Natural Computing Project Proposal

Particle Swarm Optimization for Atelectasis Detection in X-ray Images

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GROUP 25

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1 Problem Statement

Atelectasis refers to a (partial) collapse of a lung. The condition occurs when the *alveoli* (tiny air sacs in the lung) lose air [14]. A blocked airway can cause *obstructive atelectasis*. *Non-obstructive atelectasis* can be caused by pressure from outside of the lung.

Atelectasis is extremely common after surgery, with about 90% of patients developing Atelectasis after general anesthesia during surgery [5]. This is because general anesthesia during surgery changes the breathing pattern and exchange of air gases. There are multiple causes for Atelectasis. However, the common cause for Atelectasis after surgery, is due to the creation of a mucus plug. This happens because a patient cannot cough or swallow during general anesthesia. Also, the drugs given to bring patients under anesthesia make patients breathe less deeply, which also allows for mucus to build up airways, when it would normally move out of the lungs [14].

If Atelectasis due to build up mucus goes unnoticed, it could potentially lead to *Pneumonia*, which occurs when you have an infection that inflames the alveoli. Therefore it is important that Atelectasis gets discovered and treated, especially when you consider that patients are usually quite vulnerable and weak after a major surgery. If a patients is recovering from major surgery, an infection in their airways could majorly worsen their condition. Some valueable research has already been done in using PSO to detect Pneumonia (see section 2 'Related Work').

We would like to extend the current research by figuring out if we can use PSO for x-ray images to detect (partial) lung collapse (Atelectasis) *before* the alveoli become infected resulting in Pneumonia. We are particulairly interested in how early after surgery the Atelectasis can be detected, to prevent any further damage to the lungs. To the best of our knowledge, PSO on x-ray images in order to detect early Atelectasis has not been done yet. With this research, we hope to extend upon the current knowledge base to further mitigate Pneumonia caused by build up mucus in the airways after surgery.

This research is also interesting from scientific point of view, as we will measure just how early PSO can be applied to detect the Atelectasis condition. This demonstrates the capabilities of particle swarm optimization techniques, and proves their usefulness in medical image segmentation.

If we manage to finish our PSO implementation early, we would like to extend our research to include optimization techniques for PSO. We can then compare our bare PSO implementation with the optimized implementation(s) using statistical tests.

2 Related Work

2.1 PSO for image segmentation

Abdallah et. al. proposed combining Pariticle Swarm Optimization (PSO) with histogram equalization for segmenting lung CT scans and chest X-ray images. The research claims that using PSO for image segmentation enhances the segmentation accuracy, especially when dealing with complex lung images [1]. Furthermore, Lakshman Narayana et. al. [15] combined PSO with feature extraction methods to perform segmentation on chest x-ray images. Lastly, Pramanik et. al. [13] proved that PSO could be used for feature selection in Pneumonia detection from X-rays images.

Feng et. al. performed research on using PSO to do image segmentation on infrared images with a low signal-to-noise ratio (SNR). This is relevant to our research, as the x-ray images may also be of low SNR values.[1]

2.2 PSO optimization techniques

Kaur et. al. [6] provides an overview of optimization techniques for PSO. They discuss optimization technqiues with promising results, of which we have selected a few seemingly interesting ones. We highlight a them below.

Thresholding approaches. Yin et. al. [16] used cross entropy for obtaining a threshold for PSO. This reduces the execution time of the image segmentation algorithm.

Nakib et. al. [11] used PSO as an optimization for two-dimensional survival exponential entropy to solve an image segmentation problem in magnetic resonance imaging (MRI) images.

Yu et. al. [17] uses an image segmentation method based on maximum entropy thresholding and quantum behaviour of PSO. They mention that this improved method helps deal with early convergence issues and problem related to large

[1] https://www.sciencedirect.com/science/article/pii/S0167865504003289?casa_token=f08ovnGTjVIAAAAA:MVtmkDz-p59frnfqc7CX_BWB3hEdRx4rZOYibFjdxqdKrrW2_QRo6oYzVqCnzeYO-gAEdkMpJQ

calculation of multi-thresholding segmentation.

Fuzzy System approaches. Masooleh et. al. [10] researched a combination of a fuzzy system with PSO for image segmentation. They apply a set of fuzzy rules to assign each pixel to a colour class. Specifically, they use a 'Hue, Saturation, and Lightness' (HSL) system for pixel classification. In order to reduce a large number of fuzzy rules, PSO is used to automatically produce the least amount of fuzzy rules that still provide good classification.

Gopal et. al. [4] used two-phase MRI segmentation. In the first phase they pre-processed and enhanced the MRI images, removing labels and x-ray marks. Next to that, a median filter was utilized for removing high frequency components. Finally a fuzzy c-means (FCM) method is used to calculate an adaptive threshold, which is then optimized with PSO.

Genetic algorithm approaches. Forouzanfer et. al. [3] proposed a combination method of genetic algorithms with FCM clustering that was deemed promising for MRI images. Specifically, they use a 'breeding swarm' algorithm that combines PSO with a genetic algorithm. It was implemented in such a way that PSO facilitates local search, whilst the genetic algorithm is responsible for global search.

Kole et. al. [7] also proposes using a combination of genetic algorithms with PSO. In this case, PSO based dynamic clustering is used to find the optimal amount of clusters.

Wavelet approaches. De et. al. [2] integrated PSO into wavelet mutation in order to prevent getting stuck in local optima. They use a histogram of MRI images and apply entropy maximization to obtain a likely threshold grey level range for segmentating MRI scans.

Clustering approaches. Omran et. al. [12] used binary PSO clustering to properly optimize the number of clusters for k-means clustering.

Liu et. al. [9] proposed using PSO based fuzzy clustering to sonar image segmentation, in which the image are of low SNR values. They mention that their method has a high convergence speed. Additionally, they use a fuzzy measure and fuzzy integral in their fitness computation.

Neural network approaches. Lian et. al. [8] segmented MRI images based on modified adaptive probabilistic Neural Networks (MAPNN), which incorperates a self-organizing map (SOM), modified particle swarm optimization (MPSO), and a probabilistic neural network ('PNN', used for classification) for segmentation. The MPSO is used to as the smoothing factor σ (i.e. the bandwith of the Gaussian kernel) for the PNN. This means that the MPSO controls how much gets generalized instead of focussing on individual data points.

3 Approach

3.1 Methods

The general development flow of the program is depicted in figure 1.

First, we parse and prepare the data, that is; convert each X-ray images to a grid of black and white pixels and label them with the associated data.

Next, we implement the PSO algorithm and already look what parameters give a good distinction on the visual separation of the lungs (which is needed in order to detect Atelectasis).

After, a function needs to be implemented that can determine whether the silhouette (or silhouettes) of a lung, generated by the PSO algorithm, indicate Atelectasis. This is probably efficiently realized by trying to match it to a shape of a healthy lung.

When having the results, we analyze them to see where thing go right and wrong. Specifically, we iteratively try to optimize the parameters in PSO (in the amount of shades of gray for example) and our choice of function to identify Atelectasis such that the detection rate is maximized.

In table 1 it can be seen that we have reserved 3 weeks for implementing and improving our PSO algorithm for image segmentation on lung X-ray images. However if that turns out to be too ambitious, we can likely take a PSO algorithm for detecting Pneumonia in lung X-ray scans, and improve them such that they also work Atelectasis. There are also plenty optimization possibilities, of which a few are discussed in section 2 'Related Work'.

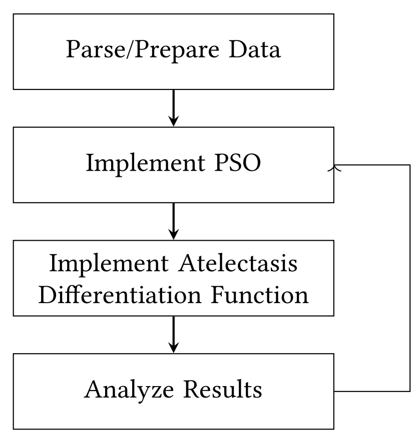

Figure 1. Development Flow

3.2 Resources

Kaggle provides an elaborate dataset containing X-ray images of the chest area of patients with labels of their respective condition (including Atelectasis), if any (https://www.kaggle.com/datasets/nih-chest-xrays/data/data). This is a good choice of data as it is labeled, diverse and large, allowing us to efficiently determine accuracy in detection rate.

As a bonus, the dataset is non-copyrighted, so no signed agreement is needed of any sort, which is quite often the case for medical data due to its sensitivity.

As the dataset is particularly large (112,120 images plus label data totalling 45.08 GB), a smaller 5% sample datasubset (5606 images plus label data totalling 2.1 GB) is available for download as well. We will start of the project with the sample data due to it being lightweight. Later in the project, we will test the full data, to see the total detection rate of Atelectasis in the full dataset.

4 Planning

Our layed-out planning can be seen in table 1. Our focus lies in getting the PSO working for the lung x-ray images. Once we are able to successfully segment those, we can try an optimization technique as discussed in the section 2 'Related Work'. However, it should be mentioned that this is seen as a bonus and not the main goal, as those methods can get complicated quite quickly.

Moreover, we have defined three 'checkpoint' moments: one in week 16, week 20, and week 23. The precize date will depend on the availability of our project supervisor. The idea is to meet with our supervisor and discuss what our progress is and what we are currently working on. This will keep our progress in check.

Week	To Do
15	Create Project Proposal
16	CHECKPOINT A, Literature Research
17	Data prepocessing
18	Implement PSO and differential function
19	Evaluation of statistical methods, update report
20	CHECKPOINT B, Improve PSO algorithm
21	Evaluation of statistical methods, update report
22	CHECKPOINT C, Improve PSO algorithm
23	Evaluation of statistical methods, finalize report
24	Buffer week

Table 1. Timeline for the final project.

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