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Multi-Model User Authentication Using Signature Verification and Graphical Password.

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ABSTRACT

Normal handwritten signature verification systems cope with the Writer-Independent (WI) method the usage of simplest bi-magnificence sturdy classifiers to deal with the maximum difficult obligations. Virtually, WI concept is the reduced period of references. One-class signature verification are nonetheless open issues in realistic instances. On this paper, we suggest a one elegance WI gadget the usage of characteristic dissimilarity measures threshold for classification and a reduced huge form of references. The proposed gadget entails the usage of contour let remodel based totally directional code co-incidence matrix function era method. The verification is achieved through a WI threshold this is routinely decided on the use of a contemporary signature balance criterion. The proposed WI concept is except addressed via the combination of diverse writer records devices in every design and verification levels. Experimental results show the effectiveness of the proposed gadget however the system verification protocol using the simplest-magnificence concept, a unique threshold for accepting or rejecting a puzzled signature, the decreased amount of writers, and the restrained sort of reference signatures.

Keywords: WI, One-class signature verification, Directional code.

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INTRODUCTION

The growing interest towards personal identity authentication is in recent times focused upon the highest severity level for a complete automation of security systems. Among biometric systems, the handwritten signature verification is one of the most widely used since it is recognized as a legal means for individual verification in administrative and economic institutions. It's also one of the most complex biometric applications because the verification is based on the analysis of the handwritten behavioural action. The main concept is that, on one hand, the behavioural aspect of handwriting is characteristically specific to each writer and, on the other hand, the relevancy of automated system lies on its generalized applicability to all writers. Moreover, a high similarity between two signatures had been skilfully reproduced by another person. Conversely, a low similarity between two signatures does not necessarily mean that it comes from two different writers because of the intra-writer variability. The signature evaluation can, therefore, change into a really complex problem requiring one-of-a kind disciplines to be concerned.

FEATURE TECHNOLOGY BASED TOTALLY ON THE CONTOURLET TRANSFORM

A major component of the device's robustness relies on the ability of the descriptors to characterize and capture the appropriate and relevant information, accordingly to the aimed application. Extracting the appropriate features from the handwritten signature is to be considered with respect to the verification or the identification. In this paper, we propose, as a part of the system, a single feature generation method deduced from the CT that allows encoding complementary pertinent information to characterize the handwritten signatures. The features describe the writer handwriting style through which directions are contained in signatures, the amount of each direction and their spatial distribution toward each other.

Step 1: Construction of the Directional Map

This step includes the selection of the dominant direction of the contour segment according to the dominant contour let coefficient amplitude for each location (n, m). Denote $S_j(n, m)$ as the dominant contour let coefficient computed by taking the absolute maximum value of all directional contour let coefficients, let:

$$S_j(n, m) = \mathrm{Max}\{|C_{jk}(n, m)|\}$$

The directional map associated with the select dominant contour let coefficient is then generated as

$$D_j(n, m) = K$$

Thus, $D_j(n, m)$ receives the index of the direction associated with the dominant contour let coefficient.

Step 2: Computation of the Co-Occurrence Matrix

The co-occurrence matrix is generally done over a grey level image to describe the distribution of co-occurring values in a predefined offset. In our case, the co-occurrence matrix is computed based on the resulting directional map. This allows analysing the co-occurrence distribution of dominant directions contained into the signature contours. Formally, a co-occurrence matrix namely COM_j is defined over an N × M directional map D_j at the resolution j, parameterized by an offset (n, m)

$$COM_j(p, l) = \sum_{n=1}^{N}\sum_{m=1}^{M} \begin{cases} 1, & D_j(n, m) = p \text{ and } D_j(n + n, m + m) = l, \\ \text{zero otherwise,} & \end{cases}$$

Where in (p, l) and (n, m) are places within the directional map, D_j, and the co-occurrence matrix, respectively. The couple (n, m) defines the offset of the region transition to be considered when computing the co-occurrence matrix. In our case, the offset couple is fixed as n = 1 and m = 0 by considering simply the adjacent directions.

PROPOSED ONE-CLASS WRITER INDEPENDENT HSVS

The handwritten signature verification based on one-class writer-independent approach can be performed. First, a questioned signature Sig q is submitted to a set of reference signatures Sig j {j = 1, …., R} such that R is the number of reference signatures. Then, the DCCM feature generation is performed on each signature in order to produce its respective feature vector namely f q and f j. The resemblance between the questioned signature and each of the reference signatures is evaluated via the Feature Dissimilarity Measure (FDM). A selection rule is then performed for selecting the representative FDM, which is as compared to a selection threshold for accepting or rejecting the questioned signature.
In the following, we describe each step of the one-class WI HSVS.

Step 1: Feature Generation

The difficulty of using the CT is mainly due to the important number of coefficients that can be generated through resolutions and directions. In order to reduce the amount of coefficients and therefore the size of the feature vector, the handwritten signature is composed only of 16 components when using the DCCM.

Step 2: Feature Dissimilarity Measure

The process of verification involves the straightforward matching of a questioned signature feature vector with a set of feature vectors of R reference signatures of the claimed writer. A feature dissimilarity measure (FDM) for evaluating the resemblance of two signatures can use several distances such as the distance. In this work, we use the Canberra distance for its relative efficiency comparatively to the Euclidean distance. It is defined as

S q j = F D M (f q, f j) = T, t=1 | f q (t) – f j (t) | / |f q (t) + f j (t) |

Step 3: Threshold Selection

The threshold selection has a sensitive impact on verification performance. The proposed selection procedure is performed during the design steps of the HSVS. Thus the population of M writers is randomly selected from different datasets each one having R genuine reference signatures. Then, Feature Dissimilarity Measures (FDM) are computed between each possible genuine-genuine (G-G) signature feature vector pair per writer. The number of FDM s deduced from all possible combinations per writer is defined as C = R (R – 1) /2.

Let sig w, i be a reference signature {i = 1, . . . ,R} belonging to the writer { w = 1 , . . . ,M } and s w to i j as the value provided by the F D Mw(fi, fj) associated to each writer computed between each pair of (Si g w to i, Si g w to j) such that i=1,. . . , R-1 and j= i+1, . . . ,R. Hence, a set of all FDMs denoted S is constructed as follows:

S = {s 1to11, . . . , S 1toR-1,R, . . . , S Mto11 , . . . , S MtoR-1,R},

Namely S or d of size L = CM containing F D M s ordered from the stable to unstable signatures is constructed as follows;

S or d = {S0, . . . , Sl-1},

Namely S or d of size L = CM containing F D M s ordered from the most stable to least signatures is constructed as follows;

S or d = [s0, . . . , s v(L-1)],

Consequently, the ordered set S or d can be divided into two subsets as follows:

S or d = S stab U S outliers

Where the subset S outliers is assumed as the less stable data and represents (1-v) of ordered set S or d, let:

S outliers = [S v(L-1), . . . , SL-1]

Therefore, the whole set S or d can be denoted as follows:

S or d = [S0, . . . , S v(L-1)]U[S v(L-1)],

The subset S stab is assumed containing the most stable samples, let:

S stab = [S0, . . . , S v(L-1)]

Finally, it defines as:

H T E R = F R R +F A R /2

The FDM corresponding to t opt is thus selected as the maximum value of FDMs contained into S stab such as

T opt = Max {S stab},

Consequently, the optimal decision threshold takes the following FDM value:

T opt = S v opt(L-1).

Step 4: Verification Step

The verification steps involve the matching of the questioned signature with R genuine reference signatures of the claimed writer carrying out R FDMs:

S q j = F D M (f q, f j),

In our case, the minimum of the FDMs is selected as the representative one using the following decision rule:

S min = Min {S q j} R to j=1

According to the decision rule:

S i g q = {Accepted if S min < t else rejected otherwise

SYSTEM ARCHITECTURE

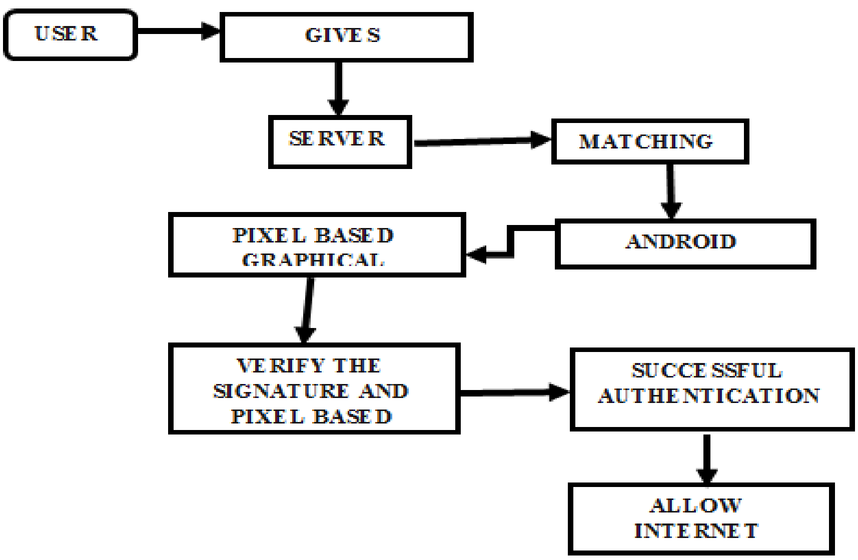

Fig 1: system architecture

(Above fig.1:user will be registering with two images and with certain number of selected pixels. User has to select the same set of images and on the range around same pixel values for authentication. User is authenticated only if both signature and graphical password are matched).

EXPERIMENTAL OUTCOMES

Description of Datasets and assessment criteria

Two popular offline signature datasets are used selected according to the classical writer-independent HSVS state-of-the art namely the centre of Excellence for Document Analysis and recognition (CEDAR) dataset and Guorp Procesado digital and Senates (GPDS). The CEDAR data set incorporates signatures of 55 writers where in each one has signed 24 genuine signatures and simulated 24 forged signatures for other signers. Therefore, the dataset contains 1320 true and 1320 forged signatures, respectively while, the GPDS dataset has to start with gathered from one hundred sixty writers and prolonged to 300 then to 960 writers, each one has signed 24 and 30 proper and cast signatures, respectively. All cast signatures of the GPDS dataset are tremendously professional for the reason that forgers have been given all of the time for reproducing as a whole lot as viable the proper signatures. therefore, the GPDS dataset is taken into consideration as greater complicated relatively to the CEDAR dataset. during the experimental evaluation, we dissipate to 472 writers from 960 writers. for this reason, we first check the proposed device. Experimental Setup We nation that if the system is author-impartial, it need to consequently be independent of data sets for this reason, to offer a worldwide version in an effort to be used for exclusive datasets and nearly unknown writers, the version must be designed the use of writers of different datasets. therefore, the proposed device is developed via two steps: layout step and verification step. all through the layout step, a populace of writers is selected through taking a discounted wide variety of writers from each one of a kind dataset for you to construct a single HSVS and a unique threshold is selected independently of datasets for use for verifying signature of all possible writers. a reduced set of writers is, consequently, decided on from both CEDAR and GPDS datasets to infer the most appropriate selection threshold thru the stability criterion. at some stage in the verification step, the device entails trying out with the remaining writers of both datasets one by one and blended as a whole dataset. in the course of the design step, a few signature samples in keeping with author are randomly selected that allows you to find the most appropriate selection threshold from handiest proper signatures. whilst, all real and solid signatures belonging to the ultimate writers now not enrolled into the gadget are used for the verification step.

CONCLUSION

In this paper a new framework for verifying the handwritten signature using conjointly the CT and the feature dissimilarity measures. The writer-independent concept is combined with one-class verification using a reduced number of genuine references. Moreover, the system does not want any robust classifier such as SVM or Neural Networks to be trained on dissimilarities. The verification step is performed using only the feature dissimilarity measure for evaluating signature’s resemblance. A unique WI decision threshold deduced from the stability parameter is required to verify signatures independently of datasets. The proposed system doesn’t refer to any simple or skilled forgery model and can be developed with a reduced number of reference signatures. Experimental effects have shown the possibility of developing a global system that can be deployed in many institutions.

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