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An approach for on-line signature authentication using Zernike moments

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ABSTRACT

In this work, shape analysis of the acceleration plot, using lower order Zernike moments is performed for authentication of on-line signature. The on-line signature uses time functions of the signing process. The lower order Zernike moments represent the global shape of a pattern. The derived feature, acceleration vector is computed for the sample signature which comprises on-line pixels. The Zernike moment represent the shape of the acceleration plot. The summation value of a Zernike moment for a signature sample is obtained on normalized acceleration values. This type of substantiation decreases the influence of primary features with respect to translation, scaling and rotation at preprocessing stage. Zernike moments provide rotation invariance. In this investigation it was evident that the summation of magnitude of a Zernike moment for a genuine sample was less as compared to the summation of magnitude of a imposter sample. The number of derivatives of acceleration feature depends on the structural complexity of the signature sample. The computation of best order by polynomial fitting and reference template of a subject is discussed. The higher order derivatives of acceleration feature are considered. Signatures with higher order polynomial fitting and complex structure require higher order derivatives of acceleration. Each derivative better represents a portion of signature. The best result obtained is 4% of False Rejection Rate [FRR] and 2% of False Acceptance Rate [FAR].

1. Introduction

An increasing number of banks and companies 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. The most personal way for authentication is signing. By providing the signature, an identity-conclusion function is observed. The conclusion function signals the finality of providing authentication via self-certification (Coats et al., 2007). Signatures are non-intrusive, culturally accepted and understood proof of authentication all over the world. New concepts that can mine behavioral knowledge in large data sets are very much essential. Like fingerprint, face, iris and other biometric features, signature also has some common characteristics. The ubiquitous signature pattern is stored in number of applications and is not dependent on age (Guest, 2006). Being a behavioral pattern, it is non-invasive.

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 depending on an available signing space. Discrimination power is achieved to deal low permanence and vulnerability due to forgery. In simple forgery, a forged signature is produced with the knowledge about genuine writer's name only. In simulated forgery, a forged signature imitating reasonably a genuine signature is captured. In unskilled forgeries, signatures are produced by inexperienced forgers without the knowledge of the spelling of name but are done after having observed the genuine specimens closely for some time. Skilled forgeries are those where forgers can see the genuine signature and have time to practice the imitations. 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 (Gupta and Joyce, 2007). Any authentication system should consider statistical matching because different features are evaluated with different user specific thresholds. The robust acquisition procedure, feature extraction process and classifier procedure are required for applications such as crypto-biometrics and bio-hashing. 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 (Kiran et al., 2001). The work done by Julian Fierrez provided explicit listing of 100 on-line features (Fierrez-Aguilar et al., 2005). Using statistical parametric method, Luan proposed a maximin distance for a subject, by ordering features (Lee et al., 1996). '*k*' best features for which distance defined by a criterion is largest from the rest of the entire population are selected. Symbolic representation is a feature based approach where, signature is described compactly to reduce enrollment data

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size (Guru and Prakash, 2007). These capture feature variations in the form of interval type data, to form a statistical parametric model. A holistic vector representation consisting of global features is derived from the signature trajectories. Each feature value is represented in the form of an interval with the aid of their respective mean and standard deviation values. The symbolic representation proposed by Guru using MCYT signature corpus achieved equal error rate [ERR] of 5.35%. Hundred features provided by Kashi et al. (1997) were used. The work has tabulated FRR and FAR for the range of feature dependent threshold values. In the work done by Oscar Miguel-Hurtado, time sequences of signature acquired by the sensor are pre-processed by a dynamic time warping algorithm and Gaussian mixture models (Migual-hurtado et al., 2007). Analysis for discriminative power is done by Fisher's ratio, with Gaussian components ranging from 4, 8 and 16. The experiment was on MCYT signature database of 2500 genuine and 2500 skilled forgeries from 100 users. The performance of 8% EER for skilled forgeries was achieved for a subset of 26 features. Shape matching through particle dynamics warping (Agam and Suresh, 2007) measures similarity by an energy term which depends only on the shape context of the particles and not on the distance between them. Hidden Markov Model has ability to absorb both variability and the similarity between patterns. In empirical risk minimization principle, the decision rule is based on a finite number of known examples in training set. It represents a doubly stochastic process governed by an underlying markov chain with finite number of states and a set of random functions, each of which is associated with the output-observation of one state. The best results in terms of learning probability can be implemented with a proper selection of a global feature. The classification, decoding and training problems are solved with forward–backward algorithm, the Viterbi algorithm and Baum–Welch algorithm respectively. The vector quantization for input vector is achieved by k-means algorithm. Forward algorithm is used to determine the verification probability. The work proposed by Fierrez et al. (2007) achieved 0.74% and 0.05% EER for skilled and random forgeries respectively with a posteriori user-dependent decision threshold. The database consisted 145 subjects comprising 3625 client signatures, 3625 skilled forgeries and 41,760 random imposter attempts. In an another regional based statistical method, one dimensional fractal coding was performed for persian on-line signature recognition. The 'n' spatially uniform points with range segment centriod, domain segment start point number and range to domain transformation parameters were sampled (Mozaffari et al., 2006). The mapping vector accumulator recorded the angle and magnitude of domain-range mapping vector. Multiple mapping vector accumulator and multiple domain-range co-location matrix [MDRCLM] was used for a signature locus. The work done by Saeed Mozaffari achieved 83% recognition rate using MDRCLM on entropy and moment. This was tested on a database of 15 signature classes, each containing 10 unconstraint samples gathered by a hyper pen 1200u digitizer tablet. Each of the sample was normalized into 300 spatially uniform points.

The synergistic method definition of a ballistic stroke using kinematic theory of rapid human movements was given by Plamondon et al. (2007). The model lead to trajectory reconstruction, both in spatial domain and in the kinematic domain. The study of outlier patterns for interactive comparative analysis by Djioua et al. (2006) represented rapid human movements in vectorial version. The delta-log normal model can produce smooth connections by ensuring the deformed strokes which are consistent. The kinematics theory describes the basic properties of a single stroke and how strokes can be added vectorially to generate a signature, from a given series of input commands. The commands are fed alternatively in two competing systems, agonist system and antagonist system to the direction of movement. The overall synergy controls the pen tip velocity to produce a signature. Panel interface was used to display simulated signals of the test pattern and to compare with standard pattern visually.

1.1. Zernike moments

Orthogonal Zernike moments are defined by the projection of the image function $f(x,y)$ within the unit circle onto the complex Zernike polynomials. The Zernike invariants are the magnitudes of the real and imaginary components of the resulting moments. When images are normalized in terms of regular low-level central geometric moments, the derived Zernike moments will be invariant to rotation, translation and scale. The image can be decomposed into a sum of basic structures. The polynomial set covers the interior of the unit circle $x^2 + y^2 = 1$. Zernike moments are orthogonally stable and provide image reconstruction. The choice of the Zernike method will avoid skeletonization as compared to Fourier descriptors (Milgram et al., 1990). Rotation in spatial domain implies a phase shift to the Zernike moments. The orthogonal property enables to separate out the individual contribution of each order moment to reconstruction process (Amin and Subbalakshmi, 2004).

Some of the applications of Zernike Moments are robust image water marking, iris, face, palm print, gait and Devanagiri handwritten numeral identifications (Xiao and Yang, 2008; Hse and Richard Newton, 2004; Wiliem et al., 2007; Hanmandlu and Murthy, 2007; El-ghazal et al., 2007). The optimum automatic thresholding is achieved using the phase of Zernike moments for edge detection (Belkasim et al., 2004). Wave aberrations in an optical system with a circular pupil are accurately described by a weighted sum of Zernike polynomials. The better classification accuracy and noise robustness to white Gaussian noise are achieved compared to blur invariant analysis methods based on complex moments (Zhu et al., 2009). The Zernike moment provide expression efficiency, fast computation and multi-level representation for describing the various shapes of pattern (Bin and Xiong, 2002). Haddadnia et al. (2002) and Pang et al. (2004) explored the use of pseudo Zernike moment invariants as facial features for face recognition. In the work done by Chen and Srihari (2005) for off-line signature verification with an on-line flavor, Zernike is applied for upper and lower contours of signature. The signature is segmented into 20 small curves linearly so that shape feature can be separately computed for each contours. Sixteen moments, up to order six are extracted. $16 \times 2 \times 20$ feature values were extracted from a signature. Applying harmonic distance as similarity measure, 83.7% acceptance rate and 83.4% rejection rate was achieved. The shape characteristic of derived feature acceleration under continuous dynamic programming provided genuine acceptance rate of 97% and imposter rejection rate of 92% using MCYT-100 on-line signature database (Radhika et al., 2009). The acceleration vector is fed as input to Zernike moment summation value computations. The imposter rejection rate of 90% and genuine acceptance rate of 80% is achieved (Radhika et al., 2009). This paper proposes higher order derivatives of the acceleration vector with a novel reference template selection method.

Some challenges exist while implementing Zernike moments in an application. The scale and translation invariance cannot be explicitly achieved. One of the indirect approaches is through expressing moments using centralized and normalized regular moments (Bin and Xiong, 2002; Belkasim et al., 2007). The square to circular mapping during the computation of moments lead to geometrical error. It is minimized by mapping all the pixels inside the unit disk. The numerical error is caused by double integral and the use of the truncated approximation series of Zernike moments (Wee and Paramesran, 2007). It is eliminated by integrating polynomials over corresponding intervals of pixels. Less shape information is used for skewed and stretched shapes (Zhang and Lu, 2002).