Intelligent Pen: A Least-Cost Search for Tracing of Handwriting

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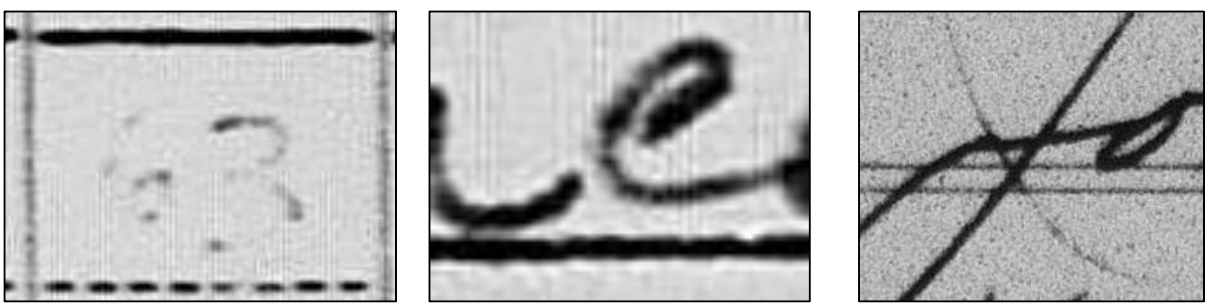
Introduction and Previous Work:

One key problem in processing historical images is properly segmenting the image into words and extracting the relevant stroke information from the handwriting. By their nature, historical documents pose many challenges for stroke extraction, a few of which are illustrated in Figure 1. These challenges include faint strokes (1a), strokes with gaps (1b), and form lines and ascenders and descenders (1e).



1a) A very faint piece of handwriting

1b) A stroke with a gap

1c) Form lines and a descender

Current methods for stroke extraction tend to rely heavily on a medial axis transform or some other method of thinning or "skeletonizing" the handwriting[1-4]. Such methods work well for high-contrast or binary images such as digitally captured signatures or other documents that are "born digital", but perform poorly on historical documents due to the conditions described above.

After obtaining a skeleton of the handwriting, most stroke extraction algorithms either use local heuristics such as the gradient to follow the handwriting, or else they convert the skeleton to a graph and use a globally optimal search algorithm [5]. Rather than rely on local heuristics we decided to also use a search algorithm, but rather than operating on a skeleton of the handwriting we decided to operate directly on the grayscale document image. Previous work done by Barrett et al. on an algorithm called Intelligent Scissors has shown that applying a least-cost path search to an image can produce highly accurate and useful results in image segmentation, so we decided to adapt this concept for handwriting extraction, which led to the creation of Intelligent Pen.

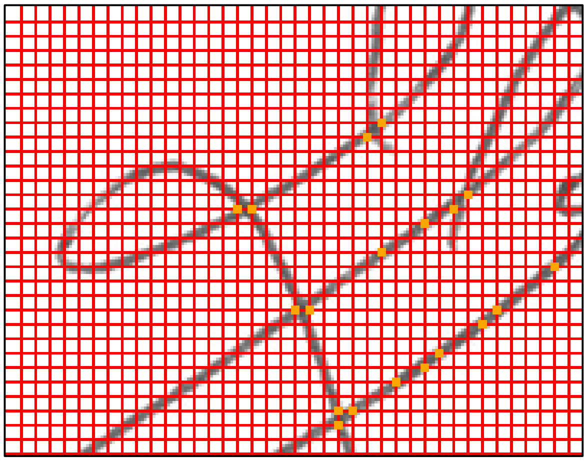
Methods:

Intelligent Pen performs a minimum cost path search using a cost function that is tuned for the domain of historical document processing. The goal is to produce an equation for which the minimum cost path is the one that passes through the handwriting, ignoring noise and properly following the original path of the author's pen, even in the presence of gaps and low-contrast segments. At this point the primary feature in determining a pixel's cost is the pixel's intensity, though we plan to eventually incorporate other features such as stroke width, stroke direction, and proximity to the edge of the form.

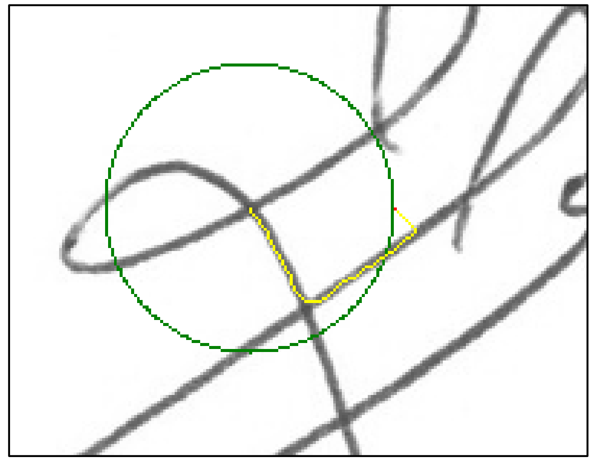
Having obtained the cost function the Intelligent Pen algorithm is as follows:

1) Identify dark regions on the image as potential start points.
2) Perform a least cost search for paths from a start point S to several points on a circle centered at S.
3) Save any points appearing on two or more of the paths from Step 2 as "consensus paths".
4) Use the consensus paths from Step 3 to generate new start points.
5) Repeat Steps 2-4 until no new start points are found

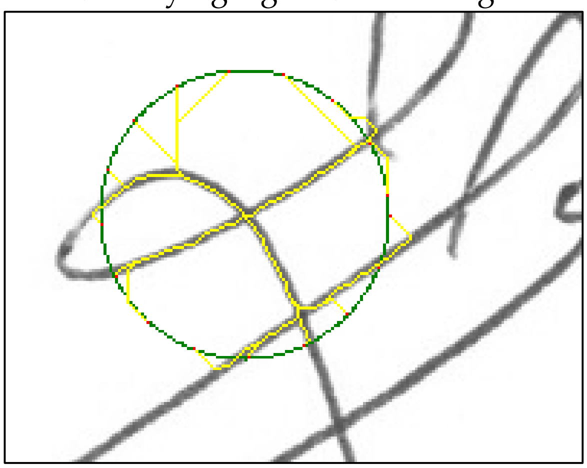
Figure 3 has visualizations of each of these steps. Figure 3a shows how starting points are identified by overlaying a grid on the image and selecting the vertices with the darkest surrounding pixels. Figures 3b, and 3c show how the shortest path is found for several "free points" evenly spaced around a circle centered at a start point S. Finally, in Figure 3d any points appearing on two or more paths from S to a free point are saved as consensus paths. The endpoints of these consensus paths are then saved as new start points, and the algorithm repeats itself until no new start points are found.



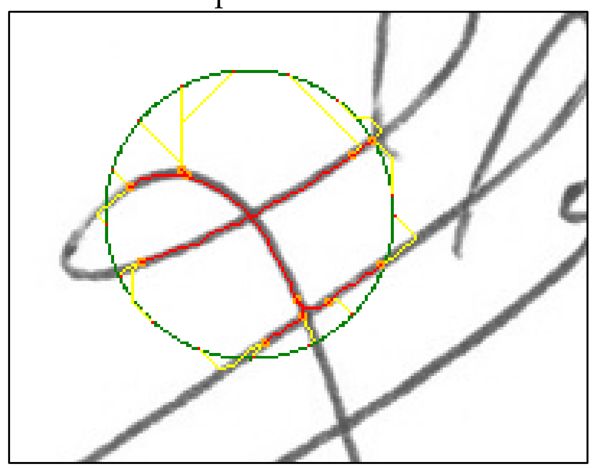
3a) Initial start points are found by overlaying a grid on the image



3b) The shortest path from a start point to a free point on the circle



3c) The shortest path is found for several evenly spaced free points on the circle



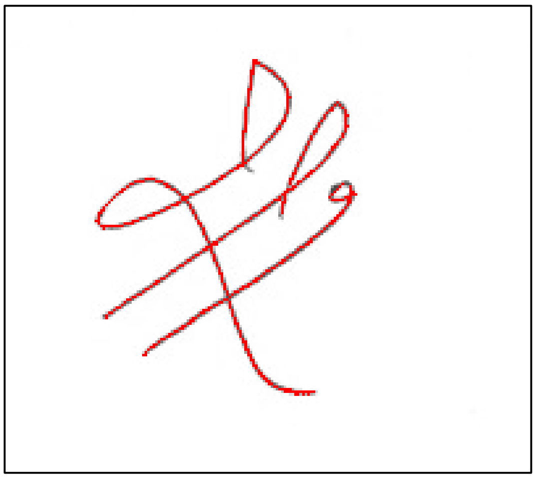
3d) Points on multiple shortest paths are saved as consensus paths (shown in red)

Project Updates:

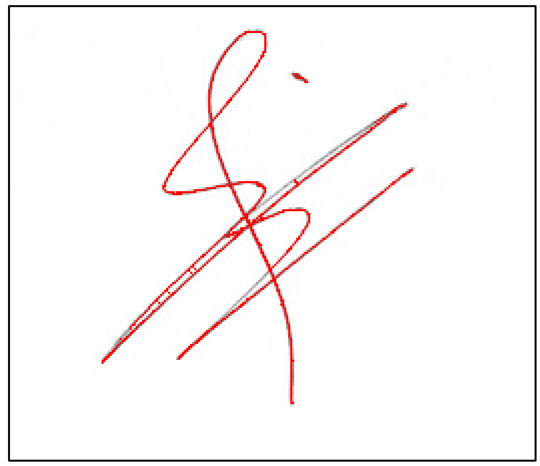
Intelligent Pen was introduced in a paper presented at last year's family history technology workshop. At the time only the base least-cost-path algorithm had been implemented. Since that time the radial search to obtain consensus paths has been implemented. Additionally, Intelligent Pen now uses an initially non-linear cost for pixel intensity. The costs for each pixel intensity are stored in a cost map that is initially i^n for some exponent n. However, as the radial search is repeated this cost map is updated for each start point, lowering the cost for commonly occurring pixel intensities. This allows Intelligent Pen to train itself to favor pen strokes of similar intensities to those already found.

Results:

Figures 4 and 5 show some of the latest results of using Intelligent Pen. Figures 4a and 4b show Intelligent Pen's output for two images from an ICDAR competition on offline stroke recovery. The eventual goal is for these images, because they are paired with ground truth, to validate Intelligent Pen's accuracy.



4a) A clean signature from the ICDAR dataset. Intelligent Pen's output is shown in red on top of the original



4b) Intelligent Pen can recover from gaps and low-contrast strokes where traditional skeletonization would not

Additionally, we have obtained a set of handwritten name images from FamilySearch, an example of which is shown in Figure 5. These images are noisy and in some cases heavily degraded. By applying Intelligent Pen as a pre-processing step for stroke extraction we hope to improve the performance of OCR engines for images such as these.

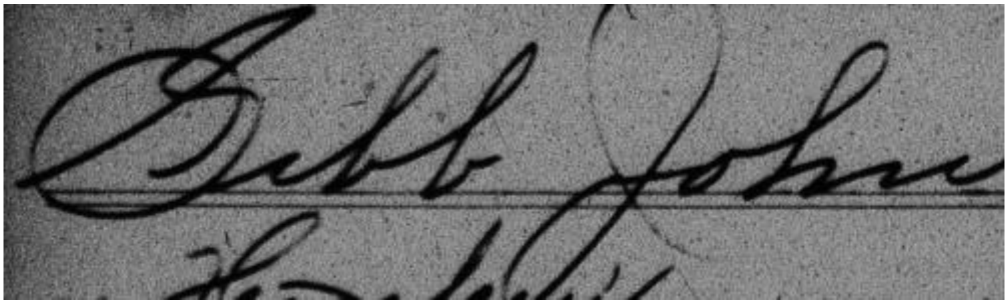


Figure 5a: A cursive signature obtained from FamilySearch

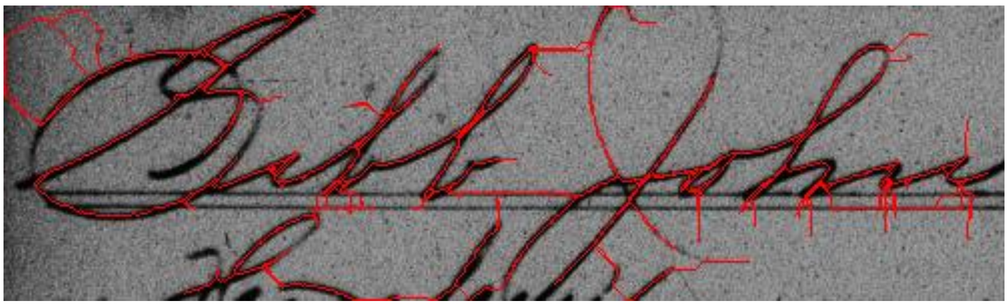


Figure 5b: Intelligent Pen is currently able to recover most of the signature, including some low-contrast areas and gaps in the handwriting, though with a few false positives

Conclusion:

Intelligent Pen is a new approach to stroke extraction that departs significantly from existing skeletonization methods. Because its search function is based on consensus it is highly robust to the noise and degradation common to historical document images. Additionally, the cost equation for its least-cost pathfinding search is easily extensible, allowing it to adapt to a variety of domains.

Bibliography:

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