On-line Signature Authentication using Zernike moments
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Abstract—Zernike moments are image descriptors often used in pattern recognition. They offer rotation invariance. In this paper, we discuss a novel method of signature authentication using Zernike moments. Instead of working on primary features such as image or on-line data, working on the derived kinematic plot is a robust way of authentication. The derived kinematic plot considered in this paper is acceleration plot. Each signature’s on-line acceleration information is being weighted by Zernike moment. The shape analysis of the acceleration plot, using only lower order Zernike moments is performed for authentication of on-line signature.

I. INTRODUCTION
The recent advances in technology and increasing requirement for security have resulted in rapid development of personal identification based on biometrics. Modern systems aim to move security from simple static passwords to more dynamic security measures to suit the comfort level of the user in mobile-commerce and web-commerce. Biometric authentication finds its application in secure electronic banking, mobile phone transactions, credit cards, secure access to buildings and network services. New pattern recognition techniques that can mine and discover behavioral knowledge in large data sets are very much essential. The major challenge in signature authentication is that, it is strongly affected by user-dependencies as it varies from one signing instance to another in a known way. It is well known that no two genuine signatures of a person are precisely the same and some signature experts note that if two signatures written on paper were same, then they could be considered as forgery by tracing [3]. Even if the forger takes great pain in remembering the styles and contours of the strokes, it is extremely unlikely that he/she would be able to match the velocity profile or any other dynamic characteristics of the original signature [2].

II. BACKGROUND
The image can be decomposed into a sum of basic structures. The Zernike moments are a set of complex polynomials inside the unit circle, \( x^2 + y^2 = 1 \). This set completely covers the interior of the unit circle. Geometric moment of an image provide scaling and translation invariance. Its basis set is not orthogonal, computationally expensive as the redundant information are coded and recovery of image is difficult [19], [21]. Zernike moments are applied on normalized image.

Zernike moments are orthogonally stable, provide rotation invariance and image reconstruction. The preprocessed derived feature can provide translation and scaling invariance inherently. Rotation of an image in spatial domain lead to a phase shift. The magnitudes of a rotated image are same as compared to the magnitudes of the image before rotation. The choice of the Zernike method will avoid edge following or skeletonization as compared to Fourier descriptors or structural approaches. High order Zernike moments are more sensitive to noise [13].

Zernike moment descriptors are used to represent symbols [10], faces [26], hand printed Devanagiri characters [27], image signatures [24]. In this paper, we aim to work on lower order of the Zernike moments with a derived feature. The derived feature depicts acceleration. This leads in reducing response time of the system as higher order moments take significantly longer time to compute. The shape characteristic of derived feature acceleration under continuous dynamic programming provided acceptance rate of 97% and rejection rate of 92% using MCYT-100 on-line signature baseline corpus [25]. An attempt is made to represent acceleration values of an on-line signature by a weighted sum of Zernike polynomials and hence to provide authentication.

Work proposed by Guru [5] used MCYT signature corpus with 8250 genuine and 8250 forged on-line signatures with all 100 features proposed by Nelson [8] achieved Equal Error Rate [ERR] of 5.35%. The work proposed by Julian [4] has verification performance results as 0.74% and 0.05% EER for skilled and random forgeries respectively with a posteriori user-dependent decision thresholds on a database of 145 subjects comprising 3625 client signatures, 3625 skilled forgeries and 41,760 random imposter attempts. DTW based approach by Kholmatov was ranked first for skilled forgeries. The work done by Oscar [6] was on MCYT signature database of 2500 genuine and 2500 skilled forgeries from 100 users with a performance of 8% EER for skilled forgeries considering a subset of 26 features. The work done by Moussa Djoua [7] used panel interface to display simulated signals of the test pattern and to compare with standard pattern simulated signals analytically and visually. In the work done by Siyuan [23] for off-line signature verification with an on-line flavor, Zernike is applied for upper and lower contours of the signature. The signature is segmented into 20 small curves linearly, so that shape feature can be separately computed for each contour. Sixteen Zernike moments, up to order 6 are extracted. 16 x 2 x 20 Zernike feature values were extracted from a signature. Applying similarity measure, 83.7% acceptance rate and 83.4% rejection rate was achieved. However, no previous work focuses on normalized
summation Zernike moment values of acceleration values as a reliable feature in on-line scenario.

III. FORMULATION

The Zernike functions are a product of the Zernike radial polynomials with sine and cosine functions. As stated earlier, Zernike moments have simple rotational symmetry properties, which lead to a polynomial product of form $z[n, m, \rho]g[\theta]$, where $\rho = \sqrt{x^2 + y^2}$ and $g[\theta]$ is a continuous function that repeats every $2\pi$ radians and satisfies the requirement that, rotating the co-ordinate system by an angle $\alpha$ does not change the form of the polynomial $g[\theta + \alpha]$ [14].

The other property of Zernike polynomials is that the radial function must be a polynomial in $\rho$ of degree $2n$ and contain no power of $\rho$ less than ‘$m$’. ‘$n$’ is order number and ‘$m$’ is a variable with value less than or equal to ‘$n$’. Both ‘$n$’ and ‘$m$’ are non-negative integers. Further, $z[\rho]$ must be even if ‘$m$’ is even and odd if ‘$m$’ is odd. $z[n, m, \rho]$ is a polynomial of order $2n$ and it can be written as

$$\sum_{s=0}^{n-m} (-1)^s \frac{(2n-m-s)!}{s!(n-s)!(n-m-s)!} \rho^{2(n-s)-m}$$

(1)

The radial polynomials are combined with sines and cosines $z[n, m, \rho] \cos[m\theta], z[n, m, \rho] \sin[m\theta]$ where $\cos(\theta) = \frac{x}{\sqrt{x^2 + y^2}}$ and $\sin(\theta) = \frac{y}{\sqrt{x^2 + y^2}}$, to derive Zernike in polar coordinates.

IV. PROPOSED SYSTEM

From signature samples, 3D on-line features are extracted. The x-coordinate sequence(x), y-coordinate sequence(y), pressure coordinate sequence (z), pen azimuth coordinate sequence and pen inclination coordinate sequence are features considered [1] as shown in Fig. 1. Azimuth is the angle between the z-axis and the radius vector connecting the origin and any point of interest. Inclination is the angle between the projection of the radius vector onto the x-y plane and the x-axis. Z-axis is the pressure axis. The acceleration values are calculated using (2) in three-dimension.

$$\ddot{a} = h1 + h2 + h3$$

(2)

where

$$r = \sqrt{x^2 + y^2 + z^2}, \theta' = \frac{d\theta}{dt}, \varphi' = \frac{d\varphi}{dt}$$

$$\dot{r} = \dot{x}\sin\theta\cos\varphi + \dot{y}\sin\theta\sin\varphi + \dot{z}\cos\theta$$

$$\dot{\theta} = \dot{x}\cos\theta\cos\varphi + \dot{y}\cos\theta\sin\varphi - \dot{z}\sin\theta$$

$$\dot{\varphi} = -\dot{x}\sin\varphi + \dot{y}\cos\varphi$$

$$h1 = \dot{r}(r'' - r\theta'^2 - r\varphi'^2 \sin^2 \theta)$$

$$h2 = \dot{\theta} \left( \frac{1}{r^2} \frac{d}{dt} (r^2\theta') - r\varphi'^2 \sin\theta\cos\theta \right)$$

$$h3 = \dot{\varphi} \frac{1}{r\sin\theta} \frac{d}{dt} (r^2\varphi' \sin^2 \theta)$$

The $r$ is the radial distance of a point from origin. $\dot{x}$, $\dot{y}$ and $\dot{z}$ are unit vectors. $\theta$ is the azimuth angle and $\varphi$ is the angle of inclination. $\ddot{r}$, $\ddot{\theta}$ and $\ddot{\varphi}$ are unit vectors in spherical co-ordinates. $r'$, $\theta'$, $\varphi'$ and $r''$ are derivatives of spherical co-ordinates. ‘$\rho$’ is norm calculated using the position of acceleration (index of pixel) and acceleration value.

The moment we are looking for authenticating hand written signature using on-line data should have following characteristics. It should provide a descriptive power which in turn deliver a similarity ordering with respect to genuine samples that help in classification. The moment should be compact to minimize the storage requirement. The moment values have to be invariant under an application dependent set of transformations such as, translation, scaling and rotation. The derived feature acceleration is considered, which is most promising to identify the genuine person even in a set of skilled forgers [2].

V. BEST FITTING ORDER

A relatively small set of Zernike moments can characterize the global shape of a pattern effectively. The low order moments represent the global shape of a pattern and the higher order represents the detail [16]. The transformation gives an infinite sequence of moments and we are compelled to truncate it somewhere, to remove abundant information, while separability of feature space is guaranteed [20]. Signature is a ballistic motion without feedback. The acceleration values are calculated for each of the sample. If there are ‘$N$’ on-line pixel values in a sample, the N acceleration values are calculated. The values are normalized to [0, 1] range. Using (1), the Zernike polynomials are generated in polar co-ordinates for $n = m$ values with $n = 1, 2, 3, 4, 5, 6$. The summation of N normalized acceleration values for a sample, applied for one of the above stated polynomials is calculated. This is repeated for all 10 training samples that are genuine, form 10 summation values for each person under one selected polynomial. In the present investigation on comparison, it is evident that, the magnitude of summation values of genuine samples are less than magnitude of summation

Fig. 1. Acquisition process of on-line signature data
values of forged samples as shown in Fig. 2 and Fig. 3, respectively.

VI. THRESHOLD VALUE

In the present work, the threshold is chosen as average of the 10 summation values for particular polynomial. The testing samples are compared with threshold to find false rejection rate (FRR) and false acceptance rate (FAR). The summation value less than or equal to threshold leads to acceptance. The summation value greater than threshold lead to rejection. It is a simple linear classifier. The experiment was conducted for 30 people on all 6 polynomials with n=m. The results are shown in Fig. 4 and Fig. 5. In the proposed experiment by the aid of the Fig. 4 and Fig. 5 it is evident that (6,6) order is the best fit for derived feature plot analysis. This order led to less FRR and FAR values. The order 6 is selected as best fit Zernike polynomial for the acceleration values. The detailed split of order 6 with m ranging from 0 to 6 were considered [14] as shown in Table. 1.

VII. EXPERIMENTAL RESULTS

The experiment was conducted for 100 X 25 X 2 samples using MCYT on-line signature database. This database consists of 25 genuine samples and 25 forged samples for a subject. The 10 genuine samples formed training set and remaining 15 genuine samples formed testing set. The rejection rate of 90% and acceptance rate of 80% is achieved for (6,1) order as shown in Fig. 6. Further, the experiment was conducted with 5 genuine samples as training samples and remaining 20 genuine samples as testing samples. In the work done by Julian [22], the system based on global analysis outperformed the local approach when training sample size was 5. The FRR value decreased and FAR value increased with increase in training samples.

VIII. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper a simple linear classification approach using lower order Zernike moments involving only a derived feature such as acceleration is proposed for the authentication of on-line handwritten signature with less computational time. It is to be noted that neither complete image nor complete online data of the sample is used. Although, previous work done have led to better results with lot of preprocessing steps like segmentation, warping and probability structures, an attempt is made for arriving at a simple robust system.

TABLE I

<table>
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<tr>
<th>n</th>
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<th>Polynomial</th>
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<td>$p^6 \cos[6\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>$p^6 \sin[6\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>$p^{5}(-6 + 7p^4)\cos[5\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>$p^{5}(-6 + 7p^4)\sin[5\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>$p^{4}[15 - 42p^3 + 25p^2]\cos[4\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>$p^{4}[15 - 42p^3 + 25p^2]\sin[4\theta]$</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>$p^{3}[-20 + 105p^2 - 168p^4 + 84p^6]\cos[3\theta]$</td>
</tr>
<tr>
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<td>3</td>
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</tr>
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</tr>
<tr>
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<td>2</td>
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</tr>
<tr>
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<td>$p^{1}[-6 + 105p^2 - 560p^3 - 1260p^4 - 1260p^5 + 462p^6]\cos[\theta]$</td>
</tr>
<tr>
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B. Future Works

The next step of improvement would be to achieve the shape analysis of acceleration plot using 3D Zernike polynomials [9], [11], [15] in fast computation mode [12], [17] with translation invariant central moments [18]. The experimental results could be given for radial basis function (RBF) classifier on the large MCYT signature database of 330 signers, 16500 signatures. This database consist of random and skilled forgeries [22].

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REFERENCES


