Morphological approach of handwritten word skew correction

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Abstract. The correction of handwritten word skew is an arduous task that must be independent of due to style and writing conditions variations. We propose here a morphology-based method to detect and correct handwritten word skew in the treatment of dates written on bank checks. Our aim is to limit the number of parameters and heuristic features necessary for a good skew correction. Our approach is based on the morphological pseudo-convex hull. We will illustrate the accuracy of this new method with real examples of dates handwritten on bank checks.
Keywords: Mathematical morphology, convex hull, handwriting.

1 Introduction

Word treatment and automatic recognition poses a difficult problem. By nature, handwriting is very unsteady in shape and quality of tracing. The fact that research in this domain has been going on for about thirty years evidences that an all-encompassing solution is still to be found.

Handwriting location and recognition stages depend to a large extent on its disposition and more especially on its skew. The extraction of reference lines from a word (superior line, baseline, lower-case letter body line) is paramount for efficient recognition. A lot of words present an unknown arbitrary skew that can generate mistakes in the extraction of these lines and failure of the recognition process. Handwriting skew correction becomes necessary. It is used both in handwritten and printed contexts. [El Yacoubi (1996)] uses it for the determination of lower-case letter bodies whereas [Trupin (1993)] uses it to localize the different lines of a paragraph.

Some authors [Côté (1997)], [Madhvanath (1996)] extract these reference lines without previous skew correction. These approaches are generally applied when words don't suffer any distortion other than rotation and translation. If some letters of a word are not aligned, that means that the skew is not constant; the application of such methods doesn't allow accurate definition of reference lines.

In the particular case of the handwriting skew correction, most works require the use of heuristics-based parameters, which render the generalization of such methods difficult. We will show that it is possible to reduce the number of empirical parameters to allow the definition of an automatic approach that can be independent from handwriting type. Our approach leans on the concept of pseudo-convex hull extracted from morphological tools.

In section 2, we will try to demonstrate that current approaches to word correction are built using heuristic factors that impair the generalization of the correction process for any kind of handwritten word. In section 3, we will show how the morphological pseudo-convex hull can solve our problem. The necessary morphological tools to obtain the pseudo-convex hull will be presented. In section 4, we will demonstrate how the pseudo-convex hull approach can serve to correct the handwritten word skew. We will illustrate the degree of application with real examples of handwritten dates affixed on bank checks, (section 5).

2 State of art of the skew correction of handwritten words

Many works in the literature describe heuristic parameter techniques. For instance, [El Yacoubi (1996)] after hav-

ing detected all possible minima of the baseline, uses the parameter "$d_{max} = 32$" to eliminate the undesirable minima. This stage is repeated with the addition of another factor "$\alpha = 3/5$". Therefore, other minima are eliminated if they are sufficiently near by using factors like height and width between co-ordinates. The filtered minima are aligned by a linear regression method and then filtered by using another factor $= 12$.

In another work, [Côté (1997)] doesn't perform word skew correction to extract reference lines. She uses several heuristic factors to determine word skew in contour projection histograms. [Côté (1997)] explains that the histogram entropy is used as a criterion to grade the skew. Reference lines are defined considering that, ideally, the histogram includes 3 picks. Heuristic factors such as the maximal frequency "f_{max}" and "$0.2 \times f_{max}$" are used. [Côté (1997)] admits that the restrictive aspects of her method reside in the lack of precision of the heuristic factors which impairs the quality of the skew value. We could mention other works such as [Bozinovic (1989)], [Senior (1989)] using vertical projections and empirical factors as well.

Due to the complexity of handwriting, we may admit that the use of empirical factors seems natural. However, this complicates the generalization of skew determination to every kind of handwritten word. [El Yacoubi (1996)]'s approach seemed to us the most promising. Our main aim will be to extract the most interesting minima and avoid eliminating some of them from empirical criteria by using the notion of pseudo-convex hull.

3 Mathematical morphology and Pseudo-convex Hull

The Mathematical Morphology consists in comparing an unknown picture X with a pattern B, perfectly defined in terms of shape, size and grayscale, named *structuring element*. One of the numerous advantages of the Mathematical Morphology resides in the fact that we can implement it with two basic operators, the erosion ϵ and the dilation δ. In the case of binary pictures, the erosion $\epsilon^{\mathbf{B}}(\mathbf{X})$ and the dilation $\delta^{\mathbf{B}}(\mathbf{X})$ are:

$$\epsilon^B(X) = X \ominus \tilde{B} = \cap_{b \in \bar{B}} X_b \quad (1)$$

$$\delta^B(X) = X \oplus \tilde{B} = \cup_{b \in \bar{B}} X_b \quad (2)$$

Many powerful morphological tools [Facon (1996)] [Vincent (1992)] can be deduced from erosion and dilation. We will present here the tools necessary to our explanation: conditional binary dilation and binary reconstruction.

Binary reconstruction of a set X (mask) from Z (marker) consists in conditionally dilating Z until convergence:

$$\rho_X^B(Z) = \lim_{n \to +\infty} \underbrace{\delta_{cX}^B \delta_{cX}^B \ldots \delta_{cX}^B(Z)}_{n} \quad (3)$$

where the conditional dilation $\delta_{cX}^B(Z)$ of Z relatively to X is easily formulated from the dilation $\delta^{\mathbf{B}}(\mathbf{X})$:

$$\delta_{cX}^B(Z) = \delta^B(Z) \cap X \quad (4)$$

The convex hull of any set X corresponds to the smallest convex set containing X. There are several manners [Graham (1983)] [Gonzalez (1987)] to deduce the convex hull . From a morphological point of view, the binary convex hull $(\mathbf{convexe-hull})^{\mathbf{B}}(\mathbf{X})$ of X can be obtained from dilation alone.

Due to the discrete nature of sets, with more than one solution, several convex hulls are expected. In general, the process consists in horizontal (vertical) dilation of the X set in the first stage, and, in the second stage, of vertical (horizontal) reconstruction of this dilated set from X. The structuring elements used are horizontal $Bhor = \{\bullet\ \bullet\ \bullet\}$ and vertical $Bver = \left\{\begin{smallmatrix}\bullet\\ \bullet\\ \bullet\end{smallmatrix}\right\}$.

The convex hull, $(\mathbf{convex-hull})^{\mathbf{B}}(\mathbf{X})$, of any set X can be formulated in the following way:

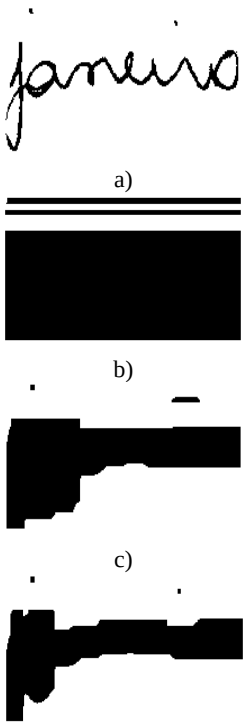
$$(\mathbf{convex-hull})^{\mathbf{B}}(\mathbf{X}) = \rho^{B_2}_{(\delta^{B_1}(X))}(X) \quad (5)$$

where B_1 and B_2 respectively represent $Bhor$ and $Bver$ or vice-versa.

Figure 1-b illustrates the convex hull with 30 dilation iterations and a complete reconstruction. We can easily observe that the convex hull eliminates most minima. By reducing the number of dilation iterations and by carrying out an incomplete reconstruction, we observed that more minima could be preserved. Our idea was therefore to obtain a richer set with more details and minima and, at the same time, to keep this convex hull aspect. We used a hull called *pseudo-convex hull* (indeed this new hull does not verify the convexity properties) that preserves the main minima while smoothing the contours. Figures 1-c and d) show the evolution of the pseudo-convex hull during the decrease in iteration. In a practical way, we chose iterating with 10 dilations and reconstructing with 10 conditional dilation iterations (figure 2).

We extracted the pseudo-convex hull in two different methods, either by horizontal dilation and vertical reconstruction, or by vertical dilation and horizontal reconstruction. It may be noted that, in both cases, the results obtained are similar but not identical. The pseudo-convex hull smoothes word contour in both cases. Minima in the case of the pseudo-convex hull are fewer, but applicable and meaningful (Figures 2-b and c). In the second method, the baseline seems to contain more minima than the first one, but the vertical parts seem less faithful than in the second one. Therefore we decided to achieve the intersection of the two previous results. We got a rich pseudo-convex hull with meaningful horizontal minima and vertical details (Figure 2-d).

Obviously, these results require the number of iterations used in dilation and partial reconstruction. Tests on



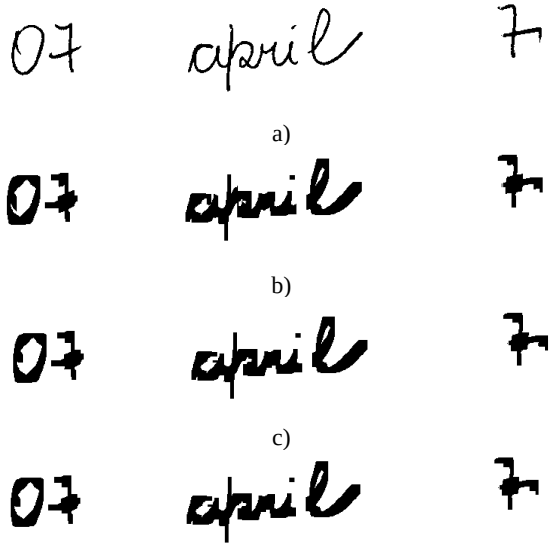
a)

b)

c)

d)

Figure 1: a) Initial image b) Convex hull c) First pseudo-convex hull d) Second pseudo-convex hull



a)

b)

c)

d)

Figure 2: a) Initial image b) First pseudo-convex hull c) Second pseudo-convex hull c) Intersection of the two pseudo-convex hulls

a small data base (about 100 specimens) of handwritten words of varying size and thickness demonstrate that the chosen values led to the obtention of meaningful pseudo-convex hulls for any kind of handwritten word (figures 3, 6, 7, 8).

a)

b)

Figure 3: a) Initial image b) Difference between the pseudo-convex hull and the initial image

4 Proposed method

We illustrated the skew correction method with the example of figure 2-a. The example chosen represents a tilted date *"07 april 7"* where the skew is not constant. The morphological pseudo-convex hull (figure 2-d) allows the creation a new, less complex image which remains faithful to the original word in terms of minima (figure 3-b).

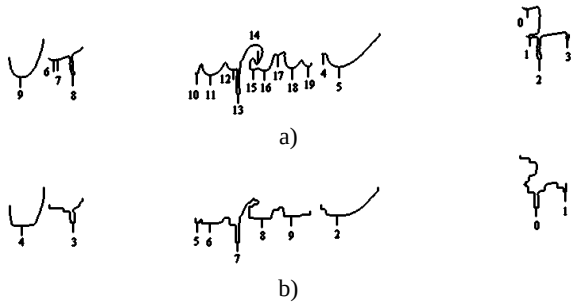
The search for minima is carried out by following the inferior contour from the pseudo-convex hull of every connected component. The algorithm of minima detection proceeds as follows: the detected minima are points corresponding to a transition between a fall and a rise on the inferior contour of the pseudo-convex hull (figure 4).

Because of the regular aspect of the pseudo-convex hull, the detection of minima is very easy. Another advantage is that all the minima are relevant and far away from one another. So we don't need to filter them.

Another advantage of pseudo-convex hull is that numbers usually provide only one minimum ("0" in our example). In case of several minima for a number ("7" in our example), only the lowest minimum is preserved. We verified that our approach extracts a few, but meaningful, minima (figure 4).

These minima are analysed by the Least Square method that allows assessing the skew of connected components. In case useless values appear (noise, words including letters with downstroke etc..), these are filtered and are eliminated from a representative factor that we have dynamically chosen as the (average + standard deviation) on the detected minima.

After the estimation of the best straight line by Least

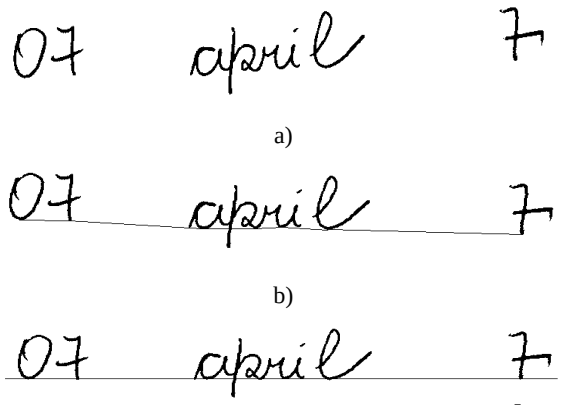


a)

b)

Figure 4: a) Minima from fig 2-a) b) Minima from its pseudo-convex hull

Square method, the skew of every connected component is therefore corrected (figures 5-b, 6-c, 7-c, 8-c). A second correction is performed, evaluating the "vertical skew" of minima from [El Yacoubi (1996)]'s algorithm (figures 5-c, 6-d, 7-d, 8-d).



a)

b)

c)

Figure 5: a) Original image b) First step of skew correction c) Complete skew correction

5 Evaluation of the method

Only two heuristic parameters are used in our approach: dilation and partial reconstruction number. The efficiency of our approach is evidenced by examples of figures 6 and 7.

These examples clearly show that a word can be corrected even in case of important distortions. Of 100 examples, 70 were perfectly processed. In remaining the 30 examples (fig 8), we observed that a bad minimum can influence skew evaluation by the Least Square method. This misevaluation increases with the decrease in the number of detected minima.

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6 Conclusions

In this article we showed that it is possible to limit the number of heuristic parameters in handwritten word skew correction. Our approach, based on the pseudo-convex hull, has demonstrated that some factors could be eliminated. Good results may be obtained in case of important distortions. Only two heuristics parameters are necessary.

Some incorrect skew corrections occur when the number of detected minima is small and when there are significant bad minima. Future works will be tested by the Weighted Least Square method.

Morphological tools have shown all their potentiality and the results obtained with real examples are opening a door toward the possibility of generalizing handwritten word skew correction.

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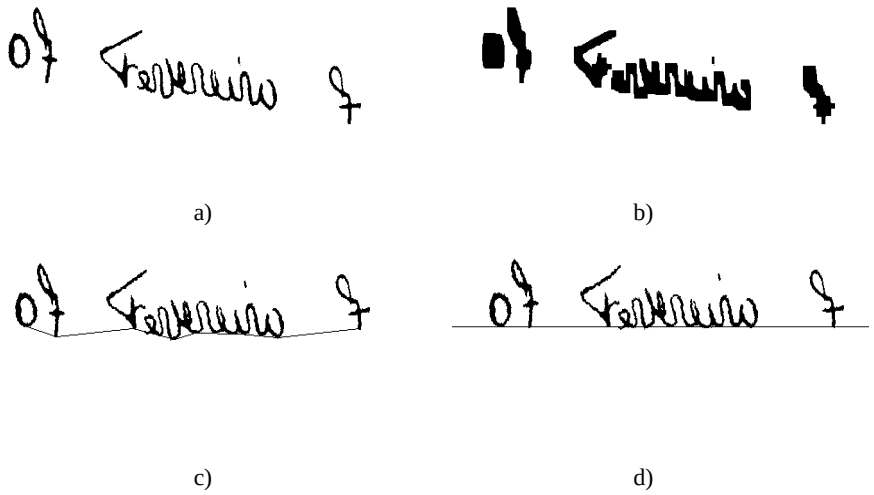

Figure 6: a) Original image b) Pseudo-convex hull c) Minima and first step of skew correction d) Complete skew correction

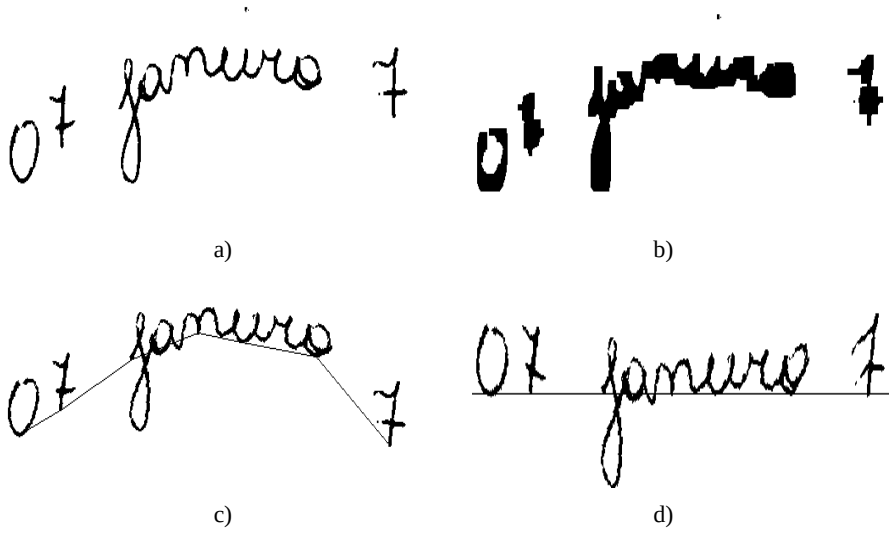

Figure 7: a) Original image b) Pseudo-convex hull c) Minima and first step of skew correction d) Complete skew correction

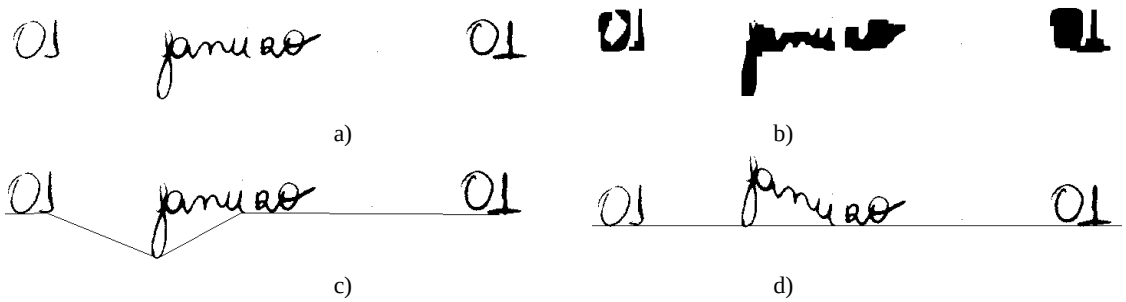

Figure 8: a) Original image b) Pseudo-convex hull c) Minima and first step of skew correction d) Incomplete skew correction

France, sept. 1996.