Estimation of the Handwritten Text Skew Based on Binary Moments

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Abstract. *Binary moments represent one of the methods for the text skew estimation in binary images. It has been used widely for the skew identification of the printed text. However, the handwritten text consists of text objects, which are characterized with different skews. Hence, the method should be adapted for the handwritten text. This is achieved with the image splitting into separate text objects made by the bounding boxes. Obtained text objects represent the isolated binary objects. The application of the moment-based method to each binary object evaluates their local text skews. Due to the accuracy, estimated skew data can be used as an input to the algorithms for the text line segmentation.*

Keywords

Document image processing, text skew, binary moments, text line segmentation.

1. Introduction

Skew angle in the document text image represents the angle of the text deviation from the horizontal or vertical axis. Its estimation is one of the main goals of document image analysis, understanding and processing [1]. Most of the document image applications require a skew identification. It has to be applied before any recognition phase. Hence, this preprocessing step has a specific importance in document image analysis and processing.

Previous work on text skew estimation can be categorized in a few directions [2]:

- Histogram analysis,
- K-nearest neighbor clustering,
- Hough transform,
- Fourier transforms,
- Cross-correlation, and
- Other methods.

Histogram analysis is a simple text skew estimation method, which is used mainly for the binary images. It is based on identifying valleys of the horizontal pixel density histogram [3], [4]. The method is suited for the uniform skew rate, but failed for the multi-skewed text lines. The exception is the small text regions, which are under consideration. In this circumstance, the histogram analysis can be used as an additional sub-method in more complex algorithms for the text segmentation [5].

K-nearest neighbor clustering method [6] assumed that only text is processing. The connected components, which are formed by the nearest neighbors clustering, are the characters only. However, it is mainly limited to Roman languages because of inferior text line segmentation.

Hough transform method relies on the transformation of the straight lines into the Hough domain [7]. It is used widely for the skew estimation of the simplest multi-skewed text [8], [9]. However, it is too specific and computer time consuming.

The Fourier transform method is a representation of the projected profile method in the Fourier domain. The results are mathematically identical, but Fourier transform is only a different approach to the same text and document properties projection profile is based upon [2], [10].

The cross-correlation method calculates both horizontal and vertical projection profiles. Further, it compares the shift of the interline cross-correlation to determine the skew rate. Although this method can handle complex layout documents, it is limited to the small skew rate angles - up to 10°[11].

Most of the proposed methods consider that the document has a unique or similar skew [12]. In contrast, the handwriting text incorporates different inclination. This represents the difficult task to be solved.

One of the other methods for the text skew estimation is based on the moments. The moments are sensitive to the rotation [13]. Hence, this method is suitable for the skew identification. However, the proposed technique is applicable for the single skew estimation, i.e. for the printed text documents only [14-16].

In the paper, the moment-based method for the skew estimation of the handwritten text is proposed. It is achieved by the incorporation of the group segmentation method. This is established by the extraction of the bounding boxes prior to the moment application. This way, the handwritten text is split into separate and isolated connected components suitable for further processing by the binary moments.

The paper organization is as follows: Section 2 presents the basic moment-based algorithm. Section 3 explains the algorithm extension by introducing the bounding box technique. Section 4 describes the experiments. Section 5 gives the results and comments them. Section 6 makes the conclusions.

2. Moment-Based Algorithm

The result of image scanning is a document text image. It represents a digital image given by matrix **D** which consists of M rows, N columns, and L discrete intensity levels of gray, where $L \in \{0, \ldots, 255\}$. During the process of binarization, matrix **D** is converted into binary matrix **B**. It is made with threshold sensitivity value D_{th} obtained from the global binarization method [17], [18]. Currently, document image is represented as binary matrix **B** featuring M rows, N columns, and levels of 0 and 1.

Moment defines the measure of the pixel distribution in the image. Its role is to identify global information of the image concerning contour. Moment of the image function $f(i, j)$ is evaluated as:

$$m_{pq} = \sum_i \sum_j i^p j^q f(i,j) \tag{1}$$

where p and $q = 0, 1, 2, 3, ..., n$, and n represent the order of the moment. From (1) central moments μ_{pq} for discrete image can be calculated as:

$$\mu_{pq} = \sum_i \sum_j (i-\bar{x})^p (j-\bar{y})^q f(i,j) \quad . \tag{2}$$

Accordingly, for the binary image the moments are given as:

$$m_{pq} = \sum_i \sum_j i^p j^q \tag{3}$$

and

$$\mu_{pq} = \sum_i \sum_j (i-\bar{x})^p (j-\bar{y})^q \quad . \tag{4}$$

It defines the measure of the pixel distribution in the image. Hence, some important features can be obtained from the moments. One of them is the object orientation. It is given as θ, which represents the angle between the object and the horizontal axis:

$$\theta = \frac{1}{2}\arctan\left(\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}\right) \quad . \tag{5}$$

All these features characterize an isolated object. This method has been utilized regularly for the printed text skew estimation. In that case, the skew estimation of each text object is similar. However, in handwritten text all objects have variable skew orientation. Hence, to be used it needs some adaptation.

3. Moment-Based Algorithm Extension

Suppose that the handwritten multi-line multi-oriented text is under our consideration. It is shown in Fig. 1.

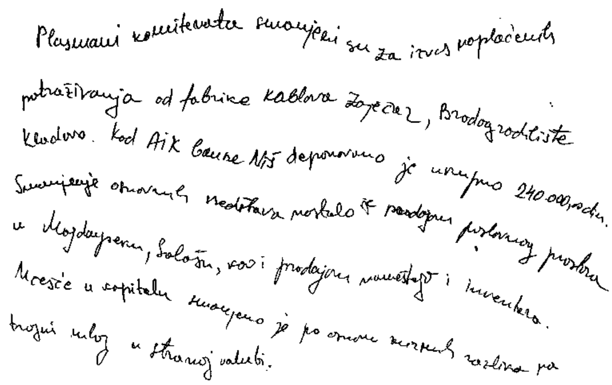


Fig. 1. Handwritten multi-line multi-oriented text.

After the noise reduction stage, the primary task is the extraction of the connected components. It is established by the bounding boxes extraction over connected components. Bounding box represents a rectangular region whose edges are parallel to the coordinate axes. Hence, each pixel $B(i, j)$ that belongs to the bounding box should fulfill the following inequalities [19]:

$$B(i,j) \big| \left(x_{\min} \le i \le x_{\max}\right) \wedge \left(y_{\min} \le j \le y_{\max}\right) \tag{6}$$

where $x_{\min}$, $y_{\min}$, $x_{\max}$, and $y_{\max}$ represent the endpoints of the bounding box. The illustration of the bounding box over text is shown in Fig. 2.

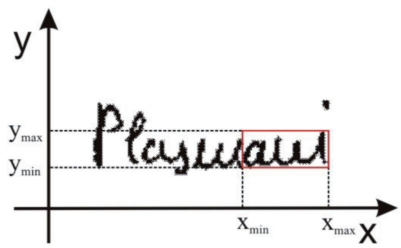


Fig. 2. The bounding box over the text (marked as red rectangle), which represents the connected component.

This way, the excerpt from a multi-line text and its corresponding bounding box extraction is shown in Fig. 3.

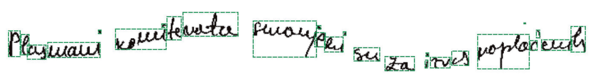
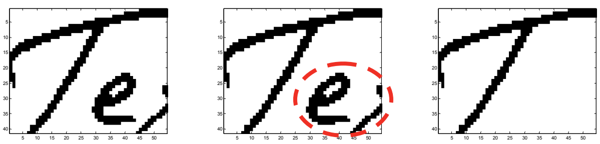


Fig. 3. The bounding box over the single-line text, which is the excerpt from the multi-line text.

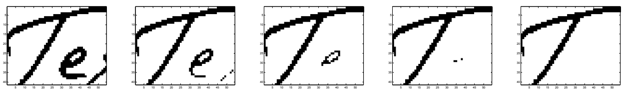
The connected component (CC) contains occasionally the small parts of the external connected components. They are called fragments and represent the noise. This circumstance is illustrated in Fig. 4.



(a) (b) (c)

Fig. 4. CC cleaning: (a) Initial CC including fragments, (b) Fragment marking, and (c) Cleaned CC.

Hence, the connected components are cleaned from the fragments by the extraction of the biggest connected component. This process is performed iteratively. It is illustrated in Fig. 5.



(a) (b) (c) (d) (e)

Fig. 5. CC cleaning procedure: (a) Initial CC, (b) Step 1, (c) Step 2, (d) Step 3, and (c) Step 4 - cleaned CC.

This way, each connected component is extracted, which represents the isolated text object. It is assigned as CC_k, where k = 1, …, m and m is the total number of detected objects. According to (5), the calculation of the angle θ_k for the connected component CC_k is made. Hence, each of the connected components CC_k has been characterized by its correspondent orientation angle θ_k. This circumstance is shown in Fig. 6.

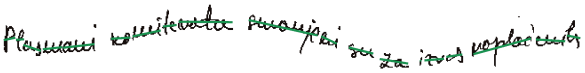


Fig. 6. Skew detection of the connected-component with the moment-based method.

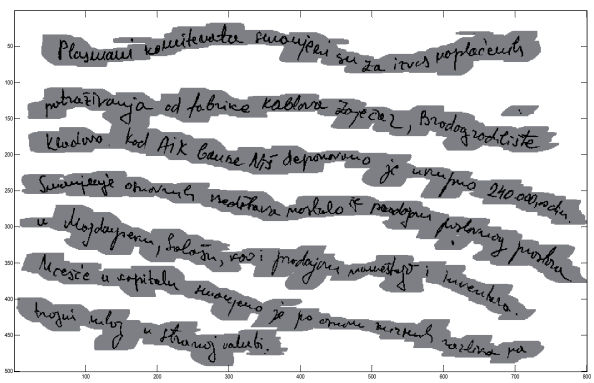


Fig. 7. The application of the text line segmentation algorithm.

In Fig. 6, each green line over connected component CC_k illustrates the orientation angle θ_k. They represent the local text orientation, i.e. skew. Hence, these angles can be the input data to the algorithm for the text line segmentation. As an example of such algorithm, the Gaussian algorithm extended by binary morphology [20] can be used. It can use the orientation given by the local text skew θ_k for improving its text line segmentation efficiency. Its application is shown in Fig. 7.

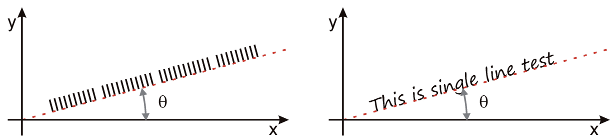
4. Experiments

The primary goal of the experiments is the evaluation of the text skew identification correctness. Hence, it should evaluate the algorithm's performance in the skew tracking domain. Furthermore, it measures the effects of its incorporation into the algorithm for the text line segmentation. The experiment consists of the following tests based on the synthetic and real datasets:

- Test of the single-line printed text,
- Test of the connected components, and
- Test of the multi-line handwritten text, and
- Test of the text line segmentation.

4.1 Test of the Single-Line Printed Text

The single-line test is based primarily on the printed text. However, it is a good prerequisite for testing handwritten text [21]. In this test, a sample printed text is rotated for the angle θ from 0° to 85° in the steps of 5° around x-axis. Two text samples are used, as shown in Fig. 8.



(a) (b)

Fig. 8. Sample text rotated up to 85° in 5° steps: (a) Text sample 1, and (b) Text sample 2.

Furthermore, the results are evaluated by the absolute deviation, i.e. error. It is defined as:

$$\Delta\theta = \left|\theta_{REF} - \theta_M\right| \tag{7}$$

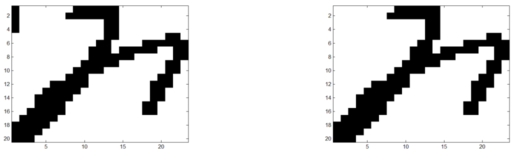
where θ_{REF} is the skew of the input text sample (referent skew), while θ_M represent the estimated skew of the text sample obtained from the moment-based method. For the sake of algorithm conformity and robustness the results for both text samples in the resolution of 150 and 300 dpi are compared as well.

4.2 Test of the Connected Components

Test of the connected components is based on a few handwritten text images. Accordingly, the moment-based method is applied to the extracted connected components. However, two types of connected components exist:

- with additional fragments (without cleaning), and
- without additional fragments (with cleaning).

This case is illustrated in Fig. 9.



(a) (b)

Fig. 9. An example of the connected components cleaning effect: (a) unclean CC, (b) clean CC.

The results from both circumstances are compared according to the absolute deviation.

4.3 Test of the Multi-Line Handwritten Text

Multi-line test exploits the handwritten text images. Firstly, the handwritten text sample is separated into connected components by the bounding box extraction. Furthermore, each connected component CC_k is subjected to the moment-based method. The skew estimation is characterized by the angle θ_k for each CC_k. To demonstrate the method robustness, the handwritten text is given in the resolution of 150 and 300 dpi. The obtained results are compared by the absolute deviation, i.e. error.

4.4 Test of the Text Line Segmentation

The main role of the testing process for the text line segmentation algorithm is the efficiency evaluation as well as the parameter optimization. As an example, the anisotropic Gaussian algorithm with its oriented extension based on binary moments is tested. Algorithm's parameters of interest are those that define the Gaussian kernel size ($2P$+1 x $2R$+1), i.e., P and $R = \lambda * P$, in y and x direction as well as the kernel's orientation angle θ. For the algorithm based on simple anisotropic Gaussian kernel $\theta = 0°$, while for the oriented one $\theta = \theta_k$. Handwritten text samples from our database consist of 220 lines of text. It includes the letters with a height of about 50 pixels. According to that P should be chosen from 10% to 20% of the letter height [22].

5. Results and Discussion

The experiment results give the angle of the text orientation θ_M obtained by the moment-based method. These results are compared to the initial i.e. referent text skew angle θ_{REF}. The results are evaluated with the absolute deviation given in (7). It represents the measure for the evaluation of the method efficiency for the text skew estimation.

5.1 Test of the Single-Line Printed Text

The experimental results contain the text skew estimation for text sample 1 and 2 (300 dpi resolution) obtained by the moment-based method (θ_M) and widely used vertical projection method (θ_{VPP}) (see Tab. 3 and 4 in Appendix for the reference). Their comparison is shown in Fig. 10 and 11, respectively.

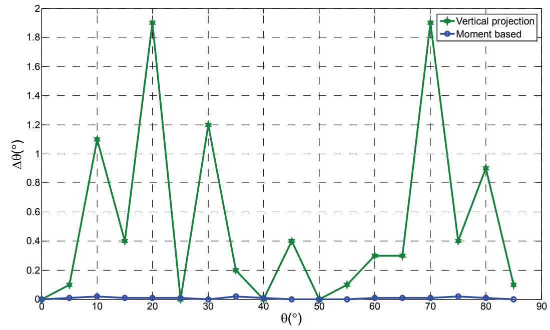


Fig. 10. Skew estimation of the text sample 1: moment-based method vs. vertical projection method.

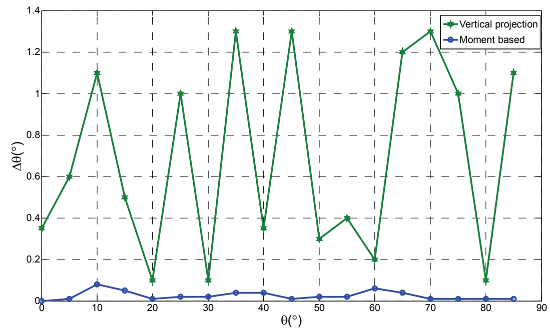


Fig. 11. Skew estimation of the text sample 2: moment-based method vs. vertical projection method.

The average absolute deviation of the moment-based method is 0.01 and 0.03, respectively. Furthermore, the average absolute deviation of the vertical projection method is 0.52 and 0.68, respectively. It is obvious that moment-based method gives considerably lower values of the absolute deviation than vertical projection method. Hence, the moment-based method gives more correct results.

Further, the skew estimation of the moment-based method for the image in different resolutions, i.e. 150 and 300 dpi, is compared. The obtained results for text sample 1 and 2 are shown in Fig. 12 and 13, respectively (see Tab. 5 and 6 in Appendix for the reference).

The results for the text sample 1 and 2 given in the resolution of 150 and 300 dpi are very similar. However, the obtained results deviate slightly more for text sample 2 than for text sample 1. This is a consequence of descender and ascender element incorporated in the text sample 2. However, all above results mean that the method implicates robustness.

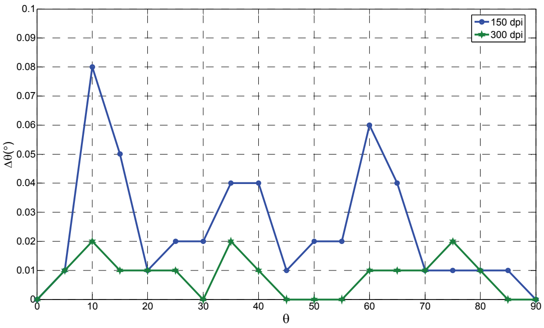


Fig. 12. Moment-based skew estimation for the text sample 1 (150 and 300 dpi).

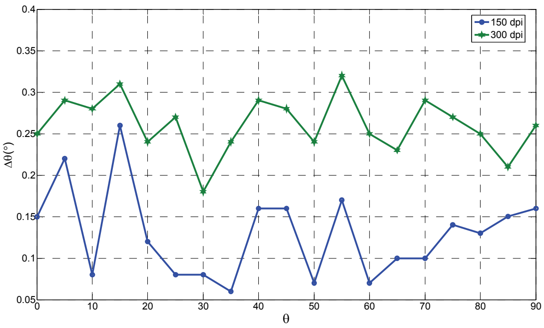
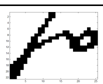
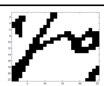
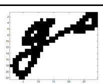
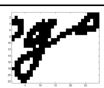
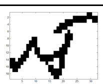
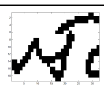
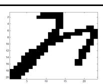
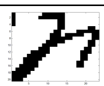


Fig. 13. Moment-based skew estimation for the text sample 2 (150 and 300 dpi).

5.2 Test of the Connected Components

The process of the bounding box cleaning has a great impact on the skew angle estimation. According to (5) for Fig. 9 (a) and (b), it gives the skew angle θ equal to 36.30° and 15.41°, respectively. This represents the deviation angle $\Delta\theta$ of 20.89°. The previous example is an extreme illustration. From the obtained results, the moment-based method is pretty the same in around 80% of the connected component samples (with and without cleaning process). Hence, the mismatch of the skew estimation with and without bounding box cleaning is present in the remained 20% cases. This is empirical data confirmed by the experiments. These mismatch results are in the range from 0.56° to 44.89°. However, they are mostly lower than 15°. As an illustration, a few examples are given in Tab. 1.

CC with clearing		CC without cleaning		
	θ_M (°)'		θ_M (°)	$\Delta\theta$ (°)
	32.9935		-11.8996	44.8931
	32.9040		26.3817	6.5223
	25.8633		13.2525	12.6108
	36.3097		15.4110	20.8987

Tab. 1. Partial results from the test of the connected components.

Obviously, the process of the bounding box cleaning is an indispensable for this skew estimation method. Hence, it should not be omitted.

5.3 Test of the Multi-Line Handwritten Text

In the multi-line handwritten text experiment, all text elements, which represent connected components CC_k, are extracted as separated objects (k = 1, …, 54). Furthermore, the moment-based method is applied to each of them. Text sample is given in the resolution of 150 and 300 dpi. Fig. 14 shows both results as well as its absolute deviation (see Tab. 7 in Appendix for the reference).

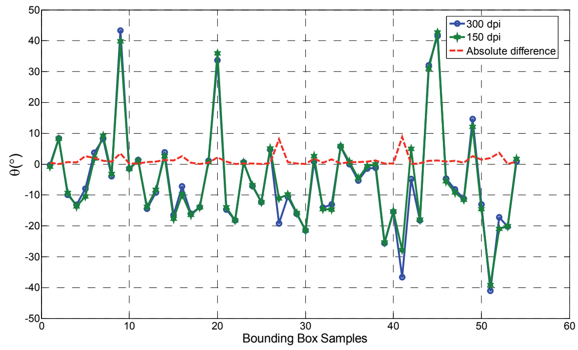


Fig. 14. Moment-based skew estimation for the handwritten text sample (150 and 300 dpi) with the absolute deviation.

Although some results are different, the absolute deviation is relatively small (in degrees). From [23], inputting the orientation data of only $\theta_{REF}/2$ is good enough for the improved effectiveness of the algorithm for the text line segmentation. Hence, the obtained results deviation between text resolution in 150 and 300 dpi is almost irrelevant for further processing. This way, the moment-based method proved its robustness.

However, the presented method can be improved as well. The "extreme" ascender and descender element, which are included in connected components, represents the problem, i.e. weak point. Hence, the process of their extraction or neutralization from the connected components should be crucial in further investigation.

5.4 Test of the Text Line Segmentation

Results from the test of the text line segmentation are evaluated with the typical measures: *precision*, *recall* and *f-measure*. They are given in Tab. 2 where R_i and P_i are the kernel size parameters, i = 1, 2 is the number of cases with the best result and θ_k is the moment estimated skew angle for each connected component CC_k.

θ_{REF} (°)	*R1, P1,* $\theta = 0°$	*R1, P1,* $\theta = \theta_k$	*R2,P2,* $\theta = 0°$	*R2, P2,* $\theta = \theta_k$
precision	50.00%	51.72%	77.78%	84.62%
recall	73.68%	78.95%	77.78%	75.86%
f-measure	59.57%	62.50%	77.78%	80.00%

Tab. 2. *Precision*, *recall* and *f-measure*.

The results show the growth of the *f-measure* after the incorporation of the text orientation θ_k in the algorithm for the text line segmentation based on the anisotropic Gaussian kernel. The improvement margin of the *f-measure* is about 2.5%. This result seems to be modest value. However, the research direction for the improvement of the Gaussian kernel based algorithm by the incorporation of the skew orientation is the correct one. Still, it needs additional fine adjustment. Further adaptation should be made by neutralizing or eliminating the ascender and descender elements in connected components or using the parameter $\theta_k/2$ as suggested in [23].

6. Conclusions

This paper introduces the extension to the moment-based method for the text skew estimation. Firstly, it gives the basic method annotated in the literature. However, it is exploited mostly in the printed text. To be used for the handwritten text, some adaptation should be made. Hence, the paper describes an extension of the moment-based method with the introduction of bounding boxes. The bounding boxes contribute to the extraction of the connected components, which represent the isolated binary text objects. The application of the moment-based method to the connected components estimates their local text skew. The evaluation of the method effectiveness is based on the experiments with printed and handwritten text samples in different resolutions. Experimental results proved the accuracy of the proposed method as well as its robustness. Due to that, obtained data should be the input to the algorithm for the text line segmentation.

Appendix

Tables referencing obtained results are given below.

θ_{REF} (°)	θ_{VPP} (°)	$\Delta\theta_{VPP}$ (°)	θ_M (°)	$\Delta\theta_M$ (°)
0.00	0.00	0.00	0.0000	0.0000
5.00	5.10	0.10	4.9942	0.0058
10.00	11.10	1.10	9.9781	0.0219
15.00	15.40	0.40	14.9902	0.0098
20.00	21.90	1.90	19.9948	0.0052
25.00	25.00	0.00	24.9896	0.0104
30.00	31.20	1.20	30.0040	0.0040
35.00	34.80	0.20	35.0191	0.0191
40.00	40.00	0.00	40.0089	0.0089
45.00	45.40	0.40	45.0030	0.0030
50.00	50.00	0.00	49.9986	0.0014
55.00	55.10	0.10	54.9982	0.0018
60.00	59.70	0.30	59.9868	0.0132
65.00	64.70	0.30	64.9887	0.0113
70.00	68.10	1.90	70.0137	0.0137
75.00	74.60	0.40	75.0188	0.0188
80.00	79.10	0.90	80.0077	0.0077
85.00	85.10	0.10	84.9996	0.0004

Tab. 3. Skew estimation of the text sample 1 given by moment-based method (θ_M) and vertical projection method (θ_{VPP}).

θ_{REF} (°)	θ_{VPP} (°)	$\Delta\theta_{VPP}$ (°)	θ_M (°)	$\Delta\theta_M$ (°)
0.00	0.35	0.35	0.2533	0.2533
5.00	5.6	0.60	5.2876	0.2876
10.00	11.1	1.10	10.2794	0.2794
15.00	15.5	0.50	15.3090	0.3090
20.00	20.1	0.10	20.2447	0.2447
25.00	26	1.00	25.2679	0.2679
30.00	30.1	0.10	30.1823	0.1823
35.00	36.3	1.30	35.2369	0.2369
40.00	40.35	0.35	40.2908	0.2908
45.00	46.3	1.30	45.2785	0.2785
50.00	50.3	0.30	50.2435	0.2435
55.00	55.4	0.40	55.3159	0.3159
60.00	60.2	0.20	60.2517	0.2517
65.00	66.2	1.20	65.2302	0.2302
70.00	71.3	1.30	70.2874	0.2874
75.00	76	1.00	75.2682	0.2682
80.00	80.1	0.10	80.2476	0.2476
85.00	86.1	1.10	85.2113	0.2113

Tab. 4. Skew estimation of the text sample 2 given by moment-based method (θ_M) and vertical projection method (θ_{VPP}).

	150 dpi		**300 dpi**	
θ_{REF} (°)	θ_M (°)	$\Delta\theta$ (°)	θ_M (°)	$\Delta\theta$ (°)
0.00	0.0012	0.0012	0.0000	0.0000
5.00	4.9932	0.0068	4.9942	0.0058
10.00	9.9196	0.0804	9.9781	0.0219
15.00	15.0457	0.0457	14.9902	0.0098
20.00	19.9928	0.0072	19.9948	0.0052
25.00	25.0198	0.0198	24.9896	0.0104
30.00	29.9751	0.0249	30.0040	0.0040
35.00	35.0434	0.0434	35.0191	0.0191
40.00	40.0412	0.0412	40.0089	0.0089
45.00	44.9893	0.0107	45.0030	0.0030
50.00	49.9796	0.0204	49.9986	0.0014
55.00	54.9772	0.0228	54.9982	0.0018
60.00	59.9359	0.0641	59.9868	0.0132
65.00	64.9593	0.0407	64.9887	0.0113
70.00	70.0125	0.0125	70.0137	0.0137
75.00	75.0067	0.0067	75.0188	0.0188
80.00	79.9889	0.0111	80.0077	0.0077
85.00	84.9860	0.0140	84.9996	0.0004

Tab. 5. Skew estimation of the text sample 1 (150 and 300 dpi resolution) given by moment-based method (θ_M).

	150 dpi		**300 dpi**	
θ_{REF} (°)	θ_M (°)	$\Delta\theta$ (°)	θ_M (°)	$\Delta\theta$ (°)
0.00	0.1498	0.1498	0.2533	0.2533
5.00	5.2163	0.2163	5.2876	0.2876
10.00	10.0751	0.0751	10.2794	0.2794
15.00	15.2592	0.2592	15.3090	0.3090
20.00	20.1154	0.1154	20.2447	0.2447
25.00	25.0766	0.0766	25.2679	0.2679
30.00	29.9191	0.0809	30.1823	0.1823
35.00	35.0574	0.0574	35.2369	0.2369
40.00	40.1647	0.1647	40.2908	0.2908
45.00	45.1620	0.1620	45.2785	0.2785
50.00	50.0696	0.0696	50.2435	0.2435
55.00	55.1655	0.1655	55.3159	0.3159
60.00	60.0728	0.0728	60.2517	0.2517
65.00	65.0975	0.0975	65.2302	0.2302
70.00	70.0990	0.0990	70.2874	0.2874
75.00	75.1367	0.1367	75.2682	0.2682
80.00	80.1339	0.1339	80.2476	0.2476
85.00	85.1545	0.1545	85.2113	0.2113

Tab. 6. Skew estimation of the text sample 2 (150 and 300 dpi resolution) given by moment-based method (θ_M).

CC_k	θ_M (°)	θ_M' (°)	$\Delta\theta$ (°)
	300 dpi	150 dpi	
1	-0.2931	-0.7841	0.4910
2	8.3636	8.2452	0.1184
3	-10.0030	-9.2785	0.7245
4	-13.1869	-13.7610	0.5741
5	-7.9123	-10.4374	2.5251
6	3.7376	1.8451	1.8925
7	8.2105	9.2242	1.0137
8	-3.9672	-3.1927	0.7745
9	43.2351	39.7430	3.4921
10	-1.4137	-1.5527	0.1390
11	1.2642	1.0220	0.2422
12	-14.5264	-13.7898	0.7366
13	-9.1658	-8.3898	0.7760
14	3.8406	2.5357	1.3049
15	-16.5084	-17.6881	1.1797
16	-7.2189	-9.8303	2.6114
17	-16.1442	-16.5413	0.3971
18	-13.9225	-13.9730	0.0505
19	1.1189	0.6392	0.4797
20	33.7003	35.8752	2.1749
21	-14.7708	-13.9902	0.7806
22	-18.2126	-18.2729	0.0603
23	0.5735	0.4148	0.1587
24	-7.0365	-6.8277	0.2088
25	-12.3287	-12.3324	0.0037
26	4.7056	5.0723	0.3667
27	-19.1778	-11.0622	8.1156
28	-10.5681	-9.8558	0.7123
29	-16.0563	-15.8941	0.1622
30	-21.5518	-21.5406	0.0112
31	0.8346	2.6106	1.7760
32	-14.1151	-14.5384	0.4233
33	-13.1567	-14.6914	1.5347
34	5.6768	5.8534	0.1766
35	0	0.6507	0.6507
36	-5.3446	-4.6351	0.7095
37	-1.4581	-0.6651	0.7930
38	-1.1927	0	1.1927
39	-25.5818	-25.4139	0.1679
40	-15.5169	-15.3834	0.1335
41	-36.6617	-27.8818	8.7799
42	-4.8754	4.9031	0.0277
43	-18.2533	-17.9216	0.3317
44	31.9795	30.9170	1.0625
45	41.5107	42.7306	1.2199
46	-4.7492	-5.5947	0.8455
47	-8.1551	-9.2232	1.0681
48	-11.2048	-11.6007	0.3959
49	14.6433	12.1108	2.5325
50	-13.0642	-14.5557	1.4915
51	-41.0772	-39.1552	1.9220
52	-17.2077	-20.9634	3.7557
53	-20.2151	-20.1153	0.0998
54	0.8590	1.6417	0.7827

Tab. 7. Excerpt from multi-line handwritten text results.

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