the image in horizontal direction, see Figure 3. To reduce noise, the profile is filtered in the Fourier domain. The first 12 Fourier coefficients are kept. The longest interval, where the intensity of the profile is above the mean everywhere, is assumed to correspond to the lung. The regions that then are considered to be outside of the lung are put to zero. Previous studies [1] indicate that the border of the lung can be considered as having an intensity of 18 percent of the maximum. Therefore all parts of the image having an intensity less than 18 percent of the maximum intensity are also set to zero.

3.2 Alignment of the perfusion and the ventilation images

Before further processing all projections are normalized so that the median of the image is one. Next step is to find six translation vectors, so that all projections could be pairwise aligned. The translation vector is set to correspond to the maximum of the 2D-convolution of the corresponding perfusion and ventilation projections. Figure 2 shows the steps of the preprocessing for the anterior projection. It was done analogous for all six projection-pairs.

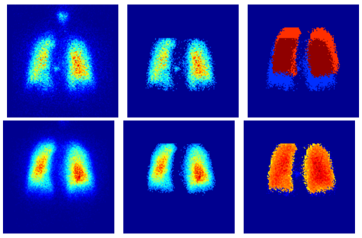

Fig. 2. Image preprocessing: to the left the original ventilation (above) and perfusion (below) images (anterior projection), in the middle the normalized, segmented lungs and to the right the ventilation/perfusion images before (upper right) and after (lower right) alignment. Notice that the trachea is visible in the non processed perfusion image.

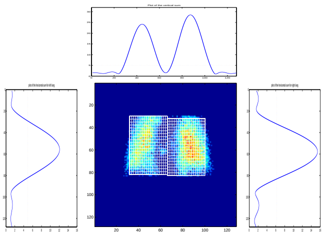

Fig. 3. The vertical profile reveals the position of the left and right lungs. The horizontal profile of the left/right lung determines the vertical position

3.3 Feature Extraction

On each aligned ventilation-perfusion image, a grid that exactly encloses the lung is placed, see Figure 3. The grid is a 20×20 matrix and the image inside the grid is transformed to a 20×20 matrix by linear interpolation. On the anterior and posterior projections one grid is placed on the left lung and one on the right. On the other projections only one grid is placed. The grid is located in a similar way as the lungs are segmented out from the liver, trachea etc. The vertical profile defines where the left and right lungs are situated. In the anterior and posterior projections the profile also reveals if there is one or two lungs. The system must also deal with cases where only one lung is present. When the horizontal position of the left and right lung are known, the horizontal profile considering only the left/right lung in the image defines the vertical position of the left and right lung. All in all eight grids are positioned, four on the anterior and posterior and one on each of the remaining four projections.

Each rectangle on each grid defines corresponding features throughout the training and test sets. Two kinds of features were used. The first kind comes from the differences between perfusion and ventilation images. Thus, negative pixels correspond to a mismatch, i.e. presence of ventilation without corresponding perfusion. The second kind of feature is ratio between the perfusion and ventilation images. Only ratios smaller than 0.75 were kept. These are typical mismatches.

Features are extracted from all projections, giving a total of eight 20×20 matrices for each case. The matrices are transformed into eight 400×1 vectors, which are used as input to the classifier.

3.4 Classification

We have chosen to use a Support Vector Machine (SVM) [2] to classify images as lung embolism or no embolism. SVM is advantageous to use when the underlying distribution is unknown. The implementation we have been using is the OSU–SVM toolbox for matlab [8].

The SVM gives for each sample a decision value. The samples are classified to one class or the other depending on if this value is below or above a threshold. By varying this threshold a receiver operating characteristic (ROC) curve was obtained. The performance of the classification was measured as the area under the ROC curve.

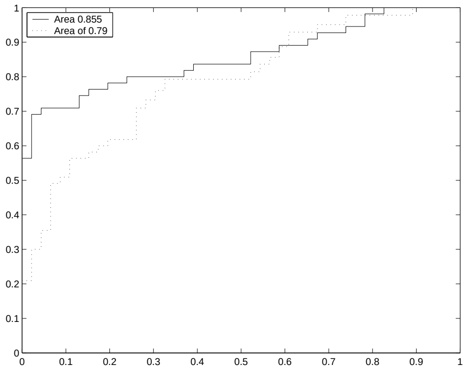

Fig. 4. ROC curves obtained in the present study and in the previous study [4]

4 Results

To measure the robustness of the algorithm, we have compared how many images that were excluded by the previous method [4] and how many that were excluded in the new system.

In [4], 31 of the 509 cases in the training set and 17 of the 104 cases in the test set were excluded automatically by a neural network, due to bad alignment. In our algorithm, samples were also excluded automatically due to bad image quality. Samples for which the algorithm can not distinguish whether there was one or there were two lungs, or samples for which it could not discriminate between the left and the right lung, were also excluded. In the training set 12 of 509 and in the test set 5 of 104 were automatically excluded, due to bad image quality.

The SVM was trained on the remaining 497 cases of the training group and was tested on the remaining 99 cases of the test group.

The area under the ROC-curve was used to measure the quality of the classification. Using the features defined on differences between the perfusion and ventilation, the area under the ROC-curve was 0.83. If only features from the quotient image were considered, the area was 0.83. An area of 0.86 was obtained if both features from difference and quotient images were used. The ROC-curve corresponding to an area of 0.86 is compared to the ROC-curve, which had an area of 0.79, obtained in [4], see Figure 4.

5 Discussion

The feature extraction of the proposed method is based on basic Image Processing methods. It turns out that the method is not only faster but also more robust than the previous method. The former method fitted the lungs to a template. For special cases where one or half a lung was missing it had difficulties. The proposed method deals with almost all cases. It excludes 10 in the training group and 2 in the test group, due to bad image quality. For a commercial product it is critical that the algorithm is fast and still robust.

The diagnosis of the cases from the test group is based on a V-P scan and a pulmonary angiography. This have been slightly problematic. It may happen that the angiography says it is an embolism, but in the same time, the V-P scan is perfectly normal. We noticed that we have about ten cases where the diagnosis of the V-P scans are surprising. Since there often is one or two days in between the two examinations, it happens that new embolism is produced in that time. This would explain why this problem has arisen.

The proposed algorithm is very versatile and can easily be adapted to lung scintigrams performed in different hospitals and modified to current projections.

6 Acknowledgements

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