Morphology based OCR

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Introduction

OCR has many real-world uses. There are many tasks that can be automated to save money that would normally be used to pay employees to spend hours doing menial tasks. In some cases, companies keep huge amounts of paper-based records. In most cases, the company cannot afford to hire people to digitize the records, or they just can't be bothered to do it because it takes a lot of time and work. By using OCR software, the process can be completed in a fraction of the time with a fraction of the work and cost.

Besides business applications, OCR can be useful to the average person. Sometimes it's just inconvenient to bring a laptop (or other electronic device) along to take notes or keep records. Typing up these things is often not worth it to the user. With OCR software, it can be as easy as just scanning the paper and running a program to get a digital version of your notes.

Development

Currently, morphological operators are use exclusively for all steps of the process. After thresholding, the image is thinned by passing these matrices, and their 90 degree rotations over the image.

0	0	0
	1	
1	1	1

	0	0
1	1	0
	1	

Fig 1.1

0	0	0
0	1	0
0		

0	0	0
0	1	0
		0

Fig 1.2

If a 3x3 block matches the matrix, the center pixel is set to 0. By iteratively applying this to a binary matrix until convergence, one can thin an image.

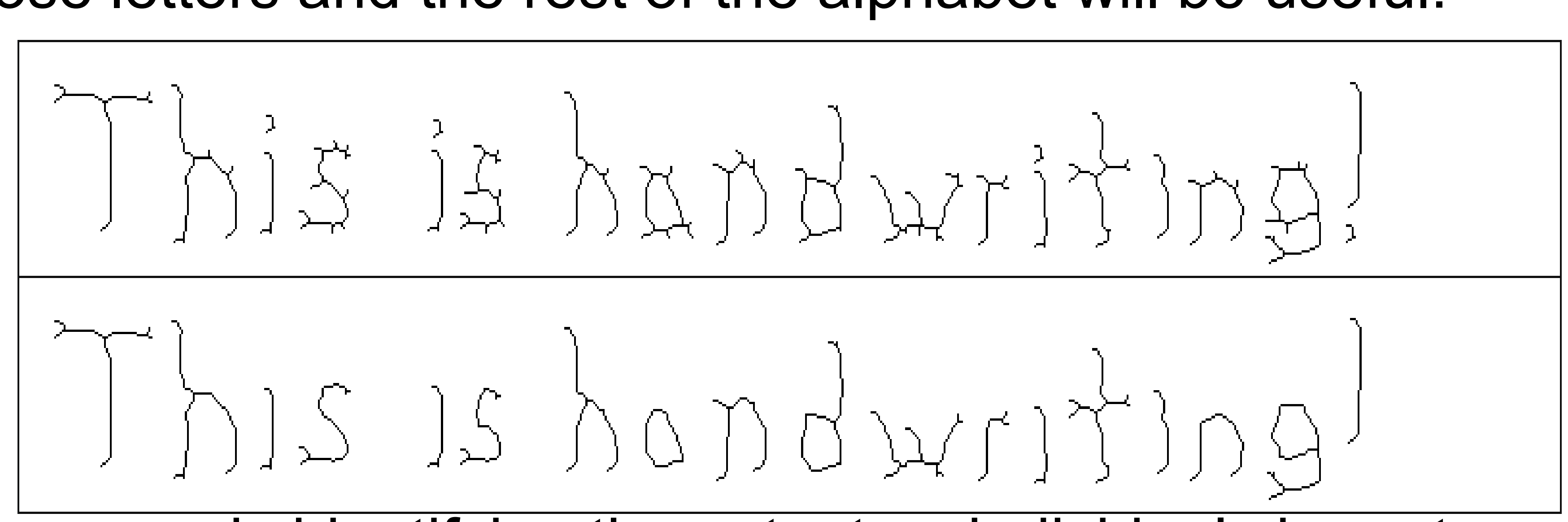
Similar matrices are used for further processing. Simply thinning the image results in a skeleton. While this is only a single pixel wide, the branches and spurs can be very detrimental to image processing. In the figure below, the top sample is before pruning, the bottom is after.

Fig 1.2, output before and after pruning.

The current pruning method consists of several steps, the first of which is a simple prune using the matrices in fig 1.2

After pruning a certain number of iterations, the pruned image is dilated and intersected with the original image.

By doing simple pruning until convergence, only the closed loops in an image remain. This will likely be useful information, as there are a number of letters that contain closed loops, being able to differentiate between those letters and the rest of the alphabet will be useful.



Conclusion

The final step in the process is identifying the output as individual characters. For this, a neural network implementation was used. The training data was obtained by thinning and pruning various handwriting images and identifying the letters by hand. The pool of training data was likely not nearly large enough to successfully train the network. The network consisted of 500 nodes per layer and 2 layers, it produces 26 output which are all either 0 or 1. Due to various issues, the network was never fully trained and its success rate could not be accurately determined. Ideally, after identification, the characters would be reassembled into their words. The resulting words would then be compared with a dictionary to further increase the accuracy of the recognition. Characters that were marked as multiple letters or as no letter could be fixed by finding the word in a dictionary and filling in the blanks.