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RESEARCH ARTICLE

Personality Recognition Based on Handwriting Types Using Fuzzy Inference

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ABSTRACT Graphology is the psycho-analysis study of personality and individual characteristics of writers based on the handwriting types. Graphology is a time-consuming and complicated task. Due to small number of expert graphologists, computerized measurement of graphology is an essential need. In this research, in addition to extraction of handwriting features, it is tried to categorize them in terms of regularity and inequality of letters and recognize person's characteristics via graphology tables. This classification includes these types of handwriting: spontaneous, with difference in pen pressure, uncoordinated, coordinated with partial variance, uniform, sharp, regular, with inequality of letter's inflexion and unequal. In this paper, 140 typical Farsi handwriting samples are used which are interpreted after giving MMPI (Minnesota Multiphasic Personality Inventory) questionnaire. The novel proposed features are used as the Mamdani fuzzy classifier inputs. Variance of baseline curves, variance of distances between words, variance of vertical letter height, variance of pen width, number of zero, acute and obtuse angles and their ratios to the number of text lines and slope angle are used as features for Mamdani fuzzy classifier inputs. In this study, there are nine handwriting types for personality recognition and 24 rules are defined for the nine fuzzy systems. Compared to our ground truth (MMPI results for the handwriting database), the proposed method showed an accuracy of 82.5% for personality recognition that demonstrated promising results.

INDEX TERMS Graphology, personality, recognition, fuzzy system.

I. INTRODUCTION

Human especially in today's world need to communicate with each other by writing. Moreover, this aspect should be associated with general and public rules along with criteria which are acceptable for people. The main reason for considering the form of writing as the most complicated way of communication is that compliance with these rules is not easy. Graphology is the study and analysis of each person's handwriting in order to get more information about various characteristics of the person's personality. Since handwriting of each person is personal just like fingerprint, studying characteristics of each manuscript can result in realization of writers' psychological characteristic. According to psychologists, analysis of each person's handwriting can reveal 100 personality characteristics [1]. In European countries (especially France), graphology is adjusted as a complementary in job interviews [2]. This can be also used in criminology and patient treatment. There exists a science called handwriting therapy which can improve patient handwriting in order to improve their mood [3], [4]. Author of [5] argues that by modifying one's handwriting one can enhance aspects of one's life. Authors of [6] determine the personality traits using handwriting features. Decision tree, SVM and KNN are employed to classify big five model.

This science can also be useful in recognizing forged documents from original. The original one can be discriminated from those which are forged by sufficient cognition of graphology. Of course, some people deny graphology science. However, being familiar with its principal can find it both attractive and useful. Advanced methods for extracting features and recognizing text are provided and many studies have been done in the field of character recognition and writer identification using computer [7], [8].

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Automatic text detection and recognition (end-to-end text recognition) is presented by [9] using a new pipeline framework. New.i.ReLU and new.i.inception layers are introduced in the proposed CNN model. A novel handwriting recognition system is used to verify user identity and to manage door security [10]. Visual and procedural handwriting analysis is investigated in [11] and graphomotor-based neuropsychological assessments and AI systems are discussed. Authors of [12] have studied the multi-script and different historical script recognition. The review focuses on the scope of the prediction, the type of dataset, the methods used to data preprocessing, and the performance metrics used for the analysis and recognition. But, so far, few researches have been done on computer graphology related to handwriting. Since the basis of graphology is extracting features from handwritten texts, extracting useful and effective features are significant. Regarding its being time consuming and complicated, using computer seems to be inevitable.

Garoot et al. [13] have presented a comprehensive survey on computerized graphology systems. Garoot et al. [13] claim that graphology is the fastest way to recognize personality through conventional personality testing methods. Graphology is suitable for cognitive psychology because handwriting (graphic expression) relies on the same principles as cognitive psychology. In [14], it has been explained that handwriting is referred to as 'brain writing'. People with the same personality share common features in their handwriting. Each written movement represents a special personality trait. Graphologists analyze these movements in handwriting and describe the characteristics of a person. Problems of manual feature extraction from handwriting and personality cognition are:

- This approach is boring, tedious and depends on a person.
- Different graphologists may take different features from the same manuscripts.
- The graphologist's decision might be affected by content of the text.

In order to solve these problems, computerized personality recognition is developed. In this paper, computational studies are considered in a cognitive system to recognize personality including fuzzy inference systems.

In this research, in addition to extraction of handwriting features, handwriting types are categorized in terms of regularity and inequality. Meanwhile, person's personalities are recognized using fuzzy inference and graphology tables based on handwriting types and this is validated compared with Minnesota Multiphasic Personality Inventory (MMPI) questionnaire results.

In the following of this research, literature review has been studied in section II. Then, in sections III and IV, database and handwriting feature extraction methods are described, respectively. After that, the proposed fuzzy systems and their rules are explained in section V. In the sections VI and VII, results, discussion and comparison are provided. Finally, the paper is concluded in section VIII.

II. RELATED WORK

Researchers are interested in recognizing personalities, especially if it works intelligently and automatically. One way to recognize person characteristics is by its handwriting. By extracting statistical parameters, we can recognize human behaviors. A biometric system of specific writers' identification based on graphology is presented in [15]. The identification accuracy achieved with five characteristics on 29 writers is reported 99.34%. An artificial neural network (ANN) is used as a classifier and a decision fusion module is exploited for writer identification in [16]. Coll et al. [17] have illustrated use of graphology in recruitment process in a human resources company using a neural network.

A simple method has been presented to extract, analyze, and classify writings from a psychological approach. In some researches, the context of the graphology is exploited for automatic signature verification [18]. The features for signature verification are: caliber, proportion, spacing, alignment to baseline, progression, form, and slant that are proposed in [18]. In [19], some new graphometric features were introduced. The idea was to simulate the most important segments of the signature by using Bezier curves and then extracting their features. Meanwhile, statistical, shape-based, similarity-based, and frequency-based features are extracted from the SVD signal of the offline signature [20]. In [21], after preprocessing, in addition to noise deletion, pen width is also calculated; then some features such as margin pattern, coarse writing, text compression, text slope, ratio of letter's upward and downward elongation to its width have been extracted from handwriting. BahramiSharif and Kabir [21] classified based on number of extracted features regarding to graphology decision-making handwriting tables for writer personality. In [22], in addition to the above mentioned features, tremor is also extracted and it is used as a tool to recognize personality of the writer by combining each feature as an input to the fuzzy system. Also, curve of the baseline, writing speed, forward and backward positions, convexity and concavity of handwriting are extracted as features. Since all words are not necessarily written on lined papers, curve of the baseline is extracted as an effective and new feature which contains line changes and its upward and downward positions. Norouzzadeh and Nezamabadi-pour [22] have also classified handwriting samples based on decision- making graphology table to identify writer's personality. In [23], a method has been presented to recognize behavior of a person from the baseline, pen pressure, the letter 't', lower loop of letter 'y' and the slant of the writing.

In [24], in addition to extracting features of handwriting, neural networks are used to predict effective parameters in psychology based on their manuscripts. First, Yaghmaee et al. [24] gave Minnesota Multiphasic Personality Inventory (MMPI) test from writers and then they found the relation between manuscripts and individual's characteristics by using a neural network. To simulate the MMPI test, a three-layer neural network is used by training structure of back-propagation error. Some features such as number of written lines, length of the lines, angle of the main written lines, line spacing, size of words and letter arrangement are extracted. Some visual characteristics have been investigated to determine the type of handwriting in terms of its regularity and inequality of the appropriate features in [22] and some features such as curve of the baseline, word's space, pen width, vertical height of letters and number of extracted angle of letters have been studied.

In [25], in addition to commonly used features like baseline, margin, slant, size and word spacing, tittle over 'i' was also added. If tittle is a dot, the corresponding traits are detail-oriented, organized and emphatic. However, if tittle is a circle, corresponding traits are visionary and child-like. In [26], a standard database has been provided for graphology study. In addition to extracting features, the MMPI test is also given in order to compare it with handwriting's graphology interpretation. Some features such as number of text's line, margin, coarseness of handwriting and slope of the line have been investigated. Also, by using a decision tree classifier system, characteristics of persons were recognized. Human personality identification based on handwriting using neural networks and importance of graphology were investigated in [27]. In another study [28], five common features of handwriting and also nine features of signature were employed to predict personality. Multilayer perceptron has been used for classification.

In [29], the effect of workload under three different conditions has been investigated by exploiting handwriting. Luria and Rosenblum [29] concluded that handwriting behavior is affected by mental workload. The selected features were 1) pressure on the writing surface, 2) time: pen duration in air and on paper, 3) space: segment-path length, width, height, and 4) angular velocity of writing. Meanwhile, pen motion pattern groups for classification of handwriting into cognitive mental workload classes were introduced in [30]. Handwritten texts written by the same person were investigated under different mental workloads. Badarna et al. [30] concluded that the pen stroke patterns were affected differently under different cognitive mental workloads and increased average cognitive load discrimination accuracy from 72.90% to 92.16%. Handwriting behavior analysis can detect deception [31]. Luria et al. [31] found that deceptive writing was broader and took longer to write than truthful writing. Handwriting is very effective in recognizing human behavior.

In [32], authors present the links between handwriting and character psychology, and examine the various methods of feature extraction to identify the author's personality. The article investigates the features and encourages the use of computer-based methods to predict personality. That survey discusses the applications of graphology in various fields.

Improvement of a formal validation method of computer-aided handwriting analysis is presented in [33]. They selected 16 personality factor questionnaire revised (16PF-R) for validation. Authors of [34] have provided a tool for forensic handwriting. A main purpose of this tool is to assist the expert in collecting data from the documents. In [35], some features such as slant, ratio, curvature and spacing are employed to examine forensic handwriting. Personality trait recognition is proposed in [36]. This research has been performed at the feature level. The experiments were implemented on a database of 543 handwritten samples. The result showed an accuracy of more than 70% for both edge hinge distribution and run length distribution and more than 55% for other features.

Deep learning was employed to predict manuscript handwriting styles in [37]. Transfer learning from the MobileNetV1 deep learning model was used to extract features. Hemlata et al. [38] provide a summary of handwriting analysis, its related characteristics, and a review of the literature on handwriting analysis articles. Moreover, different features are introduced. Personality analysis through handwriting recognition was presented in [39]. In [40], four classifiers were employed to recognize these characteristics: extravert or introvert, sensation or intuition, thinking or feeling, judging or perceiving. The accuracy results were obtained using different learning algorithms that were simple logistic, decision tree, K-nearest neighbors, and random forest. Mostafa et al. [40] achieved a maximum accuracy of 68.67%. Five main attributes are recognized by handwriting in [41]. These personality types are neuroticism, openness to experience, extraversion, agreeableness, conscientiousness. Gavrilescu and Vizireanu [41] achieved accuracies of 84.4% in intra-subject tests and 80.5% in inter-subject.

Beauchataud [1] categorizes various handwriting samples in terms of discipline and inequality; more over graphology interpretations related to types of handwriting are also explained. Some features such as space between words, margins and pen-pressure are used to detect gender from handwriting in [42]. In [43], handwriting is analyzed using 15 CNN models and the highest rate of accuracy is 80.88%.

In this paper, in addition to classification of handwriting based on a fuzzy inference system, the result has been verified by MMPI interpretation of handwriting. In the Appendix of this paper, characteristics of various handwriting samples are described. Also, obtaining fuzzy rules is explained for each type of handwriting. The summary of introducing different handwriting types and their cognitive personality are presented in Table 1.

III. DATABASE

The database contains totally 140 typical Farsi handwriting samples with the same texts provided from two groups: students of a science-applied university and prisoners in Semnan's prison including 95 men and 45 women in the age of 20 to 60 years old. The unique text is neutral in terms of stimulation feelings, so that the feelings of the writers do not change during writing. The text is simple and easy. In Farsi, texts are written right to left. Then, these handwriting samples are scanned with a resolution of 600 dpi. Meanwhile,

TABLE 1. The effective characteristic for various handwriting types.

Handwriting type	Apparent characteristics of handwriting according to [1]	Apparent characteristics of handwriting according to this work	Geophysicist interpretations of psychological characteristics [1]
Automatic handwriting (spontaneous)	Mechanical movements, simple letter shapes like printed letters that repeat evenly	Greater number of angles near zero and 90 degrees (with 5 degrees of difference) of total number of angles	Fictitious, step backward, lacking flexibility, nerve weakness, tend to tempt, lacking will and personality, machine activity, stubborn
Handwriting with difference in pen pressure	Changing in the thickness of handwriting	High pen width variance	Change in energy intensity, anger, irascibility, preparing for aggression and provocation, extreme movements
Uncoordinated handwriting	Many changes in the size and harmony of words	High variance of distances between words	Vibrant, influencing, instability, lacking discipline, disorder in behavior, non-compliance with law and ethics
Coordinated handwriting with partial variance	Order in the speed of writing and pen pressure, regular letter shapes	Low variance of distances between the words and low variance of text slope	Stable, with rule and law, durable feelings, perseverance, loyalty, courage, friendship, seriousness, resistant to fatigue, feeling the order and duty
Uniform handwriting	Uniform handwriting without any diversity	Low variance of baseline curve	One who thinks and acts through habit, lacking fun, indecency, feeling less, sadness, surrender to fate
Sharp handwriting	Sudden changes in the direction, shape and size of the letters	High ratio of sharp (obtuse) angles to rest of the angles	Intense nervousness, high sensitivity, soon anger, nagging mode, bad tempered and sometimes offensive
Regular handwriting	Equal shapes, equal size between distances of words	Low variance of distances between words	Balance, stability, regular, observe time and date, feeling the order, discipline, lacking of elegance and emotion
Handwriting with inequality of letter's inflexion	Inequality of letter's inflexion	High variance of letter angles	Cultural sensitivity, curiosity, providing content at various angles, high scope of thought
Unequal handwriting	Inequality in height of letters	High variance of vertical letters height	Inner feeling, kindness, irritability

the writers have completed MMPI test including seventy-one questions after receiving handwriting [26]. Handwriting of all participants is obtained with their full satisfaction. In addition, the forms do not include names of individuals. Fig. 1 is an example of the image of a handwriting sample in the database with diagrams related to its MMPI questionnaire responses.

IV. PROPOSED FEATURES EXTRACTION

In this section, after pre-processing, the features including width of pen, curve of the baseline, vertical height of letters, word spaces, number of angels and slope angle of the text are extracted. Fig. 2 shows an example of a pre-processed image. Pre-processing steps are described below:

-Applying Gaussian low pass filter to eliminate noise (with a 3×3 mask)

-Converting the image to a grayscale image

-Converting the image to a binary image (In an 8-bit image, if the intensity is less than 128, it becomes 0, otherwise it becomes 1.)

-Extracting connected components and labeling them

-Removing the large connected components associated with large area as a smudge (area more than three hundred pixels in our work)

Practical methods for extracting text features are presented in [21], [22]. In [44], to recognize the writer in medieval documents, full-page features such as margins, spacing between columns, and some of the writer-specific features, such as the distribution of text in lines, have been used. The number of peaks in the horizontal projection histogram is a new feature introduced in the paper.The seven features that are selected and extracted in this research are as follows:

A. NUMBER OF HANDWRITING LINES

To obtain the number of handwriting lines, first the Pre-processing steps are performed. After image dilation, number of handwriting pixels is counted in each row. The lines which their pixel numbers are more than half of maximum of pixel numbers of lines are set to '1' and the others are set to '0'. By counting the number of crossings from '0' to '1', the number of lines is obtained. Fig. 3 is an example of counting number of handwriting lines. In this figure, the horizontal axis is row number and the vertical axis is row status, '0' or '1'. The process of counting the number of text line is provided (Pre-processing means the same as described at the beginning of section VI):

-Pre-processing

-Image dilation (Structural element is a 3×3 square)

-Extracting connected components and labeling them

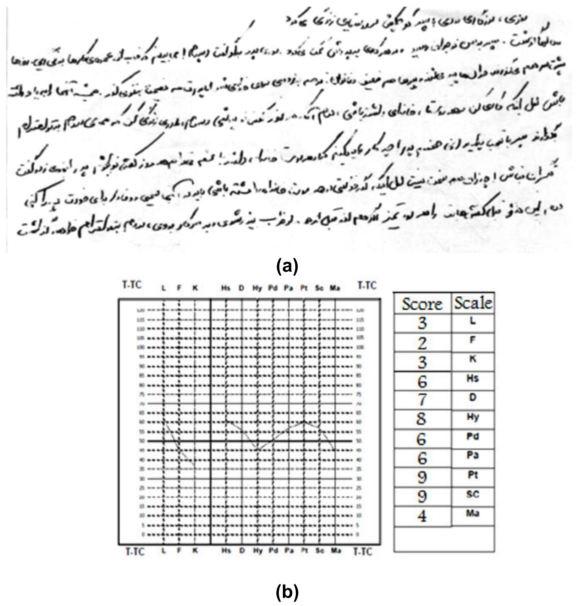


FIGURE 1. a) An example image of database, b) diagram related to its MMPI response.

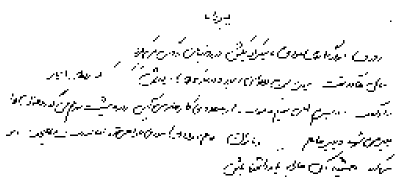


FIGURE 2. A handwriting image after pre-processing.

-Removing areas which are less than 0.4 times of the maximum area

-Counting pixels in all rows

-The rows which their pixel numbers are more than half of maximum of pixel numbers of rows are set to '1' and the others are set to '0'

-Counting the number of crossings from '0' to '1' as a number of lines

B. WIDTH OF THE PEN

In this study, width of the pen means width of the pen tip effect on the paper. To calculate width of the pen after pre-processing, the number of white pixels of each connected component is counted by scanning the image in rows and columns. Then, the most frequent number in these connected components is calculated. The number with more frequency is considered as the width of the pen. Fig. 4 shows the final image of calculating width of the pen. The extraction process is explained as follows:

-Pre-processing

-Extracting connected components and labeling them

-Counting number of white pixels of each connected component in rows and columns.

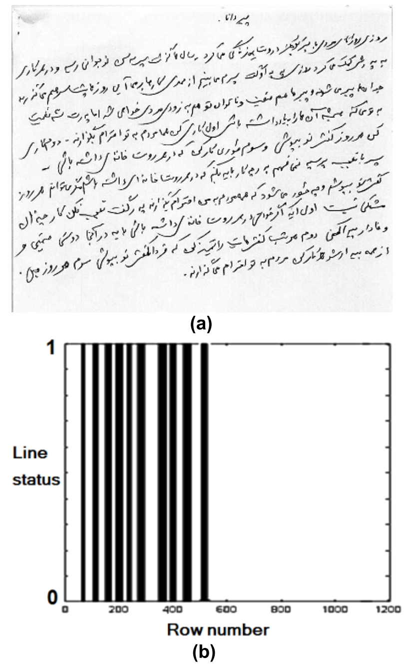
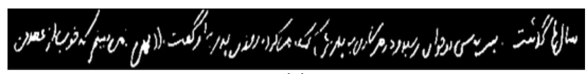


FIGURE 3. a) A sample of handwriting b) line status for each row (number of lines is number of crossings from '0' to '1').



(a)

W=11,Number=912 - W=10, Number=578 – W=12, Number=217 - …

(b)

FIGURE 4. a) A part of handwriting, b) the sorted sizes of connected component widths (Width = 11 is more frequent and considered as the width of the pen).

FIGURE 5. Extraction of baseline curve from a handwriting, a) a bonding box of a handwritten line, b) the extracted baseline curve, c) handwriting sample and its extracted baseline.

-Considering the number with more frequency as the width of the pen

C. BASELINE CURVE

After extraction lines and number of them, for each line, curves of the baseline which contain useful information about ups and downs of handwriting are achieved. The small areas which contain dots and small curved line are omitted after image dilation and calculating connected components. Then, a bonding box is considered on each calculated line. So that

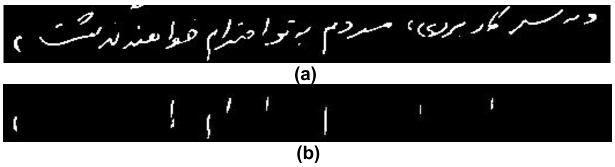


FIGURE 6. a) Part of handwriting, b) image of extracted vertical letters.

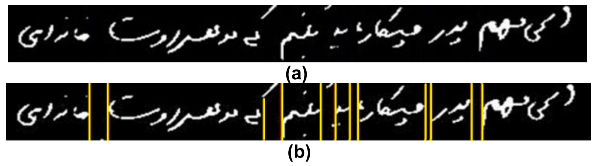


FIGURE 7. a) Part of handwriting, b) calculated distances between the words.

the maximum and minimum of x's and y's of white pixels in each line form the coordinates of the bonding box (See Fig. 5.a). For each column in the bonding box, average of the highest and lowest white pixels of the 'y' coordinate is calculated. The extracted baseline curve is shown in Fig. 5.b and matching of the text and this baseline is shown in Fig. 5.c. The baseline curve extraction is explained as follows:

-Pre-processing

-Image dilation (Structural element is a 3×3 square)

-Extracting connected components and labeling them

-Removing areas which are less than 0.4 times of the maximum area

-Finding bonding box for each line

-Finding coordinates of the highest and lowest white pixels in each column in the bonding box

-Considering average of the highest and lowest white pixels in the 'y' coordinate in all columns as baseline curve

D. HEIGHT OF VERTICAL LETTERS

To calculate height of vertical letters after pre-processing and dilation, the areas which are less than 0.4 times of the area of the maximum parts are omitted. 0.4 is achieved through trial and error in order to achieve better feature extraction.

Vertical letters are identified by erosion the low height letters along the baseline curve using a horizontal rectangular structuring element with dimensions of 2×1 by the pen width. Then, the small area (less than 0.4 times of the maximum area) is removed. After this, the image is dilated by 2×1 by the pen width structuring element and the obtained components are considered as vertical letters. The average vertical length of the components is considered as the height of vertical letters. Fig. 6 shows the image of handwriting and extracted vertical letters. The following parts provide the process of calculating the average height of vertical letters:

-Pre-processing

-Image dilation (Structural element is a 3×3 square)

-Extracting connected components and labeling them

-Removing small areas which are less than 0.4 times of the maximum area

-Counting height of the vertical elements of image and removing small columns (with less than eight pixels in this work)

-Calculating vertical letters (using erosion and dilation with horizontal rectangular structuring element)

-Considering average vertical length of the remained parts as vertical height of the handwriting

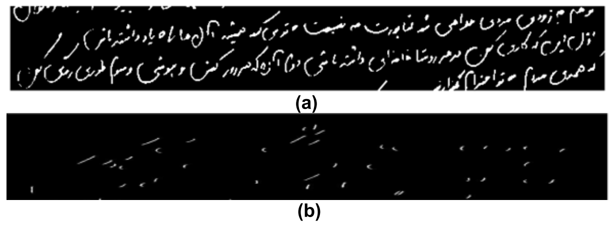


FIGURE 8. a) A section of handwriting, b) extracted skeleton.

E. DISTANCE BETWEEN WORDS

In this part, after image dilation and calculating the areas, small areas are removed. Then, the bonding box and the baseline curve are calculated for each line. Each bonding box coordinates are the maximum and minimum of x's and y's of white pixels in the line. All components that are less than the pen width in the 'x' coordinate direction are deleted. Horizontal distances between remaining components (the distances larger than 2.5 times of the pen width) are calculated and considered as the distance between the words. Average of all distances is considered as the distance between words. In Fig. 7, a handwritten part with spaces between words is shown. Following extraction spaces between words are used:

-Pre-processing

-Extracting connected components and labeling them

-Removing areas which are less than 0.4 times of the maximum area as small areas

-Calculating the bonding box and baseline curve for each line

-Deleting components less than the pen width in the 'x' coordinate direction

-Calculating average of horizontal distances (larger than 2.5 times of the pen width) between remaining components

F. NUMBER OF ZERO, ACUTE AND OBTUSE ANGLES

In this part, after pre-processing, the components more than 2.5 times of width of the pen are removed only in horizontal (x axis) direction to increase the accuracy. Then, the skeleton of the remained handwriting image is obtained. By creating vertical crops (2.5 times the width of the pen) of the skeleton image in each line and scanning them, the highest, lowest and middle points of the components are determined in each crop. Then, differences between these points are calculated using the 'x' coordinate and the angle types (zero, acute and obtuse) are determined. To find final type of angles of letters, the number of determined zero, acute and obtuse angles are counted and maximum angle type is considered. Fig. 8

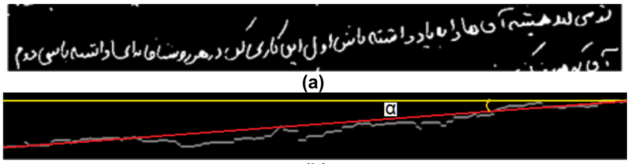


FIGURE 9. a) A part of handwriting (Farsi is from right to left), b) slope angel of the text.

shows a handwriting sample and its extracted skeleton. In the following part, the method used to calculate the number of text angle is provided:

-Pre-processing

-Labeling and calculating the area of connected components

-Removing connected components more than 2.5 times of the pen width only in the x direction

-Finding skeleton of the image

-dividing the image to vertical crops (width of each crop is 2.5 times the width of the pen)

-Finding coordinates of the upper, lower and middle points in each crop

-Finding differences between obtained 'x' coordinate in each crop

-If (|top_x-middle_x|< 4& |middle_x-bottom_x|<4), then angle is zero (or standing).

-If ((top_x-middle_x)>4& (middle_x-bottom_x)>4) or ((middle_x- top_x)>4& (bottom_x- middle_x)>4), then angle is obtuse.

-If ((top_x-middle_x)>4& (middle_x-bottom_x)<4) or ((top_x-middle_x)<4& (middle_x-bottom_x)>4), then angle is acute.

G. SLOPE ANGLE OF TEXT

To obtain line skew (slope angle) of the text, after image dilation and removing parts with smaller area, labeling and calculating the connected components are performed. In order to calculate slope angle of the text, we need to calculate the baseline (red line) and standard baseline (yellow line). Then, distance between end of baseline and standard baseline divided by length of the handwritten line is calculated and inverse tangent of it is considered as slope angle of the text. Fig. 9 shows a line of handwriting with calculated slope angle of the text (α). The red line is standard baseline and angle between the red and yellow lines is slope angle. The process of calculating slope angle of the text is provided:

-Pre-processing

-Image dilation (Structural element is a 3×3 square)

-Extracting connected components and labeling them

-Removing areas which are less than 0.4 times of the maximum area as small areas

-Calculating the lines of baseline and standard baseline

-Calculating slope angle (α)

-Calculating average of slope angles of all lines

In this study, the novel methods are presented for extracting features. For pen width, BahramiSharif and Kabir [21]and Norouzzadeh and Nezamabadi-pour [22]have calculated area of the connected components and considered the number of most frequent connected pixels in horizontal and vertical directions as the pen width. However, in this study, considering that the largest and most important change in width of the pen occurs in vertical handwritten letters, the pen width is also extracted from these vertical components. To extract the baseline curve, due to the importance of this feature, a new method has been developed. In [22], width of the pen is used to extract the baseline curve. However, this is independent of the pen width in this study. The feature is extracted using coordinates 'x' and 'y' of the cropped handwriting.

Table 1 shows the required characteristics for recognizing personality in this research. All of the features presented in this work are used to recognize types of characteristics in Table 1.

V. FUZZY SYSTEM DESIGN

In the previous section, features and characteristics of various handwriting samples were presented. In this section, a proper fuzzy system is defined to classify handwriting. Fuzzy logic allows the management of uncertain knowledge. Fuzzy systems are employed to classify uncertain information and increase the efficiency of the defined systems. The proposed method block diagram is shown in Fig. 10. Extracted features of handwriting are considered as input of the fuzzy system. To recognize each type of handwriting, one fuzzy system is defined. The inputs are features of handwriting that are defined for each handwriting type, separately.

After determining fuzzy rules, inputs and their domain ranges, we have used Mamdani fuzzy inference algorithm to classify handwriting which includes 'Or', 'And', 'Implications', and 'Aggregation' logical operators, and de-fuzzification method is 'mom'. The membership functions provided for both the inputs and outputs of the fuzzy systems are Z-shaped and S-shaped functions in this paper (zmf and smf in Matlab). These functions are shown in Fig. 11. Z-shaped function is used for low values and S-shaped function is used for high values in the inputs and outputs ranges. Different values of [x1 $\times$ 2] thresholds for the membership functions in different types of handwriting are shown in the Table 2 (Input1, Input2 and Output are introduced in Table 3. Input 1 and Input 2 are based on the second column and Output is based on the last column of Table 3). The values of Z-shaped function less than x1 are considered low and the values of S-shaped function larger than x2 are considered high. In the training phase, the features of 90 handwriting samples are extracted from the database (including 140 samples). The maximum, mean, variance and minimum amounts of features of training samples determine the parameters of the membership functions and rules thresholds. Also, fuzzy inputs are the amount of extracted features from handwriting according to Table 3, so that the specified input values were applied as the crisp input for each fuzzy system. The real

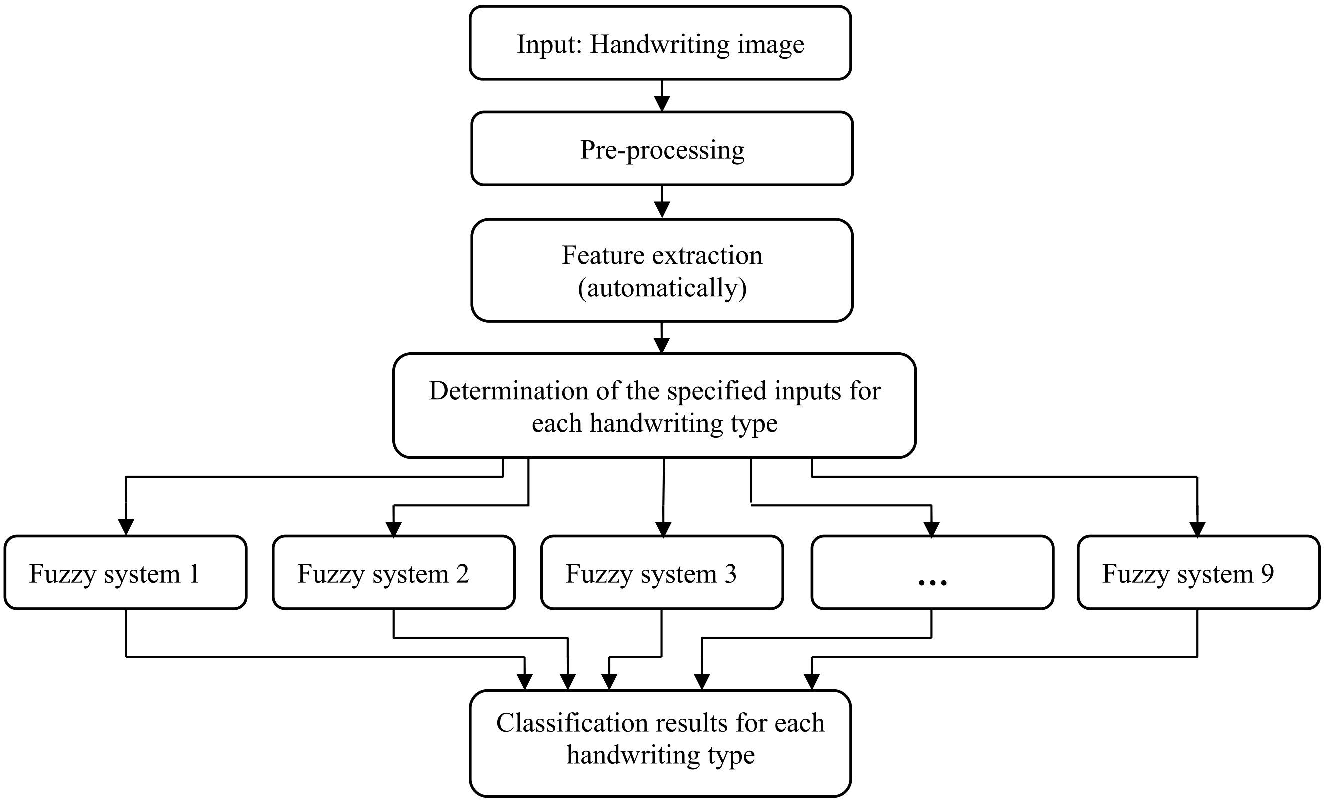


FIGURE 10. The proposed method block diagram for personality recognition.

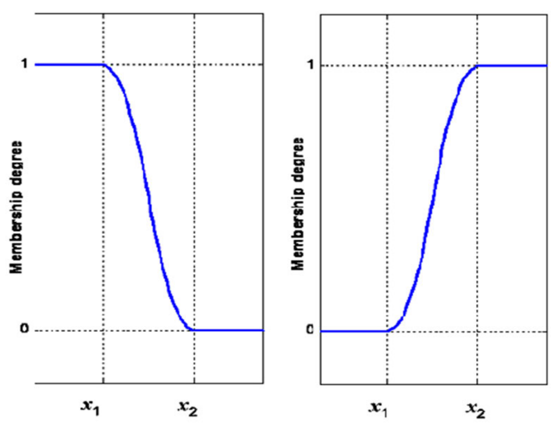


FIGURE 11. Z-shaped (left side) and S-shaped (right side) membership functions.

inputs are mentioned in Table 3. In each designed fuzzy system, one or two features are considered as the fuzzy system inputs (see Fig. 10). Table 3 entries are selected based on graphology science (Table 1 and [1]).

The output of each fuzzy system determines the type of handwriting. The number of designed and proposed rules is totally 24. The rules are various for each type of handwriting (See Table 3). In the following, an example of fuzzy rule is shown which is useful for spontaneous handwriting:

1. If (ratio of number of zero angles to line number is L) then (Out_spontaneous is L)
2. If (ratio of number of zero angles to line number ratio is H) then (Out_spontaneous is H)

The thresholds are determined based on maximum, mean, variance or minimum amounts of features of training samples in this study. Since in some handwriting samples, more than one feature is effective, this issue has been considered in designing fuzzy system and defining its rules. The fuzzy system output is in a range of zero to one hundred. This shows that the input handwriting belongs to which groups in terms of their regularity and inequality of letters. Table 3 shows handwriting types, inputs, amount of membership function, defined rules and output of the system. MATLAB software and writing m-file codes were used to create Mamdani fuzzy classifiers to recognize the characteristics. In Fig. 10, nine fuzzy systems were built according to Table 3.

VI. RESULTS AND DISCUSSION

All database samples (140 samples) were used in this paper. First of all, in training phase, feature extraction was done on 90 samples. To verify feature extraction algorithms, features for all handwriting samples have been obtained by a human expert in the database as a valid benchmark. Then, feature extraction is performed automatically by the proposed algorithms and the accuracy has been calculated compared with the database benchmark. Table 4 shows accuracy of correct

TABLE 2. [x1 × 2] values for the inputs and output membership functions in different types of handwriting.

Membership function / Handwritten type	Input 1		Input 2		Output	
	Z-shaped	S-shaped	Z-shaped	S-shaped	Z-shaped	S-shaped
Handwriting with difference in pen pressure	[0.9 1.6]	[1.1 1.7]	-	-	[13.2 29.0]	[69.2 90.0]
Coordinated handwriting with partial variance	[2.8 5.0]	[2.0 7.1]	[4.8 9.9]	[5.4 11.3]	[22.3 66.3]	[36.6 81.6]
Uncoordinated handwriting	[1.1 3.3]	[0.1 4.7]	[4.9 10.0]	[4.1 10.0]	[22.3 66.3]	[36.6 81.6]
Handwriting with inequality of letter's inflexion	[6.8 9.5]	[6.0 9.5]	-	-	[36.9 50.1]	[49.1 76.6]
Spontaneous handwriting	[0.1 7.8]	[4.1 9.8]	-	-	[53.3 79]	[0.3 78.7]
Unequal handwriting	[8.0 16.3]	[8.3 15.5]	-	-	[4.8 36.8]	[62.3 94.3]
Regular handwriting	[1.7 3.9]	[1.9 7.0]	[11.6 16.7]	[9.3 15.2]	[22.3 66.3]	[36.6 81.6]
Uniform handwriting	[4.7 10.4]	[2.2 16.7]	-	-	[6.1 37.7]	[54.4 85.4]
Sharp handwriting	[4.0 8.7]	[4.1 8.1]	-	-	[15.6 47.6]	[51.7 82.6]

extraction of the features. In fact, the amount of errors is obtained from the average percentage of relative difference of calculated feature values and the benchmark values (obtained by human expert) of all samples. The result shows high accuracy in extracting word's distance, slope angles and curve of baseline of the text in Table 4. The number of lines of handwriting also has high accuracy as an important parameter for extracting curve of the baseline. As it is shown in the table, one of the most challenging features is number of angles (zero, acute and obtuse), and the reason is the natural changes in the writing angle in a person's handwriting.

Then, to classify various handwriting samples, the amount of variance, mean, max, min of the features has been calculated. These values were used to determine the amount of membership function. To design fuzzy system in this research, some features are applied as an input of the fuzzy systems regarding the proposed features for various types of handwriting. In the fuzzy system output, there are classifications of different handwriting samples.

After extracting features, the fuzzy system was designed. The Mamdani fuzzy system algorithm has been used with 24 rules for classifying different types of handwriting. By investigating output of the fuzzy systems and their graphology interpretation [1]and comparing the graphological result of MMPI interpretations which have been investigated in [26], the accuracy of this research is calculated.

Fig. 12 shows an example of handwriting. In the following part, the result of MMPI [26]and graphologists [1]interpretation and comparison of these two theories are discussed. For handwriting of Fig. 12, our fuzzy algorithm output shows that handwriting is with difference in pen pressure, uncoordinated handwriting with partial variance, uncoordinated, with inequality of letter's inflexion, non-spontaneity, equal, irregular, non-uniform and sharp. According to graphology information [1], the owner of this handwriting is an aggressive, bad tempered, upset, nervous, sensitive, irritable, coward, non-serious, untidy, lacking discipline and emotion. The result of MMPI for this handwriting also shows that this is a dependent person, shy, lacking awareness of its own condition, with suspicion and a plaintiff of conditions. As can be seen an upset and nervous person surely is suspicious and sensitive. Non-serious and coward characteristics of this person are also related to lacking awareness of his own condition. This comparison proves the existence of a lot of common characteristics output between the proposed system and graphology information of MMPI.

In the prepared database, all handwriting writers have also completed MMPI questionnaires. The MMPI questionnaires have been reviewed by the psychological expert, and the behavioral and personality features are derived from each MMPI questionnaire based on handwriting types in Table 1. Actually, there are MMPI personality features (based on Table 1) for handwriting samples in the database. For evaluation, the fuzzy outputs are compared with these MMPI personality features. The real numbers of fuzzy system outputs are determined in the range of 0 to 100. If the output number is above 50, this is considered as high('1') and if the output number is less than 50, this is considered as low ('0'). The types of handwriting are determined depending on whether the output numbers are high (belonging to the regarding type) or low (not belonging to the regarding type).

TABLE 3. Handwriting types (9 types), inputs, amount of membership function, 24 fuzzy rules and output of the fuzzy systems (L = Low, H = High).

Handwritten type	Input	Range of membership function	Fuzzy rule and output
Handwriting with difference in pen pressure	1.Variance of width of pen	0-2	1. If (variance of width of pen is H) then (Out_ handwriting with difference in pen pressure is H) 2. If (variance of width of pen is L) then (Out_ handwriting with difference in pen pressure is L)
Coordinated handwriting with partial variance	1.Slope angle 2.Variance of distance between words	0-12 0-16	1. If (slope is L) and (variance of distance between words is L) then (Out_coordinated handwriting with partial variance is H) 2. If (slope is H) and (variance of distance between words is H) then (Out_coordinated handwriting with partial variance is L) 3. If (slope is L) and (variance of distance between words is H) then (Out_coordinated handwriting with partial variance is L) 4. If (slope is H) and (variance of distance between words is L) then (Out_coordinated handwriting with partial variance is L)
Uncoordinated handwriting	1.Slope angle 2.Variance of distance between words	0-12 0-16	1. If (slope is H) and (variance of distance between words is H) then (Out_uncoordinated is H) 2. If (slope is L) and (variance of distance between words is L) then (Out_uncoordinated is L) 3. If (slope is L) and (variance of distance between words is H) then (Out_uncoordinated is L) 4. If (slope is H) and (variance of distance between words is L) then (Out_uncoordinated is L)
Handwriting with inequality of letter's inflexion	1.Ratio of difference between acute and obtuse angles numbers to line number	0-15	1. If (ratio of difference to line number is H) then (Out_inequality of letter's inflexion is H) 2. If (ratio of difference to line number is L) then (Out_inequality of letter's inflexion is L)
Spontaneous handwriting	1.Ratio of number of zero angles to line number	0-25	1. If (ratio of number of zero angles to line number is H) then (Out_spontaneous is H) 2. If (ratio of number of zero angles to line number is L) then (Out_spontaneous is L)
Unequal handwriting	1.Variance of height of vertical letters	0-25	1. If (variance of height of vertical letters is H) then (Out_unequal is H) 2. If (variance of height of vertical letters is L) then (Out_unequal is L)
Regular handwriting	1.Slope angle 2.Variance of distance between words	0-12 0-16	1. If (slope is L) and (variance of distance between words is L) then (Out_regular is H) 2. If (slope is H) and (variance of distance between words is H) then (Out_regular is L) 3. If (slope is L) and (variance of distance between words is H) then regular (Out_regular is L) 4. If (slope is H) and (variance of distance between words is L) then regular (Out_regular is L)
Uniform handwriting	1.Variance of baseline curve	0-35	1. If (variance of baseline curve is L) then (Out_uniform is H) 2. If (variance of baseline curve is H) then (Out_uniform is L)
Sharp handwriting	1.Ratio of number of obtuse angles to line number	0-12	1. If (ratio of number of obtuse angles to line number is L) then (Out_sharp is H) 2. If (ratio of number of obtuse angles to line number is H) then (Out_sharp is L)

Therefore, this is determined that handwriting belongs to one of the nine handwriting types (defined in Table 3). These nine personality features were compared with MMPI personality results (as a reference).

TABLE 4. The accuracy of feature extraction.

Extracted feature	Accuracy (%)
Number of lines	90
Pen width	80
Baseline curve	95
Height of vertical letters	78
Distance between words	95
Number of angles (zero, acute and obtuse)	75
Slope angle	95

TABLE 5. Accuracy of the proposed system by matching with MMPI results for each handwriting type.

Handwritten type	Accuracy of output characteristics matched with MMPI feature (%)
Handwriting with difference in pen pressure	77.3
Coordinated handwriting with partial variance	89.3
Uncoordinated handwriting	90.6
Handwriting with inequality of letter's inflexion	78.9
Spontaneous handwriting	80.3
Unequal handwriting	76.7
Regular handwriting	84.6
Uniform handwriting	86.1
Sharp handwriting	79.1

In Table 5, recognition accuracy of each handwritten type is displayed for 50 test handwriting. The final result of the recognition accuracy is given in Table 6 for students, prisoners and combination of them and the final personality recognition accuracies of 85.3, 79.6 and 82.5% were achieved, respectively.According to Table 1, their measured characteristics were extracted according to the output of the fuzzy systems in the test phase. In the last row of this table, these nine types in 50 test samples (140-90 = 50) include a total of 450 (9×50) statuses. Previously, the MMPI interpretations of these 50 handwritten samples were obtained and statuses of the nine types were determined for each handwriting sample by an expert psychologist. After comparison, 371 statuses conformed to the MMPI's psychological interpretations. This resulted in the characteristics accuracy of 82.5%.

VII. COMPARING WITH EARLIER STUDIES

In [13], some important researches are reviewed. Some other important publications related to the field of graphology are introduced in Table 7. In these researches, different methods were used to extract features and classified with different systems. Due to the small number of graphology articles based on soft computing, comparisons with close graphology works have been performed. For example, Handwriting were investigated under different mental workloads in [30]and accuracy of classification of handwriting into mental workload classes is reported. Also, authors of [17], [21], [28] have used a simpler database and less personality diversity and reported

TABLE 6. Output accuracy of the proposed system by matching with MMPI results.

Number of handwriting samples (in test phase)	Number of output characteristics matched with MMPI features	Accurac y (%)
25 (students)	192 (of 225)	85.3
25 (prisoners)	179 (of 225)	79.6
50 (students and prisoners)	371 (of total 450)	82.5

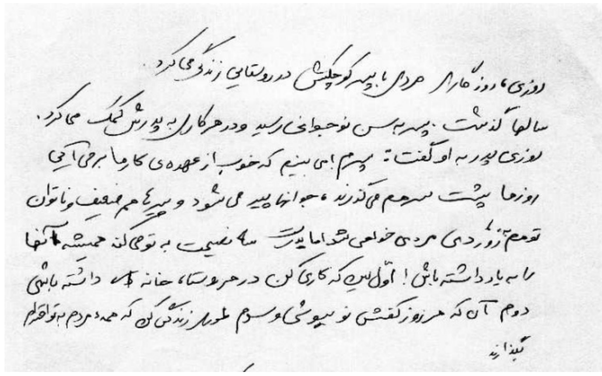


FIGURE 12. An example of handwriting.

feature extraction accuracy (not personality recognition). But, in this research, a standard database and comprehensive personality diversity have been used, and brilliant results were obtained in personality recognition accuracy. Some of these researches tried to recognize personality of handwriting owner without image processing systems and only based on visual boundaries and comparing with graphology tables [21], [22].

In [24], features such as the number and the length of handwriting lines, slope angle, margins, distance between the letters and their arrangement are considered as back-propagation neural network inputs. In [22], the aim of the research is to classify different handwriting samples in terms of their regularity and inequality of letters and to find writer's characteristics based on decision making graphology table [1]. Arabian and Ghods [26]also classified extracted features with another classification system which is called decision tree.

In this paper, a comprehensive study was carried out to introduce suitable graphology features and their extraction methods. The proposed fuzzy rules had a fundamental role in proper accuracy of personality recognition. Meanwhile, some people respond the question without regarding the content (even non-real positive or negative impression) that challenges the research.

The obvious points of this research compared with earlier studies are using optimal features with modification in feature extraction algorithms (baseline curve and pen width). Meanwhile, fuzzy rules were well analyzed and presented. The database which included the handwriting MMPI results was used. Moreover, the results of computerized graphology

TABLE 7. Earlier studies in computerized graphology and the proposed method.

Reference	Pre-processing	Extracted features	Analysis method	Database (No. of samples)	Accuracy (%)
[21]	Binary ,noise elimination	Right and left margins, word expansion, letter size, line and word spacing, line skew, ratio of vertical to horizontal of words, slant	Graphology	118	90
[17]	Not mentioned	Slant, slope, line spacing, margins, size, image contours, angular writing, fractal dimension, regularity in writing frequency, pen pressure	Back-propagation neural network	98	89
[23]	Template matching, Polygonalization, gray level threshold	Baseline, pen pressure, the letter 't', the letter 'y' loop	ANN	Not mentioned	Not clear
[24]	Binary ,noise elimination	Number and length of handwriting lines, slope angle, margins, distance between the letters and their arrangement	ANN	120	80
[29]	Not mentioned	Pressure, temporal, spatial (segment length, height and width), angular velocity of a segment	K-means	56	Not clear
[28]	Gray scale, thresholding, segmentation two areas: handwriting and signature	Margins, spacing between words and lines, zone domination, baselines and the signature features	ANN	100	52-100
[22]	Noise elimination, Fix the baseline	Baseline curve, line spacing, letters angles, speed of writing	Threshold	100	Not clear
[31]	Not mentioned	Temporal measures, spatial measures (stroke path length, stroke height and width) included, angular velocity of a stroke	K-means	98	Not clear
[30]	Not mentioned	Spatial (width, height, displacement, curve length), kinematic (velocity, acceleration), duration time, pressure, angles (tilt, azimuth, directional angle), PMPG	Random Forest Classifier	88	92.16
[40]	Not mentioned	Baseline, Slant, Letter size, Margin, Line space, Word space, Writing style, Writing speed	Simple logistic, Decision tree, K-nearest neighbors, Random forest	160	68.67
This work	Noise elimination, grayscale and binary converting, connected component labeling and area calculation	Number of lines, pen width, baseline curve, height of vertical letters, distance between words, number of zero angles, number of acute and obtuse angles, slope angle	Fuzzy system	140	82.5

were validated with the results of their MMPI for each person.

VIII. CONCLUSION

In this paper, we classified various handwriting samples based on regularity and inequality by using fuzzy inference systems. The database of handwriting samples was provided by their MMPI questionnaires. Then, achieved results of personality recognition were validated regarding available interpretations of MMPI questionnaire results. Regarding the importance of skilled graphologists and their small number, soft computing is required for this time-consuming and difficult task, i.e. extracting features and recognizing personality. In this research, we extracted the features automatically and determined appropriate fuzzy rules for personality recognition. Compared to the MMPI results for the handwriting (prepared by the expert), the proposed method showed an accuracy of 82.5% that is very promising. Considering deep learning development in the field of pattern recognition is suggested for computerized graphology in the future work.

APPENDIX A
CHARACTERISTICS OF VARIOUS HANDWRITING SAMPLES

A. FEATURES OF AUTOMATIC (SPONTANEOUS) HANDWRITING

In this type of handwriting, letters are like printed letters and hand movement is like mechanical movement with simple shapes. Therefore zero angles and 90° angles are main features. According to simplicity of the features in this type, we can consider the number of zero or 90° angles in comparison to the total number of angels as effective features. So, in fuzzy system which is designed to recognize this handwriting, the ratio of zero angles or 90° angles number to the number of lines of the text are considered as a fuzzy system input in order to classify proper rules and determine scope of the membership functions.

B. FEATURES OF HANDWRITING WITH DIFFERENCE IN PEN PRESSURE

Pen pressure changes make pen width to change on the paper. In this type of handwriting, there are many changes of pen width. Thus, variance of width of pen is considered as input of the fuzzy system and magnitude of change is considered as the slope of membership function input in order to make it possible to recognize type of this handwriting.

C. FEATURES OF UNCOORDINATED HANDWRITING

In uncoordinated handwriting, large amount of changes in size and word's space (distance) are the main obvious features. So, in designing fuzzy system to recognize the uncoordinated handwriting, variance of word's space and the slope angle of the text are considered as input of the fuzzy system and their variation is considered as the amplitude of membership function inputs. Fuzzy output shows whether the handwriting is uncoordinated or not.

D. FEATURES OF COORDINATED HANDWRITING WITH PARTIAL VARIANCE

In this type of handwriting, small changes in slope of the text angle and variance of the space between words are the brilliant features. Thus, they are considered as input of the fuzzy system. The system output is the recognition of coordinated handwriting with partial variance.

E. FEATURES OF UNIFORM HANDWRITING

Flat handwriting lacks diversity. Since curve of the baseline contains information such as ups and downs and handwriting changes, this is considered as the significant feature of this type of handwriting. Variance of the baseline curves (differences between baseline curve and the standard baseline) is introduced as input of the fuzzy system. System output determines whether the handwriting is flat or not.

F. FEATURES OF SHARP HANDWRITING

In sharp handwriting, sudden and large amount of changes are seen in breaking the letters and changing their angles. Ratio of the number of obtuse angels to the number of handwriting lines can be considered as the main fuzzy system input in order to clarify whether the handwriting is sharp or not.

G. FEATURES OF REGULAR HANDWRITING

In regular handwriting, equal shapes and equal sizes of words are seen. The input of fuzzy system which is designed for this type of handwriting is the changes in distance between the words and the slope angle. Variance of distances between words is considered to determine the amount of membership function in order to recognize regularity or irregularity of the handwriting in the output.

H. FEATURES OF HANDWRITING WITH INEQUALITY OF LETTER'S INFLEXION

In this type of handwriting, due to high curvature of letters, the angle changes are the main factor for diagnosing the type of handwriting. Thus, the difference between ratios of acute and obtuse angel number to the number of lines of a text is considered as the fuzzy system input. Output of the fuzzy system is also determines this type of handwriting.

I. FEATURES OF UNEQUAL HANDWRITING

Unequal handwriting can be identified through inequality in height of letters. Thus, by extracting height of vertical letters and calculating their variance, a proper fuzzy system can be designed. Input of this system is variance of height of vertical letters.

COMPLIANCE WITH ETHICAL STANDARDS

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

ETHICAL APPROVAL

This article does not contain any studies with human participants performed by any of the authors.

INFORMED CONSENT

Informed consent was obtained from all individual participants included in the study.

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DATABASE

Database will be available on request.

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