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Research paper

Offline Signature Verification using Intelligent Algorithm

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Abstract:-

Signature verification is important in banking, legal, financial transactions for security purpose. Offline signature verification is a complex task because active information i.e. temporal information is missing in static image. There is no standard feature extraction method for offline signature identification as in case of other behavior modalities e.g. in automatic speech recognition like LPCC (Linear Predictive Ceptral Coefficients).Our research presents an intelligent algorithm for feature extraction based on image difference of genuine signature image and questioned signature image. Six features i.e. average object area, entropy, standard deviation, mean, Euler no., and area are analyzed. Best results are reported using combination of Average Object Area, Mean, Euler No. and Area. CEDAR (Center of Excellence for Document Analysis) database is used for offline signature verification. The database consists of static signature samples taken from 55 users. The Proposed algorithm is quite efficient as it is less computationally. Experiments are performed with both models i.e. Writer-Independent (WI) system and Writer-Dependent.

Keywords: *Center of Excellence for Document Analysis (CEDAR), K-nearest neighbor (kNN), Support Vector Machine (SVM), Writer-Independent (WI), Writer-Dependent (WD)*

1. Introduction

Biometric system works by going through four phases. This includes image capturing phase, feature extraction phase, matching phase and decision phase. The sample is presented at sensor, which capture the unique information. This unique information is known as feature set. This is made into the form, which can be processed and known as template. This template is matched with stored database and decision is made to accept or reject the user. Physiological characteristics are related to the shape of the body.e.g Face, DNA. Behavioral modalities are related to human behavior that may change over time like signature, typing rhythm. Signature verification is important in banking, legal, financial transactions for security purpose .Proficient handwritten signature authentication system still plays a key role in data protection. Forensic Document Expert evaluates features in signature based on the abrupt change in the direction of strokes, pen lift, pen pause, letter forms etc. Letter forms are the important features for examination of signature. For legal and social acceptance, handwritten signature is used for personal authentication. Offline signature verification has been an intense research field. Forensic Science Institutes are in search of offline signature verification system that can be used in forensic analysis. Figure 1 shows Samples of three users.

Fig.1: Samples of three users

1.1 Advantages

1. Hardware expenditure is less in offline signature verification system.
2. Offline signature verification will decrease the disruption to receive practices with respect to dealings where Personal verification has to be authenticated.

Due to geographic location, emotional state, age, posture, illness etc., there are some variations in the signatures of the same person.

The paper is organized as follows: Section 1 describes the introduction. Section 2 presents the related work. Section 3 describes Architecture. Section 4 describes Experimentation. Section 5 presents the conclusion

2. Related Work

Each feature has its own significance and the contribution of discriminative feature affects the accuracy of offline signature verification system [1]. There is no standard feature extraction method for offline signature recognition as in case of automatic speech recognition [2]. Writer-Independent (WI) offline signature verification using feature extraction based on Average object area and entropy is proposed [3].Table 1 shows the features and classifier used by some of the researchers for offline signature verification.

3. System Architecture:

The figure 2 describes the architecture used for offline signature. The input to system is the images of a genuine and a questioned signature. Output of the system determines whether questioned signature is Genuine Signature or Forged.

3.1 Algorithm for feature selection:

INPUT: Offline Signature image pair
OUTPUT: Average Object Area, Mean, Euler No., Area
Step 1: Resize the image pair.
Step 2: Calculate the absolute difference of image pair.
Step 3: Calculate Average Object Area, Entropy, Standard Deviation, Mean, Euler No., and Area of the image obtained in Step-2
Step 4: Calculate the accuracy with combination of features obtained in Step 3 with proposed architecture.
Step 5:-Select the combination of features that gives more accuracy.

3.2 Datasets Details:-

Publically available database CEDAR [17] is used. The training data set contained offline signatures (24 original, 24 forged) of each of the 55writter. The database comprises of 1320 offline genuine images and 1320 offline forged signature images corresponding to 55 signers. The motivation was to test that system whether it works on input that it has never seen. Two forgeries differ from each other is not important to us. Table 2 shows the feature values extracted for Genuine Signature pair for one user. Table 3 shows Feature values extracted for Genuine – Forged Signature pair for one user.

Table 1: Features used by researcher

Feature Extraction	**Offline Database**	**Classifier**	**Ref:**
Histogram of Templates (HOT)	CEDAR	SVM	4
Global and Local Features	Manipuri signature	SVM	5
Histogram of curvature (HOC) and histogram of gradient (HOG)	UTSig	SVM	6
Geometric and local binary pattern	DB1	Artificial Neural Network, Support Vector Machine	7
HOG	15-People database	GRNN(General Regression Neural Networks)	8
Pyramid histogram of oriented gradient (PHOG)	FUM-PHSDB	modified K-nearest neighbor (MKNN)	9
KAZE	MCYT-75	SVM	10
Invariant Directional Feature		Longest Common Subsequence algorithm (LCS)	11
KAZE features in the BoVW model	CEDAR	SVM	12
ULBP	BHSig260, GPDS-100	Nearest Neighbour (NN) Euclidian distance	13
Entropy ,Eccentricity, Standard Deviation, Convex Area and orientation		Artificial Neural Networks ANNs):	14
LDP,LBP, LDerivP	MCYT	k-Nearest Neighbor Classifier (KNNC) , Linear Discriminant Classifier (LDC).	15
Zernike moments	CEDAR	Harmonic mean dissimilarity measure	16

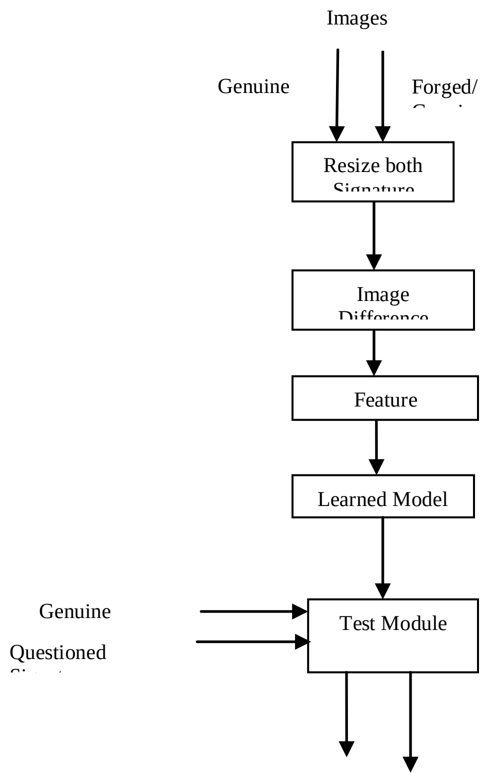

Fig2: System Architecture

Table 2: Feature values extracted for Genuine Signature pair

Entropy	Average Object area	Standard Deviation	Mean	Euler No.	Area
0.377511	16.04762	0.26037	0.073134	-18	724
0.380287	13.89796	0.261611	0.073893	-14	730.75
0.346965	10.89091	0.246532	0.064996	-18	643.5
0.392051	15.8	0.266841	0.077148	-19	763.625
0.373523	12.5283	0.258582	0.072049	5	708.625
0.374322	14.17021	0.258941	0.072266	-6	711.875
0.361812	11.14035	0.253301	0.068902	-9	682.25
0.321402	8.693548	0.234671	0.058485	-23	588.125
0.333463	10.125	0.240301	0.061523	-29	616.5
0.396696	15.38298	0.268894	0.078451	0	765.625
0.37192	15.34884	0.257863	0.071615	-12	698.25
0.352781	17.02778	0.249193	0.066515	-26	660.625
0.350295	9.790323	0.248057	0.065864	-23	658.875
0.317913	8.428571	0.233031	0.057617	-21	577.875
0.313081	11.81818	0.23075	0.056424	-2	554.125
0.408161	15.36735	0.273931	0.081706	-29	808.25
0.37192	9.041096	0.257863	0.071615	-24	714.75
0.369106	8.945205	0.256596	0.070855	-13	703.875
0.372722	12.49057	0.258223	0.071832	-24	712.75
0.3683	11.22414	0.256233	0.070638	0	695.5
0.298804	7.625	0.223949	0.052951	-4	525.5
0.375121	9.970149	0.259299	0.072483	-42	729.5
0.335167	7.320513	0.241091	0.061957	-14	620.75

Table 3: Feature values extracted for Genuine – Forged Signature pair

Entropy	Average Object area	Standard Deviation	Mean	Euler No.	Area
0.269661	9.042553	0.209746	0.046115	-2	458
0.3091	10.01961	0.228863	0.055447	3	547.75
0.286028	8.846154	0.217777	0.049913	11	487.375
0.282791	8.388889	0.2162	0.049154	-6	489.25
0.321837	10.8	0.234876	0.058594	9	575.875
0.300608	7.6875	0.224813	0.053385	12	526.25
0.280468	6.892308	0.215065	0.048611	18	477.875
0.286489	6.779412	0.218002	0.050022	9	497.625
0.279536	6.194444	0.214609	0.048394	31	474.125
0.257198	7.388889	0.20353	0.043294	17	425.375
0.351124	9.369231	0.248437	0.066081	29	640.125
0.261061	8.847826	0.205467	0.044162	7	434.375
0.268711	8.46	0.209276	0.045898	20	449.625
0.295182	10.66667	0.222207	0.052083	17	508.625
0.275324	11.5	0.212542	0.047418	20	462.125
0.31966	9.067797	0.233853	0.058051	13	569
0.282791	11.92105	0.2162	0.049154	12	479.5
0.298353	10.3617	0.223732	0.052843	15	516.5
0.250373	7.403846	0.200086	0.041775	13	410.75
0.297901	9	0.223515	0.052734	19	513.5
0.251353	7.588235	0.200582	0.041992	19	410.875
0.286489	10.47727	0.218002	0.050022	12	490.25
0.309987	8.142857	0.229284	0.055664	9	550.5

4. Experimental Setup:

The results are reported using 5-fold cross validation. K-nearest neighbor (kNN), Boosted Tree and SVM are used for classification.

4.1 Experiment Using Combination Of Features:

The experiments were performed with various combinations of features. The table 4 shows that Average Object Area, Euler Number is significant features. The
Combination of Average Object Area, Euler Number,

Table 4: Accuracy (%)

means and Area gives better result using SVM. The Performance of the two features i.e. entropy and Standard Deviation are not as good as Euler Number. The combination of Average Object Area, Euler Number, means and Area gives better result using KNN and Boosted Tree also as compared to another feature.

Table 5: Accuracy w.r.t varying number of training samples

Sample Size	Features	SVM	KNN	Boosted Tree
20	Average Object Area+mean+Euler+Area	87.9	82.9	86.7
	Euler	86.3	64.1	86.3
15	Average Object Area+mean+Euler+Area	86.4	82.4	86.4
	Euler	85.9	66.5	85.9
10	Average Object Area+mean+Euler+Arean	87.4	82.1	87.4
	Euler	85.5	73.4	85.5
5	Average Object Area+mean+Euler+Area	84.4	81.1	84.4
	Euler	83.5	73.6	83.5

4.2. Experiment with different sample size:

The experiments were performed with different sample size. Accuracy increases with the sample size increase as shown in table 5.

4.3 Experiment with different signer:

Table 6 shows Accuracy decreases with more signers.

Table 6: Accuracy decreases with more signers

Users	Features	SVM	KNN	Boosted Tree
10	Average Object Area+mean+Euler No.+Area	91	87.8	89.1
	Euler No.	87.6	78.5	88
20	Average Object Area+mean+Euler No.+Area	90.2	88.9	89.2
	Euler No.	88.2	80.7	87.9
30	Average Object Area+mean+Euler No.+Area	88.8	84.9	87.8
	Euler No.	87.8	71.2	87.8
40	Average Object Area+mean+Euler No.+Area	89.0	83.4	87.7
	Euler No.	87.8	67.0	87.9

4.4 Experiment with each user:

The experiments were performed with each user using combination of

selected features (i.e. Average Object Area, Mean, Euler No., and Area) as mentioned in feature selection algorithm. Writer dependent model have more accuracy than writer independent model. For some user, we obtain 100 % accuracy as table 7 shows.

5. Conclusion

In this paper, an intelligent algorithm for offline signature authentication has been presented. The algorithm is tested against CEDAR dataset using KNN, SVM and Boosted Tree. The comparison of the proposed algorithm with other research is generally considered a rather hard task due to various degrees of freedom regarding the type or number of signatures utilized during the training and testing phase. Proposed algorithm is quite efficient as it is less computationally. The numbers of signature pair used in WI model are less for each user as compared to other research .WD model gives better result than WI using proposed algorithm.

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Table 7: Accuracy (%) for each WI model

User	Svm	Knn	Boosted Tree(Bag)
1	91.3	95.7	96
2	89	91.3	93
3	97.8	93.5	97.8
4	93.5	91.3	93.5
5	91.3	87	82.6
6	97.8	95.7	95.7
7	89.1	89.1	87
8	91.3	91.3	91.3
9	97.8	97.8	95.7
10	100	100	100
11	97.8	97.8	95.7
12	97.8	93.5	97.8
13	97.8	97.8	97.8
14	100	100	97.8
15	97.8	97.8	91.3
16	97.8	93.5	97.8
17	100	100	97.8
18	100	100	97.8
19	78.3	69.6	78.3
20	93.5	84.8	93.5
21	80.4	78.3	80.4
22	67.4	69.6	63
23	56.5	54.3	50
24	93.5	93.5	93.5
25	100	100	100
26	89	89	89
27	97.8	95.7	97
28	100	97.8	89.1
29	93.5	95.7	91.3
30	97.8	97.8	97.8
31	93.5	87	91.3
32	100	100	100
33	97.8	97.8	100
34	97.8	97.7	97.8
35	95.7	97.8	97.8
36	91.3	78.3	87
37	97.8	978	95.7
38	93.5	95.7	97.8
39	65.2	65.2	63
40	87	84.8	84.8
41	97.8	97.8	97.8
42	71.7	73.9	84.8
43	95.7	95.7	89.1
44	89.1	82.6	89.1
45	91.3	91.3	95.7
46	100	100	97.8
47	84.8	78.3	82.6
48	69.6	65.2	67.4
49	91.3	89.1	93.5
50	97.8	93.5	95.7
51	89.1	87	89.1
52	84.8	80.4	82.6
53	80.4	76.1	87
54	97.8	95.7	97
55	89	89	89

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