Analysis of Off-line Handwritten Text Samples of Different Gender using Shape Descriptors

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***Abstract*—The human experience in the analysis of the handwriting of male and female writers indicates that gender affects the appearance of the handwritten text. These differences are usually very difficult to describe numerically. In order to analyze the handwriting differences between male and female writers, several shape description techniques, such as the tangent angle function, curvature function and Fourier descriptors, were used in this paper. As an additional contribution of the paper, a database of 3766 off-line handwritten cursive and capitalized written words has been created. The database consists of male and female handwriting samples, classified by gender and handedness. The experimental results show that typical attributes of male and female handwritings imply certain differences in shape decriptors, and those differences have the potential for usage in gender handwriting discrimination.**

***Index Terms*—handwriting, gender identification, shape descriptors, database**

I. Introduction

It is well known from everyday life, that sex, age and handedness have impact on the appearance of handwritten text. Persons that are in contact with many handwritten documents (such as teachers), quickly develop the ability to distinguish male and female handwriting. Many studies have been conducted in this field [1]–[6], and it has been shown that even untrained human examiners are able to guess the sex of the writer based on text samples, with the percentage rate up to 70%. Reports of handwriting find that female handwriting has greater circularity [1], and it is more "delicate and decorative" than for men [2]. Typically, handwriting attributes such as "large", "rounded", "neat", "regular/consistent" and "carefully executed" writing belongs to females and "sloping", "spiky", "confident", "hurried" and "untidy/scruffy" are significantly more often used to describe male scripts [3]. This is also a common understanding of handwriting gender differences of most people.

Males and females across cultures are also rated as different. Some research has shown that even hormonal influences affect male and female handwriting performance [4].

The identification of writer gender from handwriting is an important element of the field of forensic studies [7].

In order to eliminate the effects of other factors (such as age, handedness, etnicity etc.) while analysing gender differences, a database of off-line handwritten text samples was created. The database consists of 3766 entries, donated by more than 300 students of Faculty of Electrical Engineering Sarajevo. Samples are classified by gender and handedness. Capitalized and cursive written words are also separated. All students have from 19 to 22 years of age. They were all asked to write the same sentence, which consists of 8 words. The database is made freely available on the internet.

Once the database has been formed, experiments were conducted. In this paper, two approaches were used. The first one is the analysis of the samples directly from the acquired image, using Generic Fourier Descriptors [8]. The results show that higher frequencies are correlated to certain attributes that are commonly used to describe male handwriting (spiky, untidy), and that most female descriptions (such as neat), are not connected with higher frequencies. The second approach is the contour based approach. The contours are extracted from the handwriting samples, and tangent angle function [9] as shape descriptor is used. The results show that "spiky" male handwriting have faster changes of tangent angle function (larger changes of direction), and increased power in the higher spectrum. Also, a curvature function and bending energy of the contour is analysed [10], and results show that female handwriting, as expected, very often show roundedness (that manifests as writing with less changes in curvature, and hence less bending energy).

The results indicate that it is not possible to effectively distinguish male and female handwriting, using just a small number of parameters. Altough, for specific cases (such as stereotypical male/female handwriting), and common attributes (roundedness, spikyness etc.) it is possible to numerically distinguish male and female writers.

The paper is organized as follows. Section II gives an overview of male and female handwriting differences covered in literature. Section III describes the formed database, and illustrates the handwriting samples. Section IV gives an overview of the techniques used. Experimental results are given in Section V. Conclusion and guidelines for future work are given in the last section.

II. Sex differences in handwriting

There are several researchers that have demonstrated that a writers gender is predictable from handwriting [1], [2], [5],

[6], and that the accuracy of prediction is mostly around 70% [2], [5], [6], [11], [12]. Also Hayes [6] found that gender of writer was predictable at above-chance levels even with a single word. Studies have shown that men and women were equally accurate in their predictions, but some authors [5] found that both girls and boys were better at recognizing writers of their own gender. Significant gender differences in several aspects of handwriting style, including writing speed, slant, roundness, pressure, and various aspects of the size and shape of letters were reported. Hamid and Loewenthal have found that ”delicacy - decorativeness” can be used to judge femininity of handwriting [2]. Also embellishment can be used as a feature to describe female writers [13]. In one of the studies [3], [5], when children were asked to imitate the handwriting of the opposite gender, the boys tried to make their writing smaller and neater, whereas the girls made theirs bigger and scruffier.

There are several theories of gender differences in handwriting. The first one is that they are due to differences in fine motor coordination [5], the second one is that ”people communicate their sex by the way they move, both in walking and in handwriting” [6], and the third one is that hormones affect the handwriting [4].

In physiological researches (such as [5]), the cues that identified a script as female were ”neat”, ”even”, ”well organized”, ”well presented”, and ”rounded”, ”small”, ”ornate” and ”symmetrical” in style, and occasionally as ”lacking confidence”. The cues that identified a script as male were ”hurried”, ”uneven”, ”messy”, ”inconsistent”, and ”spiky”, ”sloping”,”heavy” and ”bold” in style, and sometimes ”confident”, ”assured” or ”arrogant”.

In technical types of researches, both micro (character) and macro (word) features were used [7], [14]. Usually two types of features can be distinguished: conventional and computational features [7]. Conventional features are used by forensic document examination community, while computational features are features that have known hardware or sofware tecniques for extraction. There is a total of 21 conventional features: arrangement, class of allograph, connections, design and consturuction of allographs, dimensions (vertical and horizontal), slant, spacings, intraword and interword, abreviations, baseline alignment, initial and terminal strokes, punctuation (presence,style and location), embellishments, legibility, line continuity, line quality, pen control, writing movements, natural variations, persistency, lateral expansion, and word proportions. Most conventional features should eventually become computational features, but considering the fact that most conventional features are not yet computable, the difference remains. Computational features can be divided into macro (extracted at document level) and micro (character level) features. Macro features include: measures of pen pressure, measures of writing movement, measures of stroke formation, slant and word proportion. Micro features are usually extracted using gradient,structural and concavity attributes (GSC) [7], and are widely used in automatic character recognition for handwritten postal adresses.

Fig. 1. Typical female (shown on the left), and male (shown on the right) samples of handwriting

Considering the development of on-line writing systems (such as tablets), there are computational features that can be measured using not only the static, but also the dynamic data. In [15] authors used several static (word width and height, height to width ratio, number of points comprising the image, sum of horizontal (and vertical) coordinate values, horizontal (and vertical) centralness), but also several dynamic parameters (execution time, pen lift, average horizontal (and vertical) pen velocity, azimuth, altitude, pressure). Also, in [16], authors used speed, writing direction, curvature, normalized x and y coordinate, speed in x and y direction, overall acceleration, acceleration in x and y direction, log curvature radius, vicinity aspect, vicinity curliness, vicinity linearity and vicinity slope, and ascenders/descenders. Gender classification problem is indeed proven to be a difficult task - authors used over 20 parameters to semiautomatically detect gender with confidence slightly above statistical significance.

Little work exists on automatically identifying gender or handedness, from handwriting [16]–[18], and the results of correct classification are usually slightly above 50% .

Typical examples of male and female written word ”anketa” (means ”poll” in English) are given in Fig. 1. It is clear that the handwritten words obviously differs, and that female word could be described by ”rounded” and ”neat”, while male samples could be described by ”spiky” or ”sloping”.

III. The BHDH database

In order to obtain the experimental results, a database of handwritten text samples is formed. For the results to be statistically significant, it was necessary to minimize all other effects that could affect the results. The volunteers who helped to form the database were students of the first and second year of Faculty of Electrical Engineering Sarajevo (Bosnia and Herzegovina). In order to collect enough material for testing, but not overload the students, it is decided that every student has to write a sentence ”Ovo je najzabavnija anketa koja se ikada pojavila” in Bosnian language, both in cursive and capitalized letters (the sentence means ”This is the funniest poll that has ever appeared”). Also, a writer had to declare his/hers

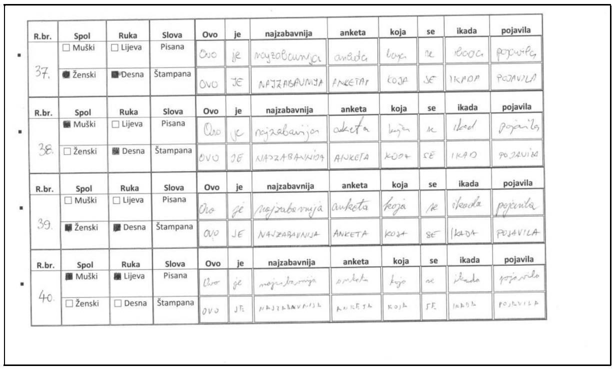

Fig. 2. Example of the form used to collect data for BHDH

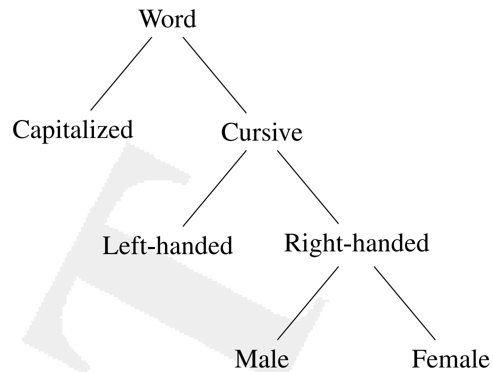

Fig. 3. Organization of BHDH database - the remaining branches of the organisational tree are not drawn for simplicity

gender and handedness. The poll was conducted anonymously, and the students were informed that their handwriting will be used as a research material. All students conducted this activity just before an exam (because many students were present at that time), so it can also be concluded that all students were under similar stress conditions. The handwriting samples were collected using pen and paper, using forms as the one shown in Fig. 2.

Then, all forms are scanned and saved in digital form. The first problem that has been encountered is that all collected forms (because of printing and scanning) are not equally rotated, and show deflection of ± 2 degrees. Automatic alignment and rotation is achieved using Hough transform. Hough transform is a popular algorithm for finding lines in images. It is based on the fact that the Hough transform transforms a point in the image space to a line in the transformation space. This means that collinear points in image space form a beam of lines that intersect in the same point in transformation space. Hough transform helps to find those points, hence determining the lines on which many image points lie. After the rotation and croping of the forms, it was relatively easy to automatically segment the words, and classify the segments into different database entries. The examples of segmented cursive-written words "anketa" for male and female, right-handed students are already given in Fig. 1. All segmented images form the B&H Database of Handwriting samples (named "BHDH"). It is the first database in Bosnia and Herzegovina of this type, and it is free to use, upgrade and edit. It can be downloaded from http://people.etf.unsa.ba/ esokic/BHDH/BHDH.html . The database is structurally organized as shown in Fig. 3.

Every sample is manually analysed for errors (not adequatly centered, misswritten word etc.), so unfortunately, from the initial 4092 entries, only 3766 are usable.

IV. Description of implemented methods

The usage of handwritten words (instead of lone characters) for studying handwriting individuality is a natural choice, especially for cursive writing [14]. Individuality analysis of handwritten words is very similar to signature verification. That is why a global, macro approach is used first.

Generic Fourier Descriptors

Fourier descriptors are a relatively old, and very popular technique for image shape recognition and classification. Although they are frequently used for shape classification [9], and have shown comparable results with other tecniques [19], they are rarely used for macro-handwriting recognition. FD technique has been used for detection of numerals [20], using character-based approach. The Generic Fourier Descriptor, developed by Zhang [8], is a region based shape descriptor which captures the global informations about the shape, avoiding the localization of the features and extraction of the contours. There are many enhancements of the GFD, such as Enhanced GFD, and several other hybrid techniques [9], but in the paper the most simple implementation is used, in order to clarify the contribution of the corresponding frequency components.

A shape image $I = \{f(x,y) | 0 \leq x < M, 0 \leq y < N\}$ is given. First the shape image is converted from Cartesian space to polar space $I_p = \{f(r,\theta) | 0 \leq r < R, 0 \leq \theta < 2\pi\}$, where R is the maximum radius of the shape, and the origin of the polar space is set to be the centroid of the space. The centroid is the analogue of the center of mass or gravity treating image as a 2d object, and it is important because its position in regard to the shape does not change with translation and rotation. Once the image is presented in polar coordinates, Discrete Fourier Transform is applied considering that a polar image is a rectangular image. This transform (noted $PF(\rho, \Phi) = \mathbf{F}(f(r,\theta))$) is also called Modified Polar Fourier Transform. Discrete radial and angular frequencies are ρ and Φ respectively. The number of radial and angular frequencies for typical images does not need to be large, in fact, Zhang [8] showed that using more than 4 radial and 9 angular frequencies to represent shape does not improve the shape discriminability, because power (or shape meaning) is concentrated at lower frequencies.

In order to achieve invariance to scale, translation and rotation, the transform coeficients are normalized.

The first magnitude value is normalized by the area of the circle in which the polar image resides ("area"), and other magnitude values are normalized by the magnitude of the first

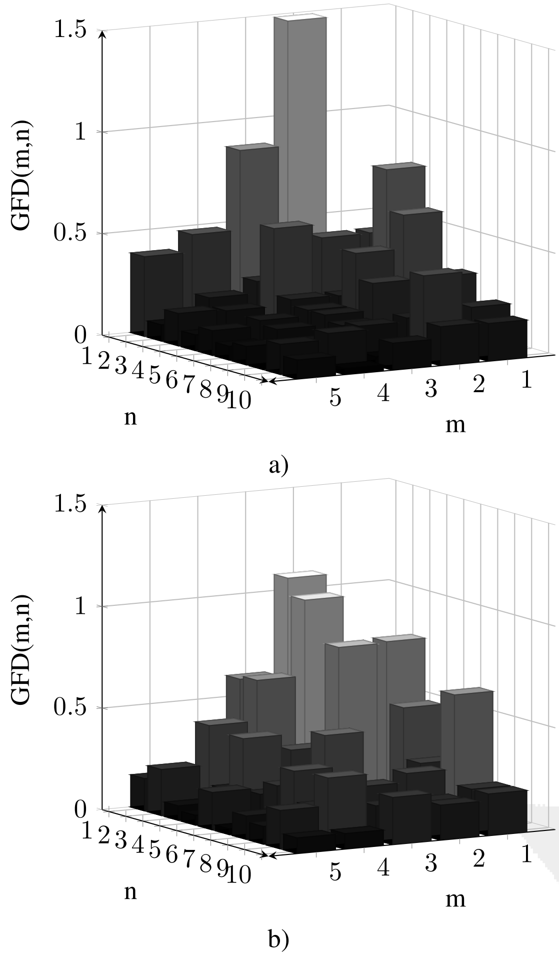

Fig. 4. Examples of a) female b) male handwriting sample GFD

coefficient. The resulting GFD feature vector is:

$$GFD = \{\frac{|PF(0,0)|}{area}, \frac{|PF(0,1)|}{|PF(0,0)|}, ... \frac{|PF(0,n)|}{|PF(0,0)|}, ... \frac{|PF(m,0)|}{|PF(0,0)|}, ..., \frac{|PF(m,n)|}{|PF(0,0)|}\} \quad (1)$$

where m and n are the maximum numbers of radial and angular frequencies selected. The similarity of two shapes (images) is usually measured using Euclidean distance between two feature vectors.

Tangent angle function

In order to analyse the behaviour of the writer, it is useful to evaluate the movements of the pen tip. Tangent angle function gives the tangential direction of the contour of the shape, or the written sample in this case. The tangent angle function in point $(x(n), y(n))$ of the contour is given with [9], [19]:

$$P_n(x(n), y(n)) = \arctan \frac{y(n) - y(n-w)}{x(n) - x(n-w)} \quad (2)$$

where w is an arbitrary long window. There are two problems that arise with tangent angle functions. The first one is noise sensitivity, so the contours have to be filtered before

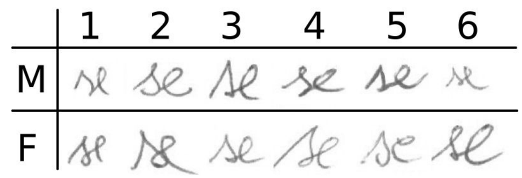

Fig. 5. Stereotypic male (above), and female (below) samples of word "se"

calculation. The second one is the discontinuity of size 2π. To overcome this problem, cumulative angular function is usually used [9], which assumes that the contour is closed, and that the variations are less than 2π. In this paper the "extended" tangent angle function was used. The function is calculated by means of postprocessing, to assure the continuity of the tangent angle function even if the tangent angle function changes directions for more than one full circle (which is quite often in handwriting).

The derivation of the tangent angle function is actually more important. It shows how fast the direction of the pen change. It is clear that one would expect that "spiky" (male) handwriting could form higher peaks in the tangent angle function derivation. In order to describe this effect, a Fourier transform of the tangent angle function derivation is obtained. A special parameter - called "Grad. Osc." is calculated. It gives the ratio of the higher frequency band power and the total power of the signal. Faster and more frequent changes will imply higher Grad. Osc. parameter.

Contour curvature and Bending energy

Curvature is a very intuitive feature to analyze, since it includes perceptual characteristics of the shape [9], [10]. The function of curvature is defined with:

$$K(n) = \frac{\dot{x}(n)\ddot{y}(n) - \dot{y}(n)\ddot{x}(n)}{(\dot{x}(n)^2 + \dot{y}(n)^2)^{3/2}} \quad (3)$$

The curvature is inversely proportional to the radius of the contour. A straight line has infinite radius of curvature, but it is the least curved ($K(n) = 0$).

Average Bending Energy is defined by [10]:

$$BE = \frac{1}{N} \sum_{n=0}^{N-1} K(n)^2 \quad (4)$$

It has its physical interpretation - it is the energy needed for drawing a contour. In order to form a closed contour, a circle has the minimum average bending energy [9].

V. Experimental results

The main task of this paper is the investigation and illustration some of the stereotypical features of handwriting of males and females using standard shape descriptors. In order to investigate the differences between genders, a short word "se" was used. Using a word with more letters would be subjected to more distortions, and could affect the observations. Also, only samples written by right handed persons were used.

TABLE I
EXPERIMENTAL RESULTS

Male			Female		
S. No	Grad. osc.	Bending Energy	S No	Grad. osc.	Bending Energy
1	0.5995	1.1178	1	0.5722	0.2658
2	0.6209	1.2630	2	0.5492	0.6412
3	0.6495	1.4825	3	0.6209	1.8107
4	0.6238	1.9566	4	0.5270	0.7563
5	0.7615	0.5563	5	0.6200	1.1910
6	0.6529	0.8811	6	0.5244	0.7684

Six representative male and female handwriting samples, are chosen from BHDH for presentation in Fig. 5. Some differences may be observed. For example, on the letter ”s”, the ”hat” is ”curly” in 4 female, but only in 2 male samples. Also, the transition from the letter ”s” to ”e” is continouos (with one stroke) in 4 female versus only 2 male samples. The female samples obviusly are more curved than male samples. It is clear that female samples use less energy to write. The conclusions (and percentages) deducted on these 12 samples are easily extended to full database.

The Generic Fourier Descriptors are shown in Fig. 5, for samples F-2 and M-5. For the ease of the representation and comparison, GFDs are given in matrix form (unlike Eq. 1). Female sample F-2 is rounded, and ”easy for the eye”, unlike male sample M-5, and so the male GFD shows greater power in higher part of the spectrum.

Unfortunately, every algorithm developed for gender classification has its own drawbacks, and so have this one. Considering that even human recognition of the writer gender is around 70%, there are a lot of examples where even an average human judge cannot tell the difference. For example male sample M-2, or female sample F-5, could easily be exchanged (mistaken gender), and there are a lot of similar examples in the database. GFD do not comply with the above made conclusions. The problem is that GFD are developed for shape recognition, and they capture the overall structure of the text, not the contours itself, nor the local details.

For that matter, two human examiners have chosen 5 male and 5 female samples that are undoubtedly male or female (according to experience, stereotypic parameters and overall appearance). The 4 of 5 cases for males, and 3 of 5 cases for females indicate that stereotypical male and female samples do differ in higher part of the spectrum. A broader conclusion for gender discrimination could not be made using GFDs because the database still does not contain so many ”typical” and undoubted cases to verify the hypothesis, and secondly, the treshold for distinguishing could be set only for a known written word.

The traced handwritten contour, the filtered extended tangent angle function, and the tangent angle function derivation for samples M-1, M-3, M-4 and F-1, F-4, F-6 are shown in Fig. 6. From Fig. 6, it could be seen that male samples shows steeper changes of direction. This is clearly seen observing tangent angle function derivations of samples in Fig. 6, where the speed of direction change is greater for male samples. Also, it could be seen that samples M-1, M-3, F-4 are written in one way, and M-4, F-1 and F-6 are written in another.

The curvature of the handwriting samples is also shown in Fig. 6, and the average bending energy (given in Table I) is calculated accordingly. For the calculation of the parameters in Table I, the peak resulting from the ”hat” of letter ”s” is excluded, because of the infinite results of numerical derivation. From the results, it is clear that male samples show greater peaks, and greater bending energy.

All methods described in this section gives satisfactory results for a selected set of representative samples, as shown. Although the Grad. Osc. parameter and Average Bending Energy is higher for male samples as shown in Table I, in the representative data itself there are a lot of exceptions. These are usually samples that could not be easily recognized even by humans. It would be naive to expect to solve a gender classification using only few features, but the methods described could certainly be used in collaboration with other techniques, and more complex decision systems.

VI. CONCLUSION AND FUTURE WORK

The evaluated results, and discussion, lead to a conclusion that stereotypic examples of male and female handwriting show quantitative differences in spectral bands of the handwritten sample, direction of the movements, speed of direction change, curvature and average bending energy. All of these parameters could be used for assistance in an automatic gender handwriting classification system. But, the results also indicate, that like many of the (semi)automatic handwriting analysis techniques, the methods needs a lot of improvement before the usage on the atypical handwriting samples, and often need some human assistance. Although the proposed methods in this paper are relatively fast, simple and not sensitive to noise, it could be concluded that unlike some more complicated solutions [14]–[18] they are not that accurate and reliable for handwriting gender recognition. In the real world there are a lot of variations in handwriting techniques, so fewer parameters and small text samples are not exceptionally effective in providing enough gender discrimination ability, especially in cases where even a human cannot distinguish the gender of the writer. Another contribution made by this work is the collecting, segmenting and sorting the samples in BHDH database, which is available for other researchers to use, free of charge. This paper is only the beginning of the larger handwriting research project. For future work, more sofisticated handwriting and image analysis tecniques will be applied in order to develop an automatic system for handwriting, gender and handedness classification.

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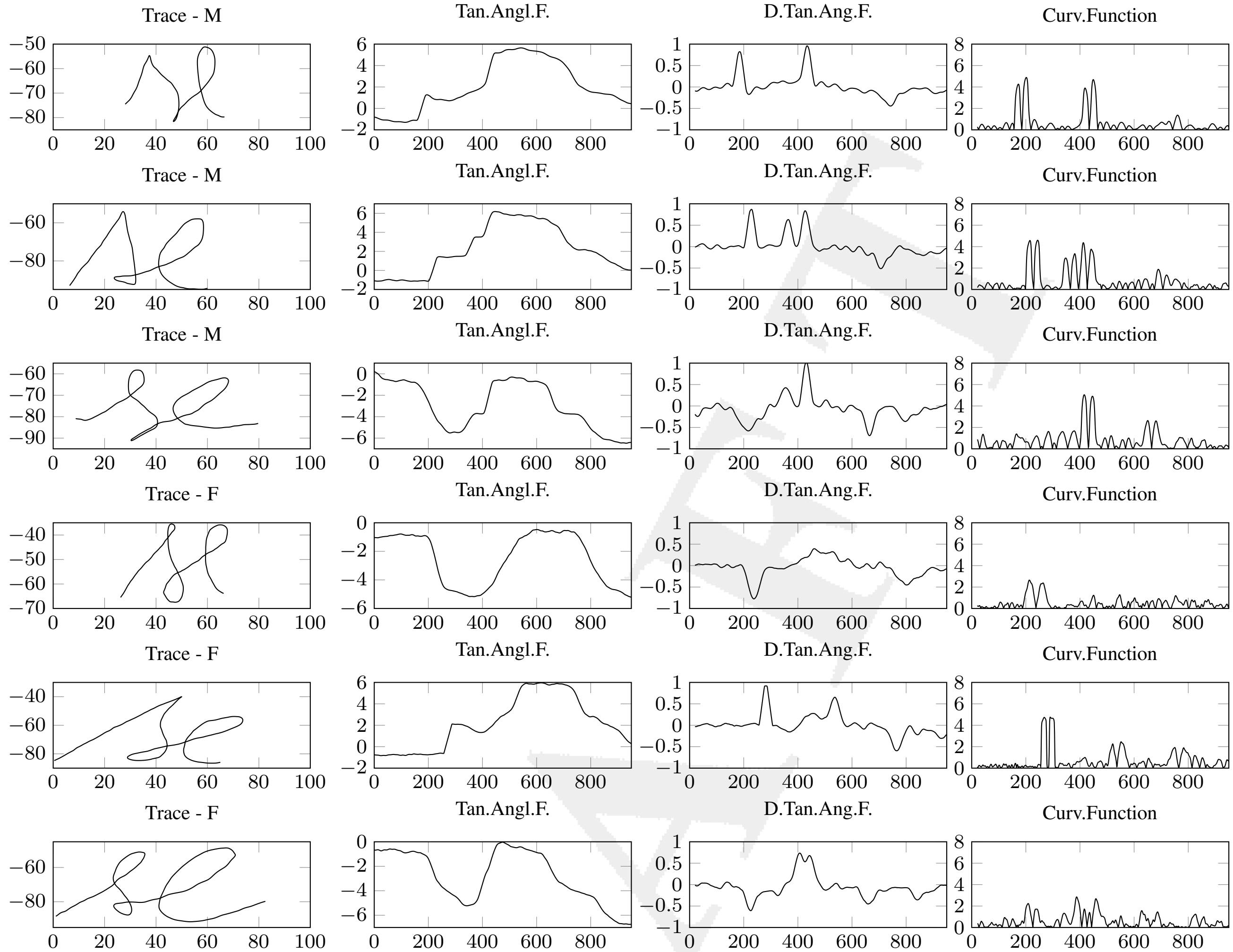

Fig. 6. Contour, the filtered extended tangent angle function, the tangent angle function derivation and curvature for samples M-1, M-3, M-4 and F-1, F-4, F-6

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