DETECTION OF TUBES IN RADIOGRAPHS USING CANNY EDGE DETECTION AND PROGRESSIVE HOUGH TRANSFORMS

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DETECTION OF TUBES IN RADIOGRAPHS USING CANNY EDGE DETECTION AND PROGRESSIVE HOUGH TRANSFORMS

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ABSTRACT

An automated method for detecting tubes and catheters in chest radiographs could improve patient safety and healthcare efficiency by helping radiologists to more quickly and accurately identify mal-positioned tubes. We propose a method for automatically detecting tubes that first uses a Canny edge detector for the initial identification of edges, followed by a windowed variant of the Hough transform, a common line detection algorithm, which is used to identify potential tube pixels.

Our method employs repeated applications of a parallel-line-specific Hough transform to the same image with progressively lower thresholds for minimum line length. Information about the parallel lines identified in the initial Hough transforms is retained and used to help later, lower threshold runs to more selectively identify potential tube sections.

The resultant technique gives an average recall of greater than 80% when measured by its ability to detect feeding tubes only. The precision rate is low, partially due to its ability to identify other types of tubes in the image. This could potentially be exploited for tube sub-classification by including other types of tubes in the target set, or by developing additional algorithms that distinguish between the various types of tubes in the radiograph.

APPROVAL PAGE

The faculty listed below, appointed by the Dean of the School of Computing and Engineering, have examined a thesis titled "Detection of Tubes in Radiographs Using Canny Edge Detection and Progressive Hough Transforms", presented by Anthony Shipman, candidate for the Master of Science degree, and certify that in their opinion it is worthy of acceptance.

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CHAPTER 1

INTRODUCTION

Verifying the proper tube placement is vital to patient well-being, particularly for infants. Pediatric patients are at increased risk of having enteral tubes, meant to be placed in the stomach or gastrointestinal tract, misplaced into respiratory tract, the result of which can be “serious morbidity and possibly mortality [1]”.

Since the consequences of tube misplacement are so dire, extra care is taken to verify proper tube placement. Chest radiographs are the most common method for identifying the proper placement of feeding tubes. Radiographs are ubiquitous and relatively cheap, making them a natural choice for verifying tube placement, and “on average, 236 chest radiographs are taken per 100 patients per year [1]”.

While radiographs are the most widely used method for verifying proper tube placement, they are not perfect, and it is sometimes difficult for even highly trained radiologists to determine the placement of the multitude of tubes that can be present in a single patient’s radiograph.

Figure 1—Radiograph with faint tubes

We aim to develop a method that will highlight the positioning of enteral tubes so that radiologists can more easily identify those instances where improper tube placement jeopardizes patient health.

CHAPTER 2

REVIEW OF LITERATURE

Several attempts have been made at detecting various types of tubes in radiographs. The methodologies involved are diverse, including the use of a convolutional neural network (CNN) [2], a Hough transform for the detection of parallel lines [3], Haar-like features with integral images [4], and random forest classifiers [5].

Mercan and Celebe [2] chose to use a convolutional neural network due the method being designed for image recognition and the lack of a need to extract features from the images before processing. The final CNN used contains layers containing 2, 32, 32, 128, and 1 nodes, with a learning rate selected as .1.

The trained CNN sometimes falsely identified "tubes" that were interrupted and unclear. To correct for this, the team added a post-processing step that used curve-fitting to connect the broken areas and form a best-fit curve. With the curve-fitting included, the team reported a 59% true-positive rate, a 99.9%, true-negative rate, and 99% accuracy.

Ramakrishna et. al. [3] used a five-step approach that included the use of a Hough transform to detect parallel lines. In the first step, they removed radiograph borders and used contrast-limited adaptive histogram equalization (CLAHE) to pre-process the images. Next, they used feature templates to identify regions of interest such as the neck, esophagus, and abdomen. Thirdly, they used a Hough transform to divide the previously identified neck region in to strips using angle and distance constraints. Fourthly, they followed "seed" points identified in step three and, using a collection of tube "properties", rejected those potential tubes that did not meet the criteria. Finally, the tubes are grouped together by similarity. Multiple tube pieces with similar properties were identified as a single tube.

This five-step process resulted in a 93% true-positive rate for endotracheal (ET) tubes and an 84% true positive rate for nasogastric tubes with 2% false-positive rates for both.

Table 1 - Existing Methods Evaluation

Paper	Method	Results
"An approach for chest tube detection in chest radiographs" [2] C.A. Mercan and M.S. Celebi (2014)	Convolutional Neural Network and curve fitting.	59.0 % sensitivity TPR 99.9 % specificity TNR 99.9 % accuracy
"An improved automatic computer aided tube detection and labeling system on chest radiographs" [3] B. Ramakrishna, et. al. (2012)	Uses parallel Hough lines and other features to determine areas of interest and grow tubes from seeds	ET Tubes 93.0% sensitivity TPR 2.0% FPR NG Tubes 84.0% sensitivity TPR 2.0 % FPR NG
"Computer-aided interpretation of ICU portable chest images: automated detection of endotracheal tubes" [4] Z. Huo (2008)	Uses Haar-like features to identify body regions as well as tubes.	91.0% sensitivity TPR for training 98.0% sensitivity TPR for test
"Pseudo random forests for tube identification" [5] K. Bingham (2015)	Uses pixel intensity, gradient orientation, gradient magnitude, and random forest generated features to identify tube pixels.	84.8 % TPR

Huo et. al. [4] use Haar-like features, a technique used by Viola and Jones [6] for face detection, to detect tubes in radiograph images. By comparing the lightness of different rectangular regions of an image, the images are rejected or accepted based upon how the delta between the rectangular regions compares to a target derived from training on other images. They report a true-positive rate as high as 98% with low false-positive rates.

Bingham uses intuitive properties such as pixel intensity, gradient orientation, and gradient magnitude to identify pixels likely to be part of tubes [5]. He then trains a random forest classifier which identifies the most important among less intuitive features such as “gradient 3 below source pixel added to gradient of source pixel”. He reports an 84.8% true-positive rate while working with a dataset that includes oddly position bodies or misshapen tubes (e.g. tubes that cross over themselves).

Limitations of Existing Approaches

Two of the four approaches examined, Ramakrishna [3] and Huo [4] require specific orientations and placements of the radiographed bodies for their methodologies to work correctly. Both methods use templates for region-of-interest detection that may prove unworkable in cases where those regions are not easily detectable. X-rays of infants are especially likely to have anatomical regions that are difficult to discern with a template-based approach. The neck is a commonly used region-of-interest for tube seeding. Figure 2 shows a chest radiograph with no clearly visible neck region.

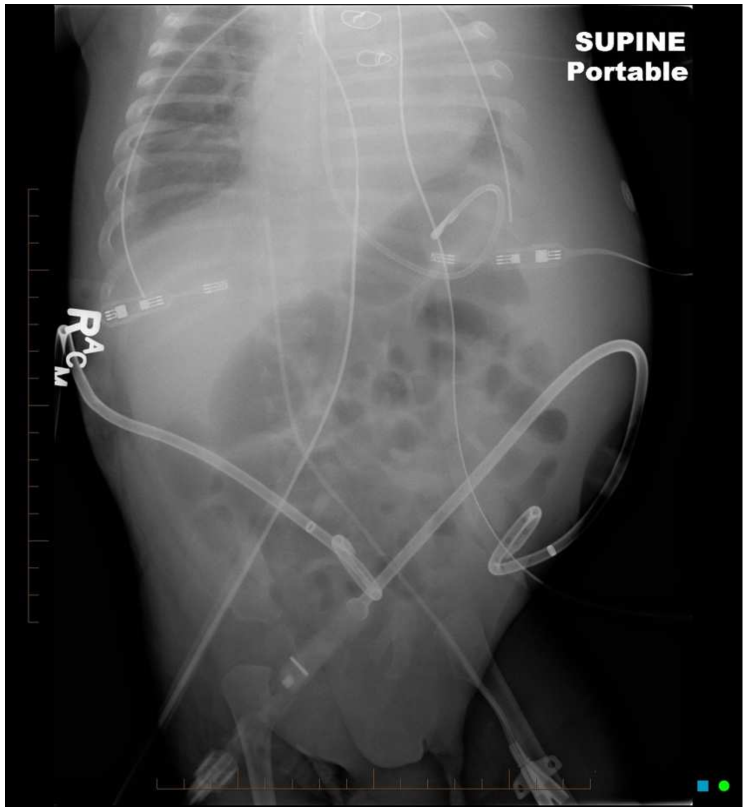

Figure 2 – Chest radiograph with no visible neck region

Both Mercan [2] and Bingham [5] use methods that are more tolerant of different body shapes and orientations. The methods used, CNNs and random-forest classifiers respectively, are computationally intensive that near real-time tube identification is not a realistic expectation.

CHAPTER 3

METHODOLOGY

Data Sources

Dr. Sherwin Chan of Children's Mercy Hospital has provided the radiographs used for this project. Sixteen images were selected for the final training. The tube location in each image had to be manually marked. A Canny edge detector was applied to each image. Amongst the edges detected, a single line corresponding to each tube wall was marked.

Figure 3 – Original, unaltered radiograph

Figure 4 – Marked tube on Canny image

Progressive Parallel Hough Transform Methodology

There are three main phases in our approach. First, we pre-process the x-ray image using and use a Canny edge detector to turn the image into a Boolean map of its input, transforming a grayscale image into a binary one in which all detected edges are pure white and all else is black.

Next, we apply a windowed variation of a Hough transform that detects parallel line segments while optimizing for the most frequently occurring distances between parallel lines segments within the image. The Hough transform variant runs multiple times against the same image, with progressively lower thresholds for minimum line segment length.

When a set of parallel lines is detected, the distance between those two lines (rounded to the nearest integer) is tracked in an accumulator. The accumulator values throughout all Hough transform runs, and distances not among the top *n* most frequently occurring distances are rejected as tube candidates. Short, parallel line segments are rejected if the distance between them is not among the commonly occurring distances between longer parallel line segments.

Finally, once the results of the successive Hough transforms have been tallied, the Canny edge detector is used once again to produce a Boolean mask that rejects all predicted pixel values that are not valid Canny edges.

Pre-Processing

The first step to detecting tubes in our x-ray images is to detect all edges within the image. We use a Canny edge detector, one of the most common edge detection methods. Some of the images contain low contrast regions. Specifically, tube walls can be difficult to detect when overlapping with the spinal column. To increase local contrast, and thereby improve the effectiveness of the Canny edge detection, we first apply contrast-limited adaptive histogram equalization (CLAHE) to the images.

The Canny edge detector bases its results upon the underlying gradient magnitudes of the pixels of the image [7]. Gradient magnitudes can be calculated from the change in pixel intensity in the horizontal (dx) and vertical directions (dy).

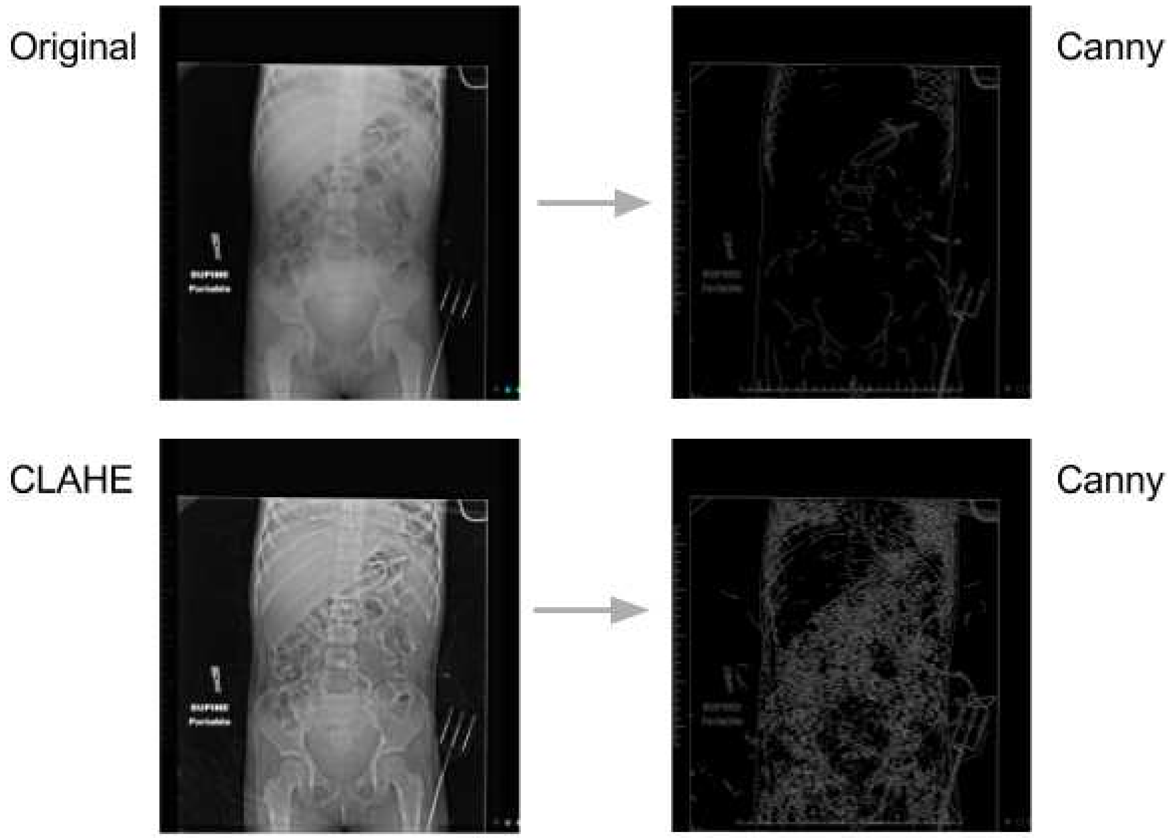

Figure 5 – Effect of CLAHE on Canny edge detector performance

The Canny edge detector uses the gradient values as a base, but then uses non-maximum suppression, double-thresholding, and hysteresis to ensure that each edge is represented by one and only one line on the resultant map of edges [7].

Hough Transform

Once the Canny edge detector has been applied to the original image, we attempt to find tube walls using a variation of a Hough transform.

The Hough transform is a method of line detection that uses an accumulator space to detect lines in images. The Hough transform accepts a binary image as an input. For each pixel in the input image with a value of 1, the accumulator space bins corresponding to all possible lines that run through that pixel are incremented by one. Each line is represented by a unique combination of r and Θ where r is the length of a perpendicular line intersecting the original line and the origin while Θ is the angle that perpendicular line makes with the x-axis. Multiple lines can pass through a single point, so multiple values of r and Θ combinations are incremented for each pixel.

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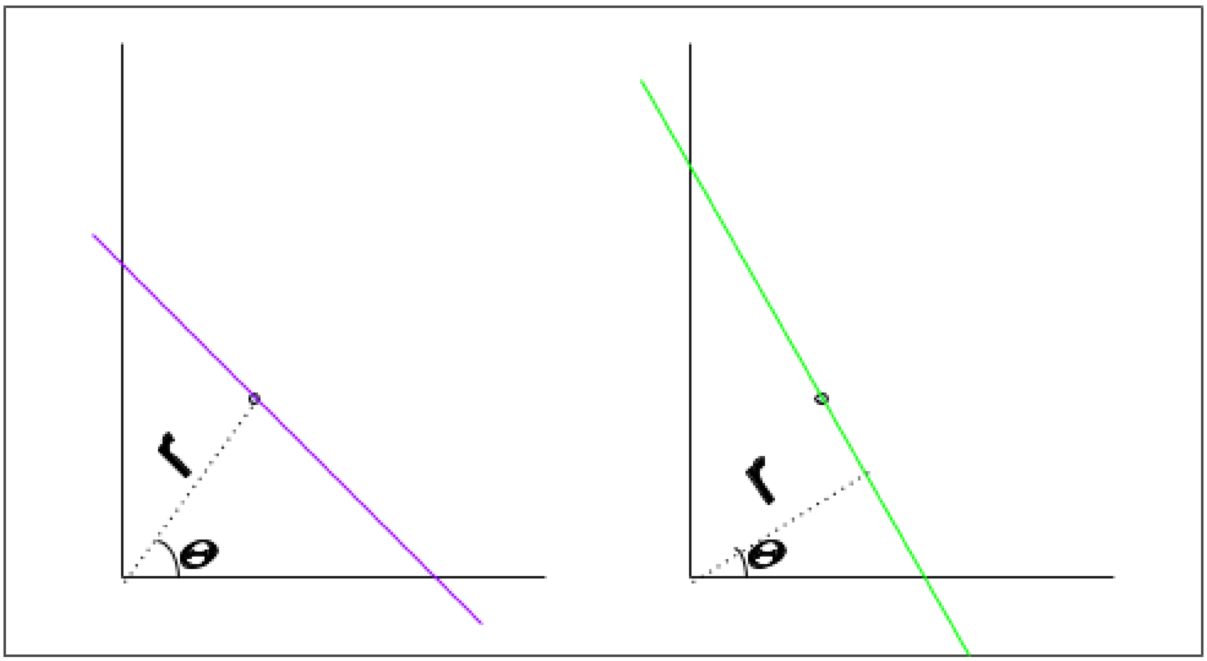

Figure 6 – r and Θ for a single point

The accumulator space is an array with dimensions of r and Θ vales. As each eligible pixel (as indicated by a 1 value in the binary image) is examined, the bins for the lines passing through those pixels are incremented. Those pixels falling on the same line result in a high value for the bin with the r and Θ representing that line. In this way, each pixel "votes" for the lines it might appear on. Those lines with the most votes are determined to be the actual lines in the input image.

We initially ran the Hough transform at a global level, hoping to identify lengthy sub-sections. For our use-case, however, running the Hough transform at a global level was not helpful. Since the tubes we are searching for are curved and only have linearity in small sub-sections, identifying those tubes at the whole-image level using a Hough transform was not possible. Most radiographs do not contain clear, image-wide lines that would be easily detected by a Hough transform. When no clear and prevalent lines exist, the Hough transform still finds the most linear-like portions of an image, even if "most linear" is not very linear at all, as Figure 7 demonstrates. Hough-detected lines are shown in blue.

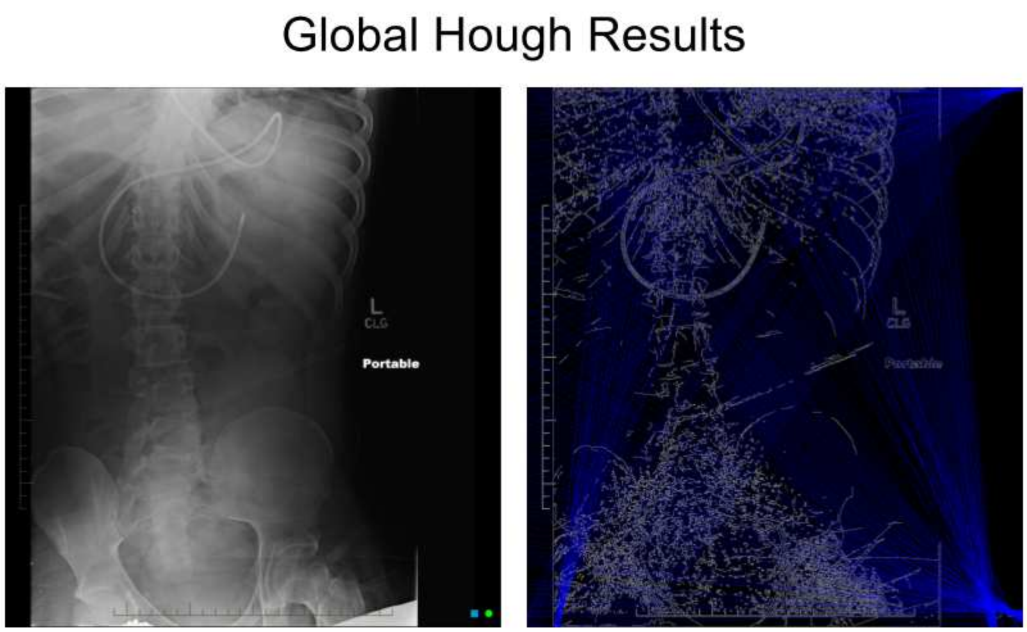

Figure 7 – Global Hough transform

The global Hough transform is not the best option for tube detection. We know, however, that tubes do show linearity in small segments. Therefore, if we use a windowing function to limit the scope of the Hough transform, we might still be able to use it to detect tube walls. Using a windowed version of the Hough transform gives very different results from its use at the global level as Figure 8 shows. Blue indicates Hough-detected lines.

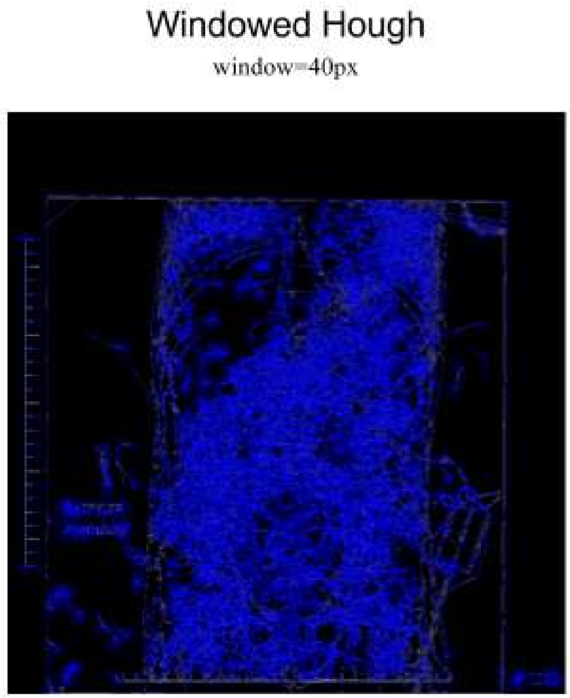

Figure 8 – Windowed Hough transform

The windowed Hough variation is better at picking up small linear sub-sections, and the long Hough-detected lines that did not correspond to tubes have disappeared. There is even some evidence of it detecting tube-walls on some sections of the image. Unfortunately, there is also a great deal of noise in the chest region of the x-ray. The Hough lines are so numerous that most of the mid-section of the x-ray appears blue. Since lengthy lines are so hard to find in x-ray images, the Hough transform is greedily marking the most linear structures it finds. How can we reduce the noise? Most tubes can be identified by the human eye in an x-ray due to the double lines of the tube wall. Our windowed Hough transform implementation is searching for single lines, but to detect tubes, we should be searching for double lines, appearing in parallel.

In the Hough accumulator space, parallel lines are those lines with matching Θ values and different r values. Constraining the results of our Hough transform to only those lines that have parallel "partners" significantly lessons the extra lines in our result set, as Figure 9 demonstrates.

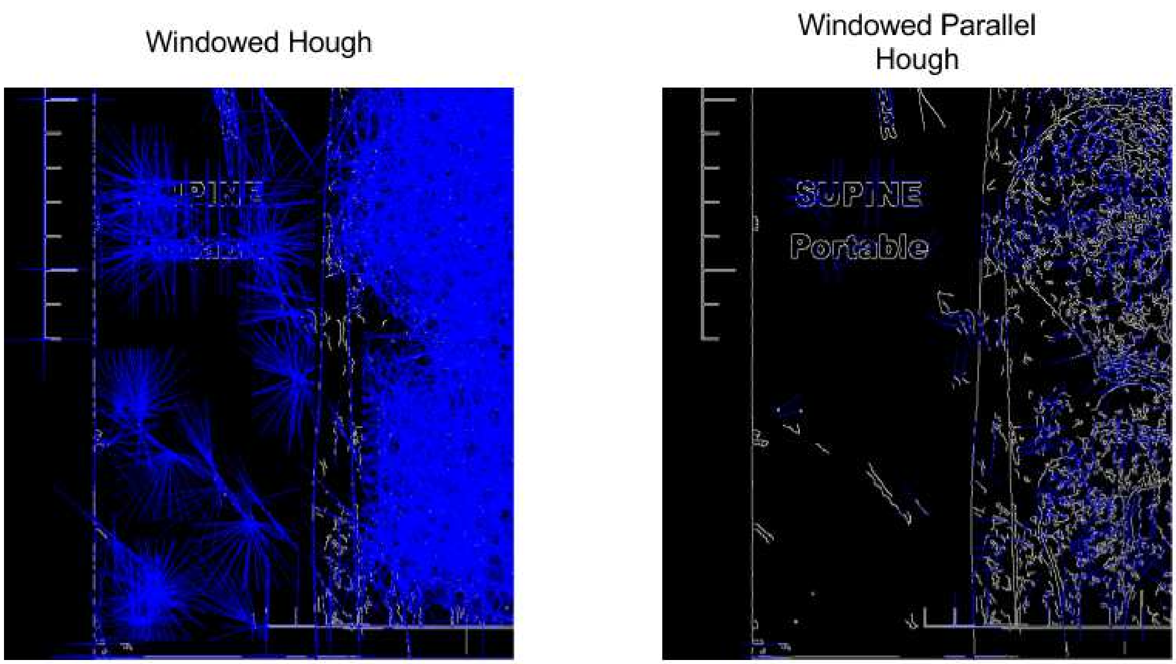

Figure 9 – Windowed parallel Hough example

The windowed parallel Hough transform greatly reduces the false-positive results. As the image on the right in Figure 9 shows, there are still several false positives that are clearly not lines, especially in the emptiest portions of the image. These false-positives are due to the way in which the Hough transform implementation that we are using defines its minimum threshold.

To determine which of the highest vote-getting lines are selected by the Hough transform, a threshold is used. Lines receiving fewer votes than the threshold are rejected. By default, the threshold is set to .5 * the maximum accumulator value in the Hough space. In regions with strong lines, that maximum value would be high, and lines with two or three votes would fall below the threshold. In windows with very weak or no lines, the max value is low. Thus, even weak line candidates exceed the threshold and are marked as lines.

To compensate, a global threshold can be used rather than using the default of .5 * the maximum of the local window's Hough accumulator space. Depending on the value of the threshold used, this approach can significantly reduce the false positives in the windowed parallel Hough transform. Figure 10 shows three different windowed parallel Hough transforms with thresholds of 30, 20, and 10 pixels respectively.

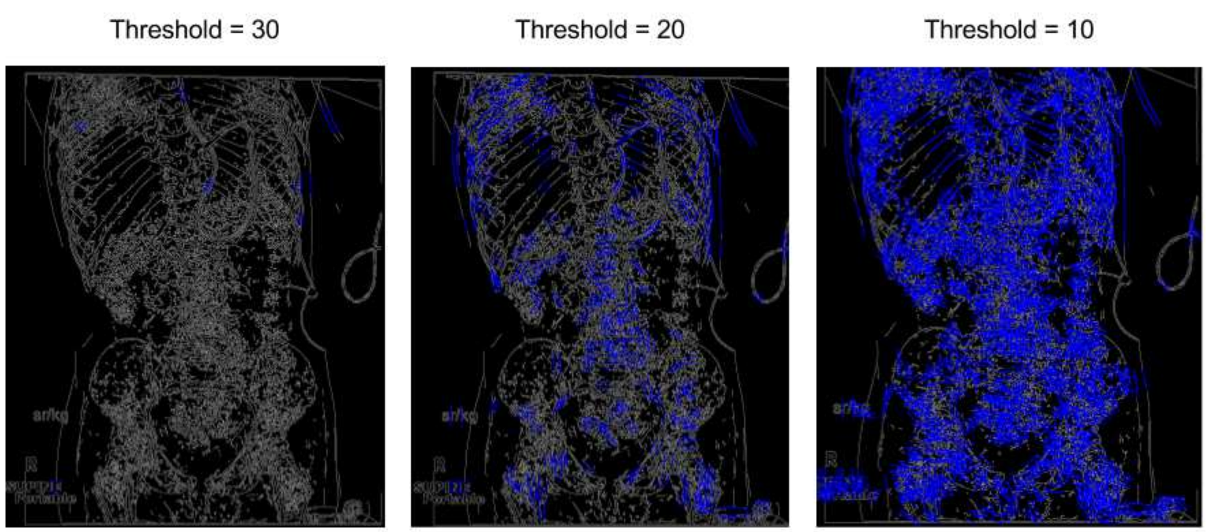

Figure 10 – Global thresholds for windowed parallel Hough transform

The use of the global threshold with the windowed parallel Hough can alter the results significantly as Figure 10 shows. A global threshold of 30 sets the bar so high that only a few, well defined lines are marked. A global threshold of 10 sets the bar so low that, once again, many weak line candidates qualify and false-positives abound. A threshold of 20 seems to be a good middle-ground, but it is still setting the threshold for linearity high enough that many small, parallel line-segments are not being identified as we would like.

We have developed a simple way to combine the best characteristics of the high and low threshold for the windowed parallel Hough. We accomplish this by running the Hough transform successively at decreasing threshold levels (e.g. 30, 20, 10).

While running these Hough transforms, we keep track of the most frequently occurring distances between the detected parallel line segments. Since the walls of our target tubes are equidistant from each other throughout the entirety of the tube, the distance between those walls should remain constant, whether in long, straight segments or in short, curvy segments. By keeping track of the most commonly occurring distances between parallel line segments detected at the high threshold levels (i.e. the distances between the longest, most prominent parallel lines), we can use that information at the lower threshold levels to reject parallel lines that do match the distances we would expect if they were part of the target tube structures.

By gradually lowering the threshold while retaining information from previous runs, we can detect less prominent lines while reducing the number of false positives. Figure 11 shows the results of the progressive parallel Hough transform, as well as a comparison between the 10-pixel threshold with and without the retained distance information.

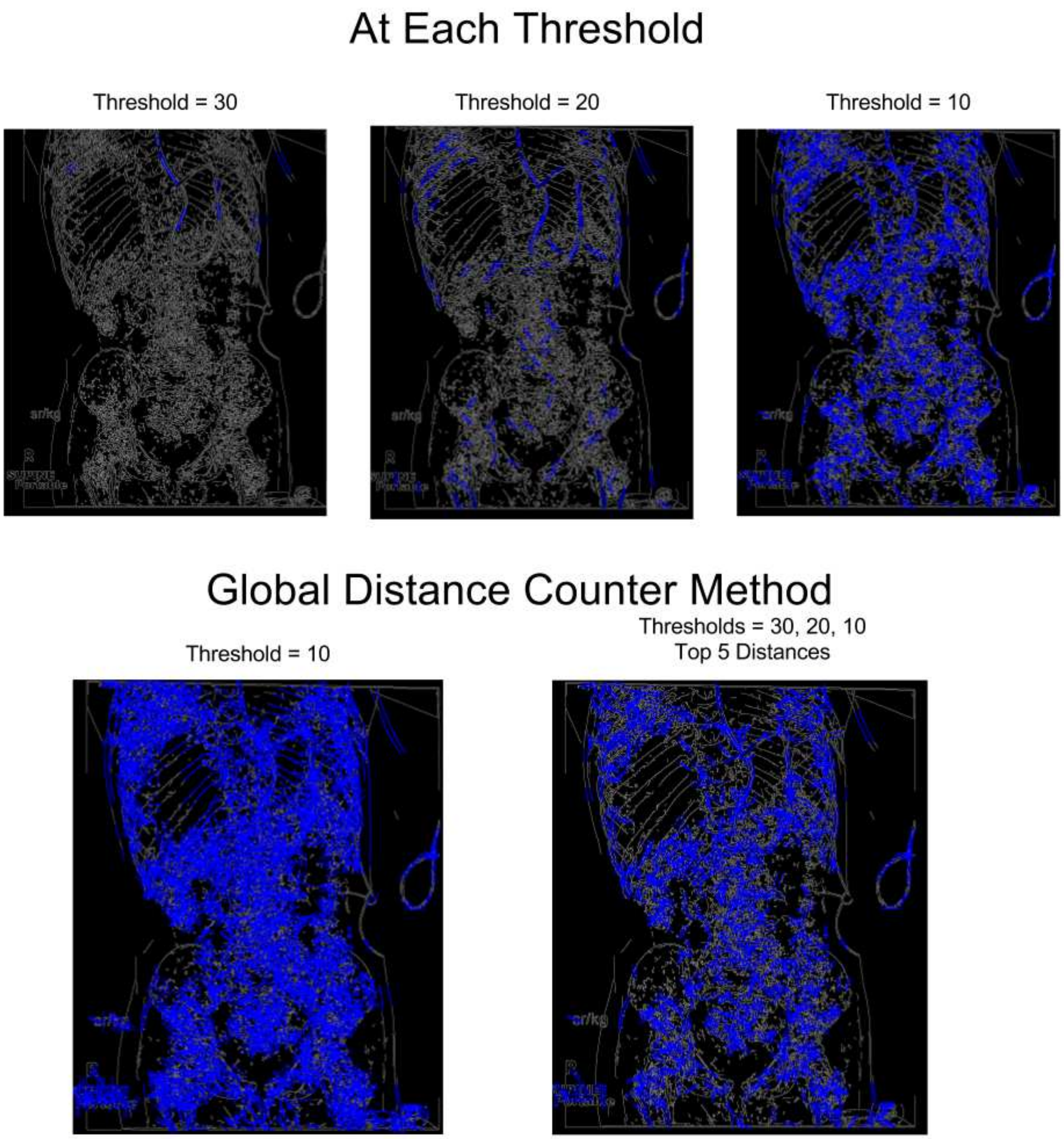

Figure 11 – Progressive parallel Hough results

Clean-Up

The progressive parallel Hough transform identifies all parts of a line candidate, even parts that may have gaps. In other words, a pixel that the Hough transform identifies as a line may be an empty pixel in the original image if that pixel falls on the same line with other pixels. To compensate for the Hough transform's tendency to over-mark, we take the results from our progressive parallel Hough transform and mask over them with the Canny edge detection image. That is, our result set is the intersection of the set of progressive parallel Hough transform results and the set of Canny edge detection results. As Figure 12 shows, the resultant image is much cleaner, and can now be scored for its effectiveness as a tube detector.

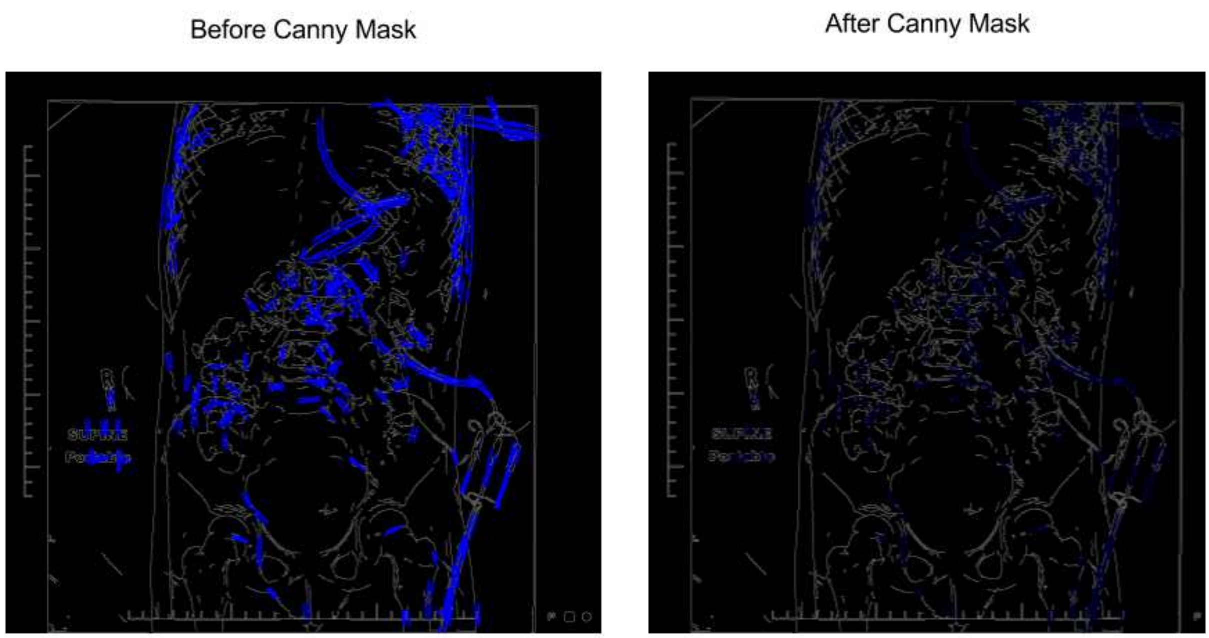

Figure 12 – Canny mask over progressive parallel Hough transform results

CHAPTER 4

EVALUATION

To evaluate our progressive parallel Hough transform results, we measure the predicted output given by the Hough transform against manually marked images like the one shown in Figure 5. In the result images shown below, red indicates a false-negative, blue indicates a false-positive, and magenta indicates a true-positive or "match". We compare the predictive power against that of a Canny edge detector (i.e. predict every edge to be a tube) and a windowed, global threshold Hough transform that does not use our decreasing threshold technique.

Figure 13 shows the output the progressive parallel Hough transform compared with the manually marked images. The stats show average performance over all 16 sample images in the training set.

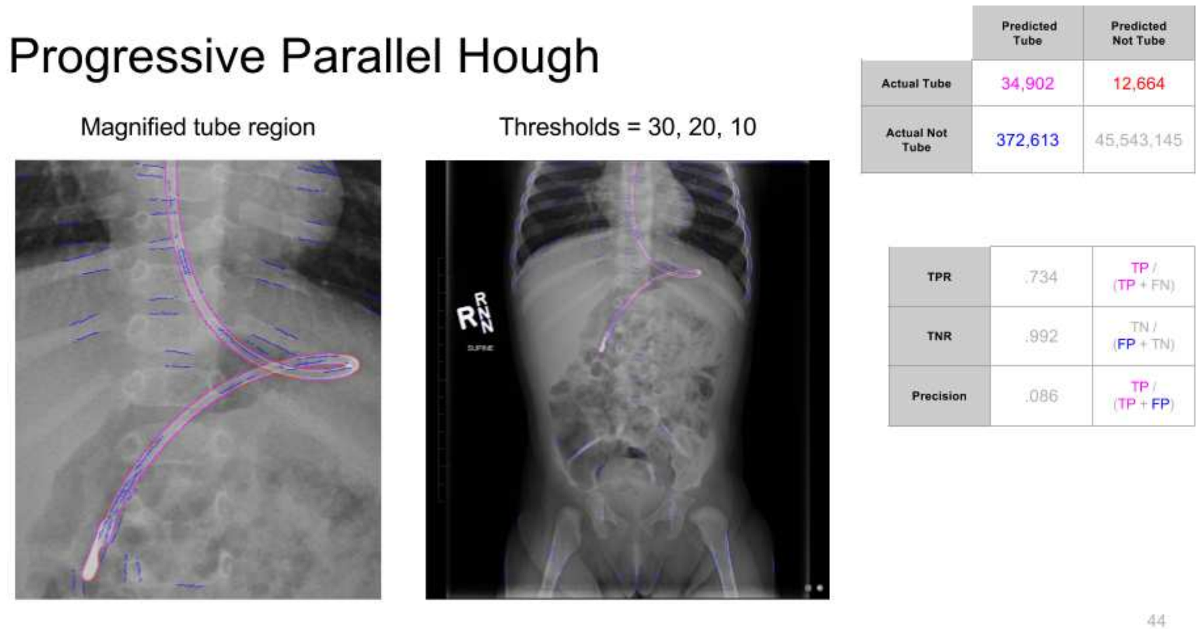

Figure 13 – Progressive parallel Hough evaluation

Table 2 shows the comparative predictive performance of the progressive parallel Hough compared to the simpler methods on which it is based.

Table 2 – Comparison of Predictive Performance

Method	TPR	TNR	PPV
Canny	.873	.964	.022
Windowed Parallel Hough	.906	.979	.042
Progressive Parallel Hough	.734	.992	.086

The progressive parallel Hough transform has a lower true-positive rate than the methodologies upon which it is based. However, its positive predictive value is double that of the windowed parallel Hough and nearly quadruple that of Canny, meaning that is far fewer false positives. Table 3 shows the predictive performance of our method compared to previous approaches.

Table 3 – Comparison to Other Methods

Method	TPR	PPV	Runtime
Progressive Parallel Hough	.734	.086	25 secs
CNN, Mercan and Celebi [2]	.590		
Hough-based Templates, Ramakrishna et al. [3]	.734		
Haar-like Templates, Huo et al. [4]	.910		
Pseudo-random Forests, Bingham [5]	.848		> 5 mins

Based upon the true-positive rate, the progressive parallel Hough performances better than CNN approach used by Mercan and Celebi. It underperforms the other methods shown. The positive predictive rate is unknown for the other methods, so it is difficult to make a direct comparison. Our method has a 10x advantage in performance compared to the Psuedo-random forests method used by Bingham.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

Conclusions

Based on its relatively high precision, we conclude that the progressive parallel Hough transform is an improvement upon the windowed parallel Hough transform. The true-positive rate is lower, but that is partially due way in which the true-positive rate is biased toward predictors that err on the side of positive classification.

We believe the performance of this relatively simple algorithmic approach is on par with the more complex CNN used by Merkan and Celebi, as well as the Pseudo Random Forest technique used by Kendall Bingham. Furthermore, this technique takes an average of only 25 seconds to classify an image.

Also, the progressive parallel Hough transform works completely independent of the orientation and position of the subject in the chest x-ray, and does not require the identification of specific regions-of-interest that might prove difficult to locate in infants as the techniques used by Huo and Ramakrishna do.

Future Work

This progressive parallel Hough transform techniques uses several different parameters for the tuning of the algorithm including window size, window pan size, canny sigma value, starting Hough threshold, and progressive Hough threshold step size. An exhaustive testing of the effects and performance of these various parameters will likely increase performance.

We believe that while the predictive performance gains demonstrated by the progressive parallel Hough transform are modest, the underlying concept can be used in conjunction with other approaches. Specifically, that information gathered from the most easily identifiable tube walls can be used to more intelligently classify those tube-candidates that are not so easily identified.

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VITA

Anthony Shipman was born on October 11, 1986 in Joplin, Missouri. He grew up and attended school in the small town of Diamond, Missouri, graduating from high school in 2005. He graduated Summa Cum Laude with a Bachelor of Arts from Missouri Southern State University specializing in English Literature and Spanish in 2009.

In 2011, Mr. Shipman was enrolled to attend law school but canceled those plans after deciding that his interest in technology and computing had been too long neglected. He began taking computer science classes from the University of Missouri-Kansas City and was accepted into the Master of Science program in 2013. He worked full-time while attending classes part-time.

Mr. Shipman currently works as a Data Engineer for Kansas City area start-up C2FO, specializing in big data processing using Apache Spark. Upon completion of his degree requirements, Mr. Shipman plans to continue his career as a Data Engineer and hopes to use his machine learning and object detection skills in real-time image analysis applications in the future.