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An Improved Method for Handwritten Document Analysis using Segmentation, Baseline Recognition and Writing Pressure Detection

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Abstract

Handwritten document analysis is a scientific technique for identifying and understanding the personality of a writer through the strokes and patterns revealed by writer's handwriting. This research proposed an off-line handwritten document analysis through segmentation, skew recognition and writing pressure detection for cursive handwritten document. The proposed segmentation method is based on modified horizontal and vertical projection that can segment the text lines and words even if the presence of overlapped and multi-skewed text lines. Proposed work also present orthogonal projection based baseline recognition and normalization method as well as writing pressure detection method that can predict the personality of a writer from the baseline and writing pressure. The proposed method was tested on more than 550 text images of IAM database and sample handwriting image which are written by the different writer on the different background. The proposed method also provides a comparative study of the details analysis of the proposed method with other existing methods.

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Keywords: Handwritten Document; Segmentation; Skew Recognition; Normalization; Projection; Pressure Detection; Personality Prediction.

1. Introduction

Handwritten document analysis is a demanding research area throughout the previous few years. Due to the cursive nature and high inconsistency of handwriting styles, handwriting analysis techniques should be more robust.

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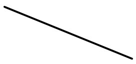
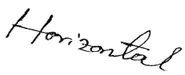
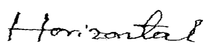
Generally, handwriting analysis for document image has four steps that are pre-processing[2,7,8,9,31,32,33,34], segmentation[10,16,17,20,22,23,24,25,26,27,28], feature extraction[35,36] and classification[35,36]. This paper proposed an off-line handwritten document analysis through segmentation, skew recognition and writing pressure detection for cursive handwritten document that can predict the personality of a writer from the baseline and writing pressure. The proposed segmentation method based on modified horizontal and vertical projection. To tolerate the text lines overlapping and multi-skewed text lines, proposed work modify present horizontal projection technique, which can segment the text lines and words even if text lines are overlapped with the help of vertical projection. In order to verify the stability of proposed word segmentation technique, the threshold which is used to differentiate between intra-word and inter-word gaps from each other is not fixed. If the threshold value is small then it may cause over segmentation whereas large threshold may cause under segmentation. Present work also proposed orthogonal projection[14] based skew recognition, normalization and writing pressure detection that can predict the human personality.

Handwriting analysis is called Brain writing because a writer can control his or her mind about what he or she want to write but cannot control how to write. How to write fully operated from writer mind with the help of psychomotor. So, handwriting is a kind of mirror that can reflect the entire personality of a writer. Analysis of handwriting helps us understand the writer's personality in a way which reveals his or her behaviour, motivations, desires, fears, emotional outlays and many other aspects. The most important handwriting features that can predict lots of personality trails are baseline, writing pressure, letter 't', slant, the lower loop of letter 'y', speed of handwriting, size of letters, and others. This paper proposed a method that can predict the personality of a writer from the features that are extracted from his handwriting. The personality traits revealed by the baseline and the writing pressure of the handwriting as found in a writer handwriting are explored in this paper. The two parameters, the baseline and the writing pressure are the inputs to the proposed rule-based algorithm which outputs the personality traits of the writer based on these two parameters. The evaluation of the baseline using the orthogonal projection method and the evaluation of the writing pressure utilizes the grey-level value of actual handwriting portion are presented in this paper. These parameters from handwriting reveal a lot of accurate information about the writer.

Technically baseline or skew[1,3,11,12,13,14] is defined as the alignment of the text lines and words with respect to the horizontal direction. The baseline in one's handwriting reveals a lot of accurate information about the writer. Baseline in one's handwriting is the line along which the writing flows. The three most common baselines found in any handwriting are ascending, descending and level as shown in Table 1. It is also true the baseline or skew tells specific personality trait of the writer such as pessimistic optimistic and level etc. Skew reveals the human's or writer's mentality[35,36] about reaching his or her goals and the energy he or she applies to various situations.

Table 1. Personality trails represented by different baselines

Baseline Features	Baseline	Emotional Identification	Sample
Descending Baseline		Pessimistic	
Ascending Baseline		Optimistic	
Straight Baseline		Level	

Generally, machine printed document skew occurs at the time of scanning process due to the incorrect arrangement of the pages. Whereas skew[3,11,12,13,14] in handwritten document can occur due to the human's behaviour as well as by the scanner during the scanning process. Generally, skew recognition in handwritten document is more difficult than the skew in printed document due to the variation of present mind condition of the writer and the difficulties at the time of scanning. In the case of the correct orientation of the pages, handwritten document still consist of smaller and larger skew[3,11,12,13,14] due to writer variation.

The other most important feature in handwriting is the writing pressure[30,36]. The amount of pressure exerted on the paper while writing is denoted as writing pressure. Based on the writing pressure the writer can be classified as light writer, medium writer and heavy writer. Table 2 shows the corresponding personality traits of the different writing pressures. Proposed writing pressure detection method fully depends on the training set. The train set should be created in such way that every writer is written with the same kind of pen on same kind of surface then only a writer can be properly classified depending on training set, otherwise, writer classification is not possible depending on writing pressure.

Table 2. Types of pressure and related emotions

Writer Category	Personality trait
Light Writer	May have emotional outburst but it will subside very soon
Medium Writer	Neither shallow nor long-lasting but average level of emotional intensity
Heavy/Deep Writer	Long lasting effect of emotional experiences

The personality trails of the writer are identified through baseline and writing pressure, which are found in the writer handwriting sample, are shown in Table 1 and Table 2. Proposed method based on some predefines rules. Here two handwriting features are used, each of which are classified into three personality trails. So total nine personality trails are identified and sets of rules are formulated which are shown in Table 3.

Table 3. Personality trails classification depending on baseline and writing pressure

Writer Category	Baseline Features		
	Descending	Ascending	Straight
Light	Pessimistic and less emotional	Optimistic and less emotional	Level and less emotional
Medium	Pessimistic and Moderately emotional	Optimistic and moderately emotional	Level and moderately emotional
Heavy	Pessimistic and heavy emotional	Optimistic and heavy emotional	Level and heavy emotional

2. Related Work

In 2016, Abhishek Bal and Rajib Saha[1] proposed a method skew detection and normalization method which uses the orthogonal projection. The proposed method was tested on IAM database. The proposed method can detect exact skew angle and also able to normalize the skew angle. The experimental result shows that proposed algorithm achieves higher accuracy for all type skew angles.

In 2015, S.V. Kedar,D. S. Bormane,Aaditi Dhadwal,Shiwali Alone,Rashi Agarwal[35] reviewed Handwriting analysis technique which used to understand a person in a better way through his/her handwriting. The main objective of this paper is to analyze the handwriting characteristics like Baseline, Slant, Pen-Pressure, Size, Margin and Zone to determine the emotion levels of a person. This will help to identify those people who are emotionally disturbed or depressed and need psychological help to overcome such negative emotions.

In 2010, Champa H N, K R AnandaKumar[36] proposed a method that predicts the personality of a person from the baseline, the pen pressure**,** the letter'**t'**, the lower loop of letter 'y' and the slant of the writing as found in an individual's handwriting. These parameters are the inputs to a Rule-Base which outputs the personality trait of the writer.

In 2012, Subhash Panwar and Neeta Nain[12] proposed a skew normalization technique which uses the orthogonal projection of lines. The proposed method was tested on different handwritten document images and achieves more than 98% accuracy.

In 2012, Jija Das Gupta and Bhabatosh Chanda[13] proposed a method for slope and slant detection and correction for handwritten document images. The algorithm was applied on IAM database and archive most promising experimental result. Comparison result showed that proposed method achieved the better result than the method proposed by B. Gatos et al and Moises pastor et al.

In 2007, Florence Luthy, Tamas Varga, and Horst Bunke[22] proposed a method for segmentation of off-line handwriting text document. Hidden Markov Models was used in this proposed method to distinguish between inter-word and intra-word gaps. The proposed method was tested on off-line handwritten document images and was appropriate for writer dependent and writer independent handwritten document.

In 2011,Fotini Simistira, Vassilis Papavassiliou and Themos Stafylakis[19] proposed an enhancement method of their previously word segmentation method by exploiting local spatial features. The proposed method has been tested on ICDAR07, ICDAR09, ICFHR10 and IAM handwriting databases and performs the better result than winning algorithm.

3. Proposed Work

At first proposed work collect color and gray scale handwritten document from the IAM database[20,21] and scanned sample handwriting images which are written by the different writer on the different background. Proposed approach assumes that given handwritten document perfectly scanned so only the skew which is introduced by the writer considers. This present work considers that scanned handwritten document may consist of Salt and Pepper noise[31,32] and Background noise[31,32] which may be occurred before or after scanning process. The steps of the proposed work are as follows.

3.1. Pre-processing

Image pre-processing technique[2,17] is used to increase the excellence of image quality for easy and efficient processing in next steps. Handwriting analysis needs to perform pre-processing steps such as binarization[7,8] and noise removal[9,31,32,33,34] etc for better recognition. In this proposed method Salt and Pepper noise is removed using median filter technique[34] and Otsu[7] thresholding technique is used for image binarization.

3.2. Writing Pressure

After noise removal and binarization, depending on the binary image, the background of the handwritten gray scale image converted to 255 and foreground or handwriting portion contain actual gray scale value. To measure the handwriting pressure, the present work extract only gray scale value of handwriting portion and discards the background portion. Standard deviation is used in this proposed work for measuring the handwriting pressure. Standard deviation technique is chosen instead if mean deviation or simple arithmetic average because the standard deviation is used mostly in research area and is regarded as a very satisfactory measure of dispersion in a series. It is amenable to mathematical manipulation because the algebraic signs are not ignored in its calculation, which is not considered in the case of mean deviation. Standard deviation is defined as the square-root of the average of squares of deviations, when such deviations for the values of individual items in a series are obtained from the arithmetic average. The proposed writing pressure measurement method extract the gray scale value of the original handwriting portion from the document image then the standard deviation is calculated for those extracted portion. After that standard deviation value is compared with the threshold value. If the standard deviation value of extracted handwriting portion is greater than or equal to the threshold value then the writer is identified as light or medium writer, otherwise, writer is identified as heavy writer. Here the threshold value is calculated as a mean value of standard deviation of all handwriting samples.

3.3. Segmentation

3.3.1. Line Segmentation

After measuring the witting pressure, text lines are segmented from the binary document image. The present work implements a modified horizontal projection method of an image that can segment individual text line from the previous and following text lines based on rising section of the horizontal projection histogram of document image which is shown in Fig. 3.

Seine in English handwritten document image, most of the time no gaps are present between two lines, which may create incorrect line segmentation due to overlapping between two lines if simple horizontal projection histogram is concern. In the proposed method, after creating the horizontal projection histogram of a binary document image, count the number of rising section and height of each rising section. The average height of the rising sections is treated as the threshold. Then consider each and every rising section and check the height of that rising section is greater than or equals to the threshold or not. If yes then based on that rising section of the horizontal histogram, the line is individually segmented from the actual binary document image, otherwise neglect that rising section as a false line segment. These types of the false rising section may occur due to overlapping between two lines or presence of a bar in an upper letter. The most important are that when a rising section is treated as a false line segment and next rising section is treated as a true line segment then the portion of the false line segment is added to true line segment for the segmentation of next line from the actual document image, otherwise, some features are removed. Fig. 4 shows the segmented line sample.

After line segmentation, it may happen different lines may have the different skew angle. To normalize the skew angle, orthogonal projection method that applied on the segmented lines to normalize the skew angle which is shown in Fig. 5. The normalized line corresponding to the skewed line is shown in Fig. 6. Here skew normalization process is based on orthogonal projection length which is shown in Fig. 1. This method efficiently deals with higher as well as smaller skew of handwritten document.

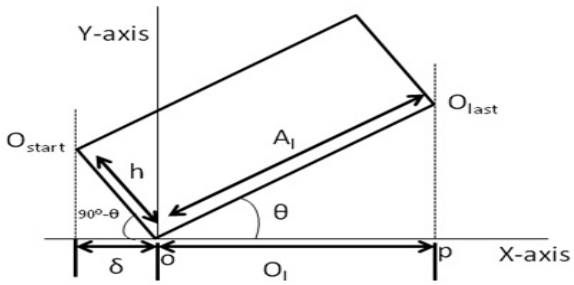


Fig. 1. Orthogonal projection of image

In Fig. 1, shows the orthogonal projection of the handwriting image. The handwriting is considered to be written within the rectangle box. The skew angle is θ and the first and last black pixels of the word are pointed by O_{start} and O_{last}. The actual length of the word denoted by A_l and projected length is denoted by O_l. The orthogonal projection of the text line is calculated as

$$O_l = O_{last} - O_{start} - \delta \quad (1)$$

Here δ is the projection and h is the actual height of the text line. The relationship between text line and the projection is

$$\delta = h \times \cos(90^0 - \theta) \quad (2)$$

$$\theta = \tan^{-1}((y2-y1)/(x2-x1)) \quad (3)$$

In this case value of δ belongs 0 to h. If θ = 0 then value of δ is 0 and if the value of θ $=90^0$ then the value of δ is h. The proposed method normalizes the skew angle using the orthogonal projection length which is clearly explained in the experimental part. Here (x_1, y_1) is the first left down most black pixel of the word that is starting of the baseline coordinate and (x_2, y_2) is the last right down most black pixel of the word that is ending of the baseline coordinate.

3.3.2. Word Segmentation

In the case of word segmentation, to segment, the words from the line, firstly inter-word and intra-word gaps are measured. Inter-word gaps denote gaps between two words and intra-word gaps denote the gaps within a word. Generally, gaps between the words are larger than the gaps within a word. These proposed methods construct the vertical projection histogram to measure the width of each inter-word and intra-word gaps then it measures the threshold value to differentiate between inter-word and intra-word gaps. If the width of gaps is greater than or equals to threshold then gaps are treated as inter-word gaps and words are segmented individually from the line depending on the threshold. In Fig. 6 shows the intra-word and inter-word gaps details. If a line has global skew then it may possible that several words within a line may have different skew. So it may require normalizing the skew of the words for a single line. For that reason again proposed skew reorganization and normalization method is applied to the each segmented word separately. After measuring the baselines for all lines of the handwritten document, the proposed method calculates the average baseline and depending on average baseline personality trails are classified. The three most common baselines found in any handwriting are ascending, descending and level. The personality trails corresponding to baselines are shown in Table 1.

After getting the information about writing pressure and baseline, proposed method classify the personality trails of the writer, which are found in the individual's handwriting sample. Proposed method based on some predefines rules[35,36]. Each of two handwriting features is classified into three personality trails. So total nine personality trails are identified and sets of rules are formulated which are shown in Table 3.

3.4. Algorithm

3.4.1. Algorithm for Line Segmentation

Line segmentation algorithm is carried out by horizontal projection as follows
Step 1: Read a handwritten document image as a multi-dimensional array.
Step 2: Check the image is a binary image or not. If binary image then stores it into a 2-d array IMG[ ][ ] with size M×N and go to Step 4,otherwise go to Step 3.
Step 3: Convert the image to binary image and store into a 2-d array IMG[ ][ ].
Step 4: Construct the horizontal projection histogram of the image IMG[ ][ ] and store into a 2-d array HPH[ ][ ].
Step 5: Measure the height, starting row position and ending row position of each horizontally rising section of horizontal projection histogram image and store into 3–d array LH[ ][ ][ ] sequentially.
Step 6: Count the number of rising section by counting the rows of the 3-d array LH[ ][ ][ ]. Then measure the threshold (T_i) value by calculating average height of rising sections from the 3-d array LH[ ][ ][ ].
Step 7: Select each rising section from 3-d array LH[ ][ ][ ] and check the height of that rising section is less than the threshold or not. If yes then this rising sections is not considered as a line and go to Step 9, otherwise rising section is treated as a line and go to Step 8.
Step 8: Find the rising section's starting and ending rows number from the array LH[ ][ ][ ]. Let starting and ending row are r_1 and r_2 respectively. Extract the line segment between r_1 and r_2 from the original binary image denoted by IMG[ ][ ].
Step 9: Go to Step 7 for next rising sections till all rising section are not under consideration, otherwise go to next Step.
Step 10: End

3.4.2. Algorithm for Word Segmentation

Word segmentation algorithm is carried out by vertical projection as follows
Step 1: Read a segmented binary line as 2-d binary image LN[ ][ ].
Step 2: Construct the vertical projection histogram of the line LN[ ][ ] and store into a 2-d array LVP[ ][ ].
Step 3: From the vertical projection histogram (LVP[ ][ ]), measures width of each inter-word and intra-word gaps and store the width into 1-d array GAPSW[ ].
Step 4: Count total number gaps as TGP by calculating the size of GAPSW[ ]. Add width of all gaps by adding the

elements of GAPSW[ ] and store into TWD.
Step 6: Calculate the threshold (T_i) as follows:

$$T_i = TWD/\ TGP \tag{4}$$

In equation (4), T_i is the threshold value denoting average width of inter-word gaps, TWD denotes total width of all gaps and TGP denotes the total number of gaps.
Step 7: For each i($1 \le i \le$sizeof(GAPSW[ ])), if GAPSW[i] $\ge T_i$ then this gaps is treated as inter-word gaps, otherwise gaps is treated as an intra-word gaps. Depending on inter-word gaps width, words are segmented from the line.
Step 8: End

3.4.3. Algorithm for Skew Normalization

Skew Normalization algorithm is carried out by orthogonal projection as follows
Steps:

1. I $\leftarrow$BW
2. $\theta \leftarrow$angle_find_word(I) // Calculate the skew angle of a word denoted by 2-d array I
3. $O_l \leftarrow$ orthographic_projection(I) // Calculate the orthographic projection length denoted by 2-d array I
4. $I_1 \leftarrow$ rotation_binary_word(I,+1) // Rotate the image denoted by 2-d array I with given degree
5. $O_+ \leftarrow$ orthographic_projection(I_1)
6. $\theta_1 \leftarrow$ angle_find_word(I_1)
7. $I_2 \leftarrow$ rotation_binary_word(I,-1)
8. $O_- \leftarrow$ orthographic_projection(I_2)
9. $\theta_2 \leftarrow$ angle_find_word(I_2)
10. x $\leftarrow$ 1
11. if($\theta < 0$ AND $O_+ > O_l$) then
12.   write “Positive skew”
13.   while($O_+ > O_l$) do
14.   I$\leftarrow$ rotation_binary_word(I,+x)
15. $O_+ \leftarrow$ orthographic_projection(I)
16. $\theta_1 \leftarrow$angle_find_word(I)
17.   if($\theta_1 > 0$) then
18.   break
19.   end if
20.   x$\leftarrow$x+0.25
21.   end while
22. elseif($\theta > 0$ AND $O_- > O_l$) then
23.   write “Negative skew”
24.   while($O_- > O_l$) do
25.   I$\leftarrow$ rotation_binary_word(I,-x)
26. $O_- \leftarrow$ orthographic_projection(I)
27. $\theta_2 \leftarrow$angle_find_word(I)
28.   if($\theta_2 < 0$) then
29.   break
30.   end if
31.   x$\leftarrow$x+0.25
32.   end while
33. end if
34. imshow(I) // Display an image denoted by 2-d array I
35. Stop

3.4.4. Algorithm for measuring Writing Pressure

Writing pressure measurement algorithm is carried out by standard deviation of actual handwriting portion as
Steps:

```
1.  BW ← binarization(IMG)
2.  [r c] ← size(BW)
3.  n ← 1
4.  for i ← 1 to r do
5.     for j ← 1 to c do
6.         if(BW(i,j) != 1) then
7.              I(n)←IMG(i,j)
8.              n←n+1
9.         end if
10.     end for
11. end for
12. pressure← standard_deviation(I)
13. if(pressure<thresh)
14.    write "Heavy writer"
15. else
16.    write "light or medium writer"
17. end if
18. End
```

In the above algorithm (*Algorithm 3.4.4*) binarization() function returns the binary image which takes a gray scale image as input. After extraction of actual handwriting portion, standard_deviation() function calculates the standard deviation value of that portion. Here thresh is the threshold value which is calculated as a mean value of standard deviation of all handwriting sample.

3.4.5. Algorithm for Personality Prediction

Personality prediction algorithm is carried out with the help of baseline and writing pressure as follows
Steps:

```
1.  if(pressure=light and baseline=descending) then
2.      write "Pessimistic and less emotional"
3.  else if(pressure=light and baseline=ascending) then
4.      write "Optimistic and less emotional"
5.  else if(pressure=light and baseline=straight) then
6.      write "Level and less emotional"
7.  else if(pressure=medium and baseline=descending) then
8.      write "Pessimistic and moderately emotional"
9.  else if(pressure=medium and baseline=ascending) then
10.     write "Optimistic and moderately emotional"
11. else if(pressure=medium and baseline=straight) then
12.     write "Level and moderately emotional"
13. else if(pressure=heavy and baseline=descending) then
14.     write "Pessimistic and heavy emotional"
15. else if(pressure=heavy and baseline=ascending) then
16.     write "Optimistic and heavy emotional"
17. else if(pressure=heavy and baseline=straight) then
18.     write "Level and heavy emotional"
19. end if
20. Stop
```

4. Experimental Result

The proposed work implemented in MATLAB on IAM database[20] over 550 text images containing 3800 words and some sample handwriting image which are written by the different writer on the different background.

At first noise removal techniques are applied on the handwriting text document if noise is present. Image quality is improved by removing noise from the handwriting text document. After that thresholding technique is applied on noiseless gray scale handwriting image for converting the gray scale image to binary image. Then proposed line segmentation method is applied on binary document image that segment individual text line from the previous and following text lines based on rising section of the horizontal projection histogram of the document image. After line segmentation, different segmented lines may contain different skew. During recognition process, handwritten document should free from the unbalanced skew angle for better recognition. Proposed skew normalization method is applied on each segmented line to normalize the segmented line with respect to skew angle. Sample outputs for text line normalization process are shown in Fig. 4 and Fig. 5. After lines skew normalization, proposed method measures width of each inter-word and intra-word gaps from the vertical projection histogram and segment the words from the line depending on the threshold value. Here proposed method calculates the threshold value to differentiate between inter-word and intra-word gaps. Inter-word and intra-word gaps details are shown in Fig. 6 with the help of vertical black lines and segmented word are shown in Fig. 7. If a line has global skew then it may possible that after word segmentation several words within a line may have different skew. So it is required to normalize the skew of the segmented words for each line. For that reason again proposed method applied to the each segmented word separately. Sample outputs of skewed and skewed free words are shown in Fig. 8-9.

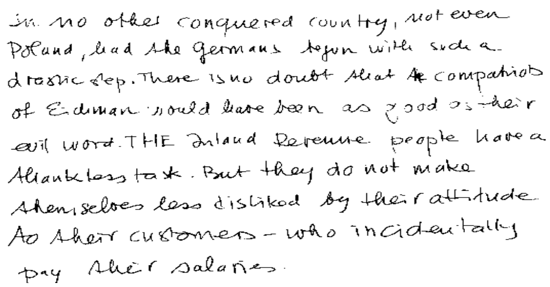


Fig. 2. Binary image after noise removes

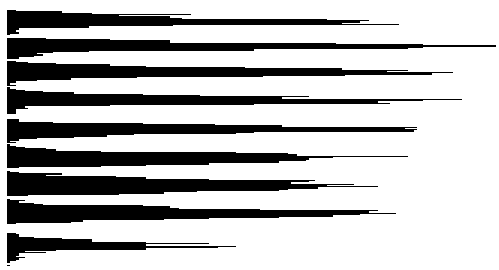


Fig. 3. Horizontal projection of binary image

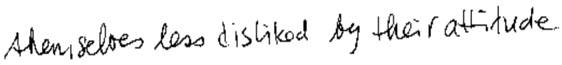


Fig. 4. Segmented line before skew correction

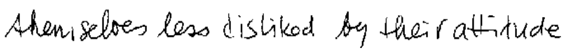


Fig. 5. Segmented line after skew correction

Fig. 6. Inter-word and intra-word gaps with in a line

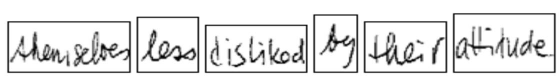
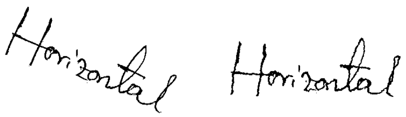


Fig. 7. Words after segmentation

In order to enhance the performance of the algorithms, proposed method has been applied on subset [a-f] of the IAM database and sample handwriting image which was written by the different writer on the different background. Test datasets consist of more than 550 handwritten document images of IAM database. Further details for the IAM datasets are included in the related papers[20,21]. The evolution results of proposed segmentation and skew normalization methods are shown in Table 4 and Table 5 respectively. The percentage of over and under-segmented lines and words information are shown in Table 4.

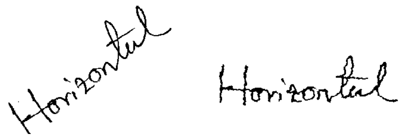
Table 4. Segmentation accuracy on form a-f and percentage of over and under segmentation results for lines and words

Segmentation Type	Accuracy	Over	Under
Line	95.65%	1.45%	2.9%
Word	92.56%	2.85%	4.59%



(a) (b)

Fig. 8. (a) Positive skewed image; (b) Normalized image



(a) (b)

Fig. 9. (a) Negative skewed image; (b) Normalized image

In Fig. 8(a) and Fig. 9(a) contain positive and negative skewed words respectively. After applying the proposed method on above skewed words, resultant normalized skewed free words are shown in Fig. 8(b) and 9(b). Experiment results for skew normalization method which was tested on the dataset are shown in Table 5. The significant improvements of proposed skew normalization method over existing methods are shown in Table 6. Experimental part considers that the words with the skew range between -1 degree and +1 degree are normalized words because these small amounts of skew angle do not make so much effect on words characteristic.

Table 5. Skew Normalization Result Produced by Proposed Method

Sl. No.	Actual Skew	Normalized Skew	Accuracy
1	+29.4275	+0.1916	99.4%
2	+16.5838	-0.8654	95%
3	+29.2170	-1.5608	94.7%
4	+18.1757	+1.4730	92%
5	+24.9967	-0.2906	98.9%
6	+3.0128	+0.1609	95%
4	+0.8551	+0.8551	100%
8	-0.7162	-0.7162	100%
9	-16.7861	+1.2825	93%
10	-14.8455	-0.4308	97%
11	-20.2931	+1.6211	93%
12	-12.5860	-0.5439	96%
13	-13.3768	-0.1758	98.7%

From the Table 5, it is observed that proposed method is much efficient for skew normalization and can deal with any types of skew angle up to 360^0. The comparative evolution results of 4 different algorithms with proposed algorithm are shown here. The success rate of proposed skew normalization method is 96% which is better than the existing methods. Further evolution results are shown in Table 5. The failure cases of the proposed method are mainly caused by misclassified to lower case letters.

Table 6. Skew Comparison with existing methods

Methods	Skew Angle in degree	Normalization rate	Error
Proposed Method	0-360	96%	4%
Houng Transform	0-180	95%	5%
Bounding Box Method	0-25	81%	19%
Linear Regression	0-360	82%	18%

At the time of text segmentation and normalization process, present work also measures the average skew angle or baseline and writing pressure from the handwritten document image. After getting the information about writing pressure and baseline, proposed method classify the personality trails of the writer through the rule-based method, which are found in the individual's handwriting sample show in Table 3. Writing pressures information for subset of handwritten documents are shown in Table 7.

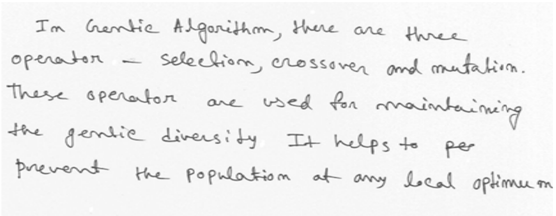


Fig. 10. Handwriting sample with light writing pressure and straight baseline

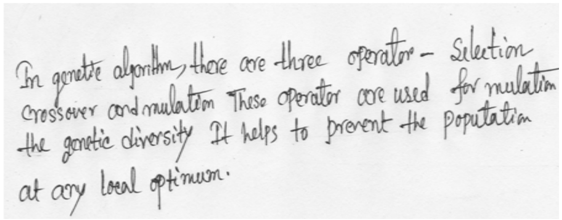


Fig. 11. Handwriting sample with heavy writing pressure and ascending baseline

Above two handwriting sample written by two different writers with the same pen and the same type of A4 size paper with more or less same background, although background does not make much effect the proposed method. Proposed method fully depends on the training set. The train set should be created in such way that every writer is written with the same kind of pen on the same kind of surface then only a writer can be properly classified depending on the training set, otherwise, writer classification is not possible depending on writing pressure. Handwriting sample in Fig. 10 denotes the writer with light writing pressure and straight baseline where as Fig. 11 denotes the writer with heavy writing pressure with ascending baseline. These writing features are treated as the inputs to the rule-based classifier which produces the writer personalities as outputs which are shown in Table 3. In Table 7 shows writing pressure information of subset of handwritten document which was written by the different writer on the different background with the same pen and the same type of A4 size paper.

Table 7. Result of writing pressure for subset of handwritten document

Respondent	Writing Pressure
1	39.5486
2	27.4030
3	49.6270
4	46.0389
5	29.4653
6	38.8548
4	51.6186
8	26.0420
9	39.0526
10	54.8207
Average	40.2471

5. Conclusion and Future Work

This paper proposed an off-line handwritten document analysis using text segmentation, skew recognition and writing pressure detection of cursive handwritten document that can predict the human personality. The proposed method has been applied to more than 550 text images of IAM database and sample handwriting image which are collected from surroundings and written by the different writer on the different background. Using the proposed method 95.65% lines and 92.56% word are correctly segmented from the IAM dataset. Proposed work also normalizes 96% lines and words perfectly with very small error rate. Proposed skew normalization method deals with the exact skew angle and extremely efficient with compare to on hand techniques. The proposed method can also predict the writer personality through two different writing features that are baseline and writing pressure. Proposed method could be applied to various languages writing style with more or less same accuracy.

The future work can include more handwriting features with the proposed method like character recognition and some others personality traits determining in order to override the weakness and some constant factor and obtain the more robust system. As a whole, future target to develop a tool for behavioral analysis which can predict the personality trails with aid of computer without human interaction.

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