Classification of Arabic Autograph as Genuine And Forged through a Combination of New Attribute Extraction Techniques

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Abstract

This study proposes a new framework for an Arabic autograph verification technique. It extracts certain dynamic attributes to distinguish between forged and genuine signatures. For this aim, this framework uses Adaptive Window Positioning to extract the uniqueness of signers in handwritten signatures and the specific characteristics of signers. Based on this framework, Arabic autograph are first divided into 14X14 windows; each fragment is wide enough to include sufficient information about signers' styles and small enough to allow fast processing. Then, two types of fused attributes based on Discrete Cosine Transform and Discrete Wavelet Transform of region of interest have been proposed for attributes extraction. Finally, the Decision Tree is chosen to classify the autographs using the previous attributes as its input. The evaluations are carried out on the Arabic autograph. The results are very encouraging with verification rate 99.75% for sequential selection of forged and genuine autographs for Arabic autograph that significantly outperformed the most recent work in this field.

Keywords: Arabic autograph verification, adaptive window positioning, attributes extraction, classification

الخلاصة

تقترح هذه الدراسة إطارا جديدا لتقنية التحقق من التوقيع العربي. وهو يستخلص بعض السمات الديناميكية للتمييز بين التوقيعات المزورة والحقيقية. لهذا الغرض، يستخدم هذا الإطار التكيف وضعية النافذة لاستخراج تفرد من الموقعين في التوقيع بخط اليد والخصائص المحددة من الموقعين. وبناء على هذا الإطار، تقسم التوقيعات العربية أولا إلى نوافذ 14 × 14؛ كل جزء واسع بما فيه الكفاية لإدخال معلومات وافية عن أنماط الموقعين وصغيرة بما فيه الكفاية للسماح بالمعالجة السريعة. ثم، تم اقتراح نوعين من الميزات على أساس تحويل جيب التمام المنفصل، تحويل المويجة المنفصلة لاستخلاص الميزات من المنطقة ذات الاهتمام. وأخيرا، يتم اختيار شجرة القرار لتصنيف التوقيعات باستخدام الميزات المذكورة كمدخلات لها. وتجرى التقييمات على التوقيعات العربية. وكانت النتائج مشجعة جدا مع معدل تحقق 99.75٪ لاختيار سلسلة من للتوقيعات المزورة والحقيقية للتوقيعات العربية التي تفوقت بشكل ملحوظ على أحدث الأعمال في هذا المجال.

الكلمات المفتاحية: التحقق من التوقيع العربي ، وضع النافذة المطورة، استخلاص الميزات، التصنيف

1. Introduction

Handwritten autograph plays an important role in modern life as it is routinely used in every sphere of human activity. (Couto, 2005) utilizes a lexical similarity technique for each entity identified. This frequently makes it impossible to distinguish between a forged signature and a signature created under influence. (Chung, 2009) applied Fuzzy groups to handle uncertainty. Although there are contributing studies in this area, research often failed to take into account the influence of contributing factors such as distractions and singers' stress which may affect the signatures being signed (Ben Jlaies, 2007; Shrivastava & Kumar, 2010). It is widely used for authenticating financial and business transactions (Arora, 2010; Miroslav, 2011). There are online and offline authentication systems. In contrast, online signature systems require special hardware such as digitizers and pressure tablets. These devices extract dynamic information including pressure, signer's speed, and the static image of signature. Unfortunately, both online and offline signatures can easily be imitated or forged, leading to false representation or fraud (Kekre , 2010). (Yang, 2010) used learned dictionary to check samples. This method has been successfully utilized in image recognition lately. According to (Alattas 2011), financial institutions are interested to benefit from the reliability and safety of offline signature-recognition systems. Another major reason is that online authentication systems require more complex processing and high-tech gadgets than offline systems. Offline signatures are usually presented on a piece of paper, which is the norm in documentation.

Currently, there is a need for efficient online and offline systems to ascertain the genuineness of personal signatures. Verification of handwritten signatures usually consists of a series of processes. These processes are pre-processing (where images are enhanced, binarized, divided into fragments and other related operations), feature extraction (features of the signatures are extracted as raw forms), feature selection or reduction (extracted features are reduced for efficiency), identification and verification of the signatures against the signature database based on the selected features. A good verification result can be performed by likening the strong features of the sample against the signature of a signer sample utilizing suitable techniques or classifiers (Yazan, 2011).

Methods depend on local tests, which concentrate on the analysis of the essential features of different scripts (Kanoun, 2000), (Yazan, 2011) & (Zhang, 2014). Some studies utilized evolving curves which do not move away to near by features decreasing the superfluous fragmentation (Tan, 2013).

Based on the available gap in the literature, in this paper, we propose a new method to identify and authenticate Offline-Arabic signatures. This method uses a combination of techniques including adaptive window positioning technique for signature feature extraction and feature selection method for reduced features and selection of important features. In this paper, enhanced Discrete Cosine Transform (DCT) and, Discrete Wavelet Transform (DWT) method is used to extract features. Further, these extracted features are reduced to the best features only. This process is accomplished by Principal Component Analysis (PCA). In this research, in order to classify genuine and forged signature two types of classifiers: 1) Decision Tree and 2) Support Vector Machine (SVM) are used. The classification outcomes of Decision Tree and SVM are compared to choose a better classifier.

2. Proposed Scheme

In this part, an offline Arabic autograph identification system based on classification techniques is introduced. The procedure consists of four phases: pre-processing, features extracting, selected feature by (DCT and DWT) technique, and matching. The complete process begins with acquiring the images of autographs to undergo a pre-processing stage, and then identification and verification process, which are illustrated in figure 1.

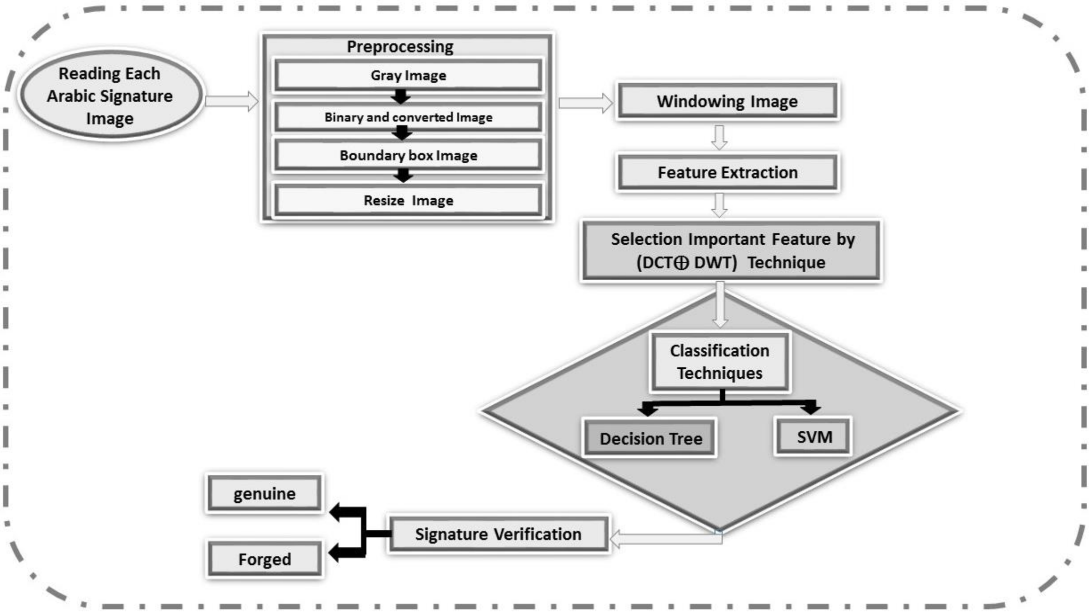


Figure 1: Proposed methodology

2.1 Pre-processing

In this step, data are acquired and autograph images are pre-processed. For the purpose of this study, Arabic autograph is used as the data consisting of 500 true samples and 250 forged samples. True samples are obtained from 50 different persons. Every signer is asked to sign 10 times using common types of pens. The 10 signatures collected from each person are used as follows: six of these signatures are selected randomly for system learning and the remaining four are used for system testing in addition to "ve forged" samples. There are enough signatures to ensure sufficient samples for both training and testing. The distribution of the number of genuine and forgery samples for different signatories is illustrated in figure 2. Arabic signature images are then pre-processed in order to improve the quality of images. Noises, such as irrelevant data, are removed from the features to improve the performance of identification. These images are then converted into binary images before feature extraction process this step is using by (Sulong & Anwar, 2014; Ghazali & Anwar, 2015).

forged signatures genuine signatures

Figure 2: Examples of genuine signatures and their respective forged counterparts.

2.2 Feature Extraction

Adaptive window positioning technique is used to separate Arabic signature images into small fragments or sub-images. The goal of form representation is to get form measures. These measures are used as classification features in models. Moreover, sub-images are presented from the set of obtained features (Feng, 2000), (Abdalla Ali, 2009). This makes the process of removing redundant data easy and facilitates the comparison of segmented fragments (Samuel, 2010; Rivard, 2013). A 14x14 segment size is chosen for the images for an optimum output (Tan, 2013). Further, the signature image which represents a group of features are extracted from the approaches. To analysis data accurately, a variety of observations as well as a number of significant individual features are needed to be organized. Such data can be given and analysed by machines or humans (Bharathi, 2014).

The features are then normalized using a feature matrix. The normalization process is very important. This is because when features are in different ranges, higher values may dominate lower values, which may change the results. Normalization places the feature values within the same scales and ranges to enable comparison. The projection and profile features are normalized by using window height, while the other descriptors are normalized by their maximum possible respective values. After normalization, each feature of the main window is composed to form a vector. This scales and translates each feature individually to a fixed range on the training set, which is a number between zero and one (Anwar, 2014).

2.3 Attributes Selection

The study proposes two fusions of attributes namely, Discrete Cosine Transform and Discrete Wavelet Transform (DCT + DWT). The former represents the high pass in vertical, diagonal and horizontal directions, respectively in signature images whereas the latter is proposed to discriminate between genuine and forged Arabic signatures. The reason for homogeneity between DCT and DWT features is best choice for combining. Fusion combines the useful information from both images. The motivation to combine these both features are numerous similarities found in DCT and DWT features. This proposed technique uses the high pass signature images to extract the necessary information for the signature verification.

Because success of the feature selection, the twelve DCT features and the eight DWT are extracted features. These features are then fused in order to classify signatures into genuine and forged classes. Suppose twelve DCT features are represented by $\alpha 1, \alpha 2, \alpha 3, \ldots \ldots \ldots, \alpha 12$ and eight DWT features are represented by $\beta 1, \beta 2, \beta 3, \ldots \ldots, \beta 8$. These subsets of features can be combined by concatenating DCT features with DWT features to form a single features vector (DCT⊕DWT) of 20 features as shown in equation (1).

DCT = [α1, α2, α3, α 4, α5, α6, α 7, α8, α9, α 10, α 11, α12] and
DWT = [β1, β2, β3,β4, β5, β6, β7,β8], [μ, σ, E, A]
(DCT⊕DWT) = [α1, α2, α3, α4, α5, α6, α7, α8, α9, α10, α11, α12, β1, β2, β3,β4, β5, β6, β7,β8] (1)

This set of 20 features represents one signature.

2.4 Classification

In this step, the model is presented based on training and testing. The various performed sub-steps are as follows.

3. Signature Alignment

In order to perform a meaningful comparison of images of different lengths, Extreme Points Warping (EPW) method (Feng, 2003) was applied. EPW method modifies a shape using peaks and valleys as pivoting points, rather than warping the whole shape. The algorithm fixes the optimum linear alignment of two vectors by using the smallest overall distance between them. The distances are recalculated between feature vectors at each iteration. The alignment was considered to achieve optimal status in case the average dimension between feature vectors attain a low value. The distance between two signature samples is calculated as the median of the distances between the fully aligned feature vectors.

3.1 Enrolment

To enroll enrolment into the system, 54 signatures are selected from each user for training. Each pair of Arabic signatures are aligned to determine their distance, as described in the previous section. Using these aligned distances, the following measurements are evaluated:

1) Median dimension to the farthest sample (dmax).
2) Median dimension to the nearest sample (dmin).

The training group of Arabic signature images is used to determine the threshold parameter in order to distinguish dubious group from the genuine class.

4. Training

The 2-dimensional feature vectors (Pmin, Pmax) normalize the feature values by matching averages of the reference set (dmin, dmax) which obtained by using the EPW algorithm. These are calculated depending on equations (2) and (3) to represent the allocation of the feature group.

$$N\,max = dmax / Pmax \qquad (2)$$
$$N\,min = dmin / Pmin \qquad (3)$$

Normalization of information ensures the genuineness or forgery of signatures in the training set. We train a decision tree classifier to recognize the genuine and forged signatures in the normalized feature area (Figure 3). To facilitate comparisons, two classifiers are used: The tree classifier and SVM classifier are used the 2-dimensional feature vectors. A linear classification is made by choosing a threshold value separating the two classes within the training set. This threshold is used in the verification process.

4.1 Classification based on SVM

For offline Arabic signature verification and identification, Support Vector Machines (SVM) are used. Important features in the Arabic signature images are extracted and the samples are confirmed with the assistance of Gaussian empirical law. SVM is applied to record corresponding results to compare all signatures from database with the test signature. The suggested method is tested on Arabic signatures containing 500 samples of 50 users and the outcomes are obtained to be encouraging.

In a high dimension feature area the principle of SVM, depends on a linear isolation where information are mapped to take into consideration the final non-linearity of the issue. SVM classifier (Feng, 2000), (Abdalla Ali, 2009) is trained with corresponding result vectors for each distance. This is to obtain a good level of generalization capability. To establish the rating of signers' relationship to the inquiry samples, firstly these processing points we use and then the results of the entire samples are combine.

4.2 Decision Tree Classifier

Evaluation of Tree Classification (Bagged Trees) technique is used in the same way and on the same samples from Arabic signatures as SVM. MATLAB 2014 bagged tree classification and trees software are used in the training and classification simulation. To predict a reaction, the decision procedure in the decision tree from the root (starting) node (feature) down to a leaf (feature) node is followed. Responses are included in the leaf feature. Decision trees grant responses, such as 'true' or 'false'. Decision tree is created to perform classification (Quinlan, 1986), (Suttan, 2005). The described steps are presented in Algorithm 2.

Algorithm 1

Step 1: Start first with all input features and then examine all potential binary divides on each predictor
Step 2: Choose a divide with good optimization standard
Step 3: If the divide leads to a child node with less than the least leaf parameter), choose a divide with the better optimization standard. Subject to the least feature constraint
Step 4: Put the divides and reiterate recursively for the two child (features) nodes
Step 5: If it made up of only observations of one category, a (feature) node is perspicuous. Therefore, the node is fewer than minimum parent observations

5. Outcomes and Discussion

In this section, is discussed the outcomes of the suggested methodology on some of samples of Arabic signatures.

5.1 Pre-Processing

The input image in RGB color space is first converted to grayscale image by using (Otsu, 1979) as shown in figure 3 (a) which represents gray image. Then, the image is smoothened with median filter and converted to binary as shown in figure 3 (b). Further, the image is passed from boundary box to find the boundaries of the text area as presented in (c), while in (d) the image is resized to apply the adaptive windowing algorithm to divide it into fragments as shown in (e).

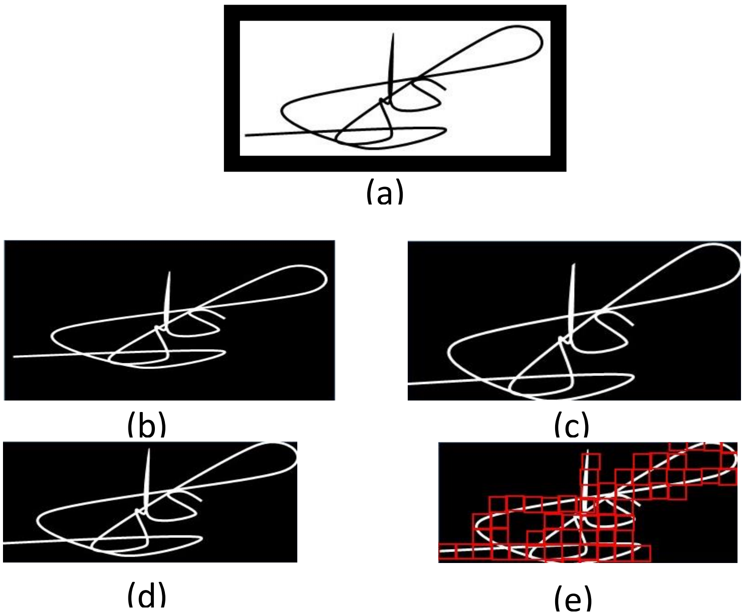


Figure 3: The different stages of the pre-processing phase, (a) Gray image, (b) Binary and converted image, (c) with boundary box image, (d) Resized image, (e) Windowing image

5.2 Feature Extraction

In this phase, the sub-images represent set of features. The result of the feature extraction is shown in table 1(a). Initially, these features are not normalized. The values shown in table 1(a) which represents the frequencies of the patterns extracted from each window. Higher values mean there is a more specific model with the genuine signature, which suggests that the Arabic signatures are highly similar to the test signature. The features are then normalized using a composed matrix of feature. The projection and profile features are normalized using window height, while the other descriptors are normalized by using their respective maximum possible value. Normalization places different feature values in the same ranges are shown in Table 1(b). After normalization, each normalized feature of the main window is concatenated into a single feature set, which represent each window by a vector. This process can standardize all features by scaling each feature to a given range.

Table 1: Feature extraction (un-normalized and normalized)
(a) Un-normalized features

F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
3.000	1.0001	6.0000	1.0000	3.0000	2.6106	4.088	3.0000	2.0020	0.0848
1.0000	1.0000	8.0000	1.0000	3.0000	1.057	4.764	1.0000	3.0000	2.6463
1.0000	1.0000	9.0000	1.0000	3.0000	1.5523	4.472	1.0000	4.0000	3.9281
1.0000	1.0000	11.0000	1.0000	1.0000	0.0523	7.352	1.0000	3.0000	2.491
1.0000	1.0000	1.20000	1.0000	1.0000	0.1469	5.336	1.0000	6.0000	1.8671
1.0000	2.0000	10.0000	2.0000	2.9066	1.6021	3.152	1.0000	8.0000	1.3205
2.0000	3.0000	10.0000	2.6463	1.6974	1.0000	3.376	2.0000	2.6463	0.4722
3.0000	1.0000	9.0000	3.9281	1.0000	1.0000	6.424	3.0000	3.9281	0.596
4.0000	1.0000	6.0000	2.491	5.0000	1.0000	2.4	4.0000	2.491	0.6366
3.0000	1.0000	3.0000	1.8671	4.0000	1.0000	0.024	3.0000	1.8671	0.0231

6.0000	1.0000	1.0000	1.3205	5.0000	1.0000	0.304	6.0000	1.3205	0.6366
8.0000	1.0000	1.0000	0.3367	6.0000	2.0000	0.056	8.0000	2.6463	0.054
9.0900	1.0000	1.0000	0.839	1.0000	1.3205	0.464	9.0080	0.9079	3.0010

F_{11}	F_{12}	F_{13}	F_{14}	F16	F15	F_{17}	F_{18}	F_{19}	F_{20}
6.0000	1.0000	3.000	1.0001	3.0000	2.6106	4.088	3.0000	2.0020	0.0848
8.0000	1.0000	1.0000	1.0000	3.0000	1.057	4.764	1.0000	3.0000	2.6463
9.0000	1.0000	1.0000	1.0000	3.0000	1.5523	4.472	1.0000	4.0000	3.9281
11.0000	1.0000	1.0000	1.0000	1.0000	0.0523	7.352	1.0000	3.0000	2.491
1.20000	1.0000	1.0000	1.0000	1.0000	0.1469	5.336	1.0000	6.0000	1.8671
10.0000	2.0000	1.0000	2.0000	2.9066	1.6021	3.152	1.0000	8.0000	1.3205
10.0000	2.6463	2.0000	3.0000	1.6974	1.0000	3.376	2.0000	2.6463	0.4722
9.0000	3.9281	3.0000	1.0000	1.0000	1.0000	6.424	3.0000	3.9281	0.596
6.0000	2.491	4.0000	1.0000	5.0000	1.0000	2.4	4.0000	2.491	0.6366
3.0000	1.8671	3.0000	1.0000	4.0000	1.0000	0.024	3.0000	1.8671	0.0231
1.0000	1.3205	6.0000	1.0000	5.0000	1.0000	0.304	6.0000	1.3205	0.6366
1.0000	0.3367	8.0000	1.0000	6.0000	2.0000	0.056	8.0000	2.6463	0.054
1.0200	0.836	1.0000	1.3205	0.464	9.0080	0.907	3.0010	1.0200	0.836

(b)Normalization

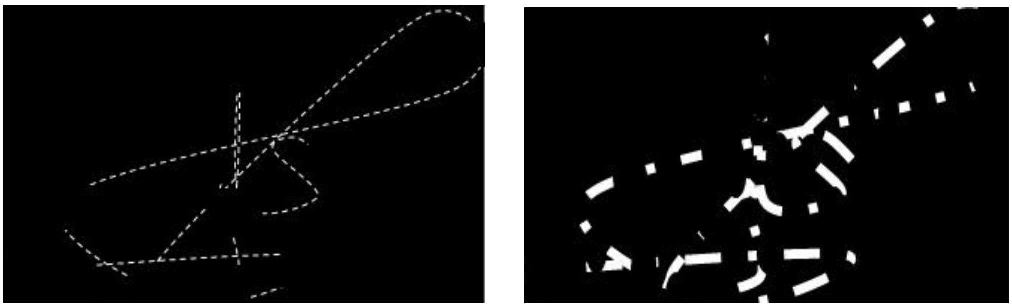
F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}
0.502	0.681	0.0811	0.199	0.610	0.081	0.625	0.823	0.572	0.681
0.3055	0.1576	0.741	0.6727	0.0157	0.76	0.62	0.7600	0.355	0.1506
0.8495	0.0661	0.705	0.386	0.523	0.472	0.2794	0.8887	0.875	0.0921
0.477	0.4585	0.3925	0.8651	0.0523	0.352	0.6446	0.3109	0.477	0.4585
0.3422	0.1398	0.3274	0.952	0.1468	0.396	0.424	0.5577	0.322	0.1098
0.8581	0.0582	0.3645	0.4175	0.6021	0.152	0.6012	0.9066	0.8581	0.0582
0.6463	0.4802	0.4722	0.915	0.2531	0.376	0.6831	0.6974	0.6463	0.4802
0.9281	0.2093	0.596	0.9235	0.3451	0.424	0.1576	0.7784	0.9281	0.2093
0.491	0.6716	0.6366	0.4185	0.6649	0.411	0.0621	0.9262	0.491	0.6716
0.8671	0.1161	0.0231	0.1315	0.8189	0.024	0.4585	0.9862	0.8671	0.1161
0.3205	0.5974	0.6366	0.3969	0.6633	0.304	0.1098	0.9257	0.3205	0.5974
0.3367	0.4185	0.054	0.2144	0.794	0.056	0.0582	0.9165	0.3367	0.4185
0.888	0.0895	0.4361	0.4279	0.6213	0.199	0.4802	0.9129	0.8938	0.0595

F_{11}	F_{12}	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}	F_{18}	F_{19}	F_{20}
0.621	0.547	0.611	0.299	0.910	0.581	0.725	0.623	0.572	0.881
0.8888	0.0484	0.741	0.6727	0.0157	0.76	0.62	0.7600	0.855	0.956
0.016	0.348	0.705	0.386	0.523	0.472	0.2794	0.8887	0.875	0.921
0.1208	0.6883	0.925	0.8651	0.0523	0.352	0.6446	0.3109	0.477	0.585
0.0953	0.964	0.274	0.952	0.1568	0.398	0.424	0.5577	0.8322	0.198
0.1392	0.2759	0.645	0.4175	0.6021	0.152	0.612	0.906	0.881	0.082
0.0613	0.7266	0.722	0.915	0.2531	0.376	0.6831	0.6974	0.663	0.482
0.6423	0.794	0.596	0.9235	0.3471	0.424	0.1576	0.784	0.9281	0.293

0.6104	0.9817	0.666	0.4185	0.6649	0.411	0.021	0.962	0.891	0.676
0.2786	0.9571	0.231	0.1315	0.8789	0.024	0.4585	0.9862	0.7671	0.1861
0.7744	0.4075	0.666	0.3969	0.6673	0.304	0.1098	0.9257	0.3205	0.5974
0.0347	0.8988	0.754	0.2144	0.7794	0.056	0.0582	0.9165	0.3367	0.485
0.8325	0.016	0.461	0.479	0.6613	0.199	0.482	0.929	0.898	0.595

5.3 Representation of Attribute Selection

When the procedure of attribute selection technique for windows is accomplished, those features with sufficient number of windows are kept. The features contain stroke patterns which occurring in the windows. Generally, the number of patterns for each feature selection is proportional to the size of the Arabic autograph sample. According to figure 4, one important point to note is the number of selected features. This is a property of the signer as can be observed from figure 5, where the number of selected attributes is presented. In this case, feature selection is generated from 40 different signers using two samples from each one. As can be seen, the curves represent the number of selected features in the two samples of the same signer are close to each other for DCT and DWT method. This seems consistent with the supposition that the number of selected attributes is a signer-dependent attribute.



(a) *(b)*

Figure 4: After selection attribute step of (F_1- F_{20})

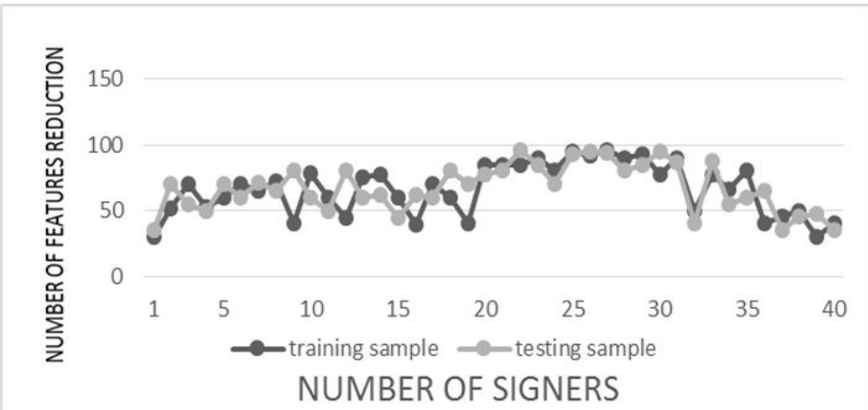


Figure 5: The number of selected important attributes of DCT+DWT method for the two samples of 40 signers

5.4 Matching

The matching phase happens when the model is created using Classification and regression tree decision and Support Vector Machines Classification (SVM) with different input parameters. Based on a person's signature, a model is created for the original and forgery signatures. The performance of the proposed method on 22 signers from Arabic signatures used to identify classification using DCT features and DWT features for selected important features with SVM classifier achieves the verification rate of 98.5%, and same DCT features and DWT features with Tree classification achieve the verification rate of 99.75%, as shown in algorithm 1 which is better than other techniques, as shown in table 2. The objective of this study is to create a system that 1) can identify handwritten signatures and verify their authenticity, and 2) distinguish forgery from genuine ones, and those which created under pressure and other influences. Using 330 Arabic signatures samples. The results of the matching phase are shown in table 2.

This implies that a forger may not skillfully repeat all aspects of the original signature. It also shows a forger pattern, which has small variations. Evidence shows that the mean of a feature produced by a forger in multiple attempts at forging tends to lie in a small range. Conversely, genuine autographs produced by a signer may vary under unusual conditions. Signers possess certain unconscious features that remain consistent and stable despite the interference of influencing factors. Such natural features are almost impossible to imitate, even by the original signers.

Table 2: Experimental results obtained from 22 signer based on Arabic autographs

Classification Techniques with Features Selection Technique	Verification Rate	Recognition Rate
Tree+ DCT+DWT method	99.75%	98%
SVM+ DCT+DWT method	98.5%	96%

6. Validation of Results

The validation of the achievements of the suggested system is carried out using the verification rate and DCT and DWT method. Both are computed and compared against the two other widely accepted signature verification methods. Table 3 shows the simulation results with the Arabic signatures consisting 330 signatures from 22 various signers. The validation rate for the proposed technique is 99.75% attesting to its superiority against the others. It can be concluded that DCT and WDT features technique and Decision Tree classifier are credible and reliable technique for verification of offline Arabic signatures.

Table 3: An evaluation table comparing between the proposed autograph recognition system with other previously known methods

Authors	Methods	No. of Training Samples	No. of Testing Samples	Language	Verification Rate
Ismail *et al.* (2000)	New Algorithms for Signature Verification Based on Fuzzy Concepts	6	4	Arabic	98%
Margner al.(2005)	Arabic Handwriting Recognition	6	4	Arabic	94%
Ubul *et. al.* (2012)	K-Nearest Neighbor (K-NN)	10	10	English	93.53%
Al-Saegh (2015)	Weightless Neural Network (WNN)	5	15	English	99.67
Proposed method (2017)	DCT+WDT Features Technique	6	4	Arabic	99.75%

7. Conclusion

In this research, a method is developed to important attribute extraction by using DCT and WDT features technique in offline Arabic autograph verification. Signature samples is segmented into 14x14 windows and generate the attributes extracted for each window. Then, this attribute selection is used in classification. the mentioning the limitation of the study in the use of set of Arabic autographs to collect the Arabic autograph samples used in this study. To judge our findings objectively, we used Arabic autographs, which includes Arabic signers. The results of our study show that this method is a credible technique for offline Arabic autograph feature selection. This method can be used as an Arabic autograph verification method for the exposure of offline autographs. In the simulation phase, two different comparisons have been made. The first is the performance of support Vector Machine classifier and DCT and WDT features technique, and the second is the performance of Decision Tree classifiers with DCT and WDT features technique working together. The Decision Tree classifiers and DCT and WDT features technique produce the best verification rate of 99.75%, which improve the performance of offline Arabic autograph verification.

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