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# Offline Signature Identification System to Retrieve personal information from cloud

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***Abstract :*** *Signature is a very accepted biometric way for personal authentication and identification due to the fact that each person has their own unique signature with its specific behavioral feature. Therefore, it's highly important to recognizing the signature itself. Signature system is a behavioral biometric method, and it is divided in; online signature system and Offline signature system, the first one captures dynamic properties like time, pressure of the hand and speed during writing, while the second type analyzes stationary images of signatures, post the writing operation. Off-line system has no dynamic information available, and thus, it is a harder procedure than on-line system. An offline signature is of interest in cases where only hard copies of signatures are available, especially in which many documents have to be authenticated. We proposed applying the Novel Offline signature identification system to retrieve the personal's information, this system can be apply by using cloud server according to the type of input taken by the Client. After the signature will be identified on cloud which been uploaded by client, user information can be retrieved. As a result, a (98.86%) test accuracy is obtained by using the proposed method and (*SigComp2011*) dataset to train and test the classifier (identifier).*

***Keywords:*** *offline signature – identification – SIFT – Bag of Word - SVM – cloud.*

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## I. Introduction

Since computers were introduced, people have become more dependent on the electronic information storage and transferring. In a wide variety of transactions the electronic personal verification of identity has established itself to be advantageous, which inspired developing many different automatic verification systems. Biometrical identification and verification is lately considered as an active research field due to its effective implementation in law enforcement, forensic sciences as well as its increasing requirement in many different civil applications for improved security. [1]Biometric is a science and technology of authentication, and automated approaches of personal identification or identity verification based on a physical or behavioral features. Where physical biometrics which measure features which may be experimentally identified, like face, finger-print, palm-print, and iris. While behavioral biometrics which includes signature, voice, and keystroke. [2]In a biometric authentication system, persons who require using the system must be enrolled. Initially, users are enrolled to the system via registering their biometrical samples (for example, in signature identification and verification situation, a signature). [3] Signatures are a behavioral biometrical property, which is influenced by physiological and emotional state of the signatory. [4] Every individual has a distinctive style of hand-writing and, thus, a distinctive signature. A convenient benefit of a signature-Identification system is that the signature is already an acceptable type of personal recognition. Thus, it may be incorporated into existing business procedures, [2] and they have been accepted in governmental, legal, and commercial transactions as an approach of identification or verification [4]. In offline systems, a signature is a static signature image, is the only input to off-line systems. Identification and Verification of signatures found on bank cheques and vouchers are some of the most important areas where off-line systems are implemented. In on-line systems, besides the signature image, time dimension is also present for dynamically acquired signatures captured via pressure sensitive tablets or smart pens. Those input devices collect the signatures at a high frequency, resulting in a time ordered stream of signature trajectory points [5]. Due to the fact that on-line signatures include dynamical information as well, forging them is difficult. Offline systems have to take background noise and changes in stroke-width under consideration as well. Thus, it is not surprising that offline signature verification systems are of quite less reliability than online ones [6]. Handwritten signatures are socially and legally widely accepted as an easy way of document authentication, authorization and writer recognition. Due to the fact that the majority documents, such as bank cheques, must be signed, automated offline signature identification produces an important element in the authentication of documents with hidden signatures [7]. The design of the handwritten signature identification systems based on the off-line system is harder compared to the on-line system since several wanted properties such as the velocity and the pressure are not available throughout the process of capturing.

Although handwritten signatures are consider not most reliable methods of personal recognition, but the signature as yet the most socially and legally accepted ways, and In many transactions (eg. vouchers and bank cheques) Depends on signatures for identification, for that we proposed this system for identify the personality of the signature .In most government institutions, banks and others, there is more than one branch in different places, ever since computer networks have been introduced, modern systems were built on sharing data by using common database. (e.g banks) so we proposed to build signature system on the cloud environment to fit with these, and to be a common system with the common database.

Our system start from upload the offline signature from client, this communicate will be over TCP/IP protocol, in order to reliable transport between sending and receiving process , when the cloud receive the signature some process are performed to obtain the signature class (ID) .In this system the cloud contains a database in addition to the classifier, the database contain the basic information of each person, who are signed in dataset, And the classifier was trained by dataset sample and tested by the other part from this dataset, this process start with Scale-Invariant Feature Transform (SIFT) [8]this algorithm used to extracting features for each signature, that is independent of scale, rotation, and lighting state. For this system , SIFT is fit for the extraction of local properties which can describe various signatures , even if they have almost identical properties, SIFT will give feature descriptors , after that in the Bag Of Word model (BOW) [9]constructing that by Grouping descriptors to the set of clusters , which computes the how many properties enter each cluster , in this Model use K-means algorithm to determine the centers of features , and K Nearest Neighbor (KNN) for clustering this features , briefly ,BOW model utilized for the construction of histogram which is locate feature relative . And in the last step of training the bag of words as feature vectors, to constructing the classifier (identify) of the signatures by using Support Vector Machine (SVM) [10], with RBF kernel, it is widely used in bioinformatics and other disciplines because of it has highly accurate, to compute and process the data, after training system performing test for the system to measure the accuracy and error rate of the identification in this system. After this processes in cloud the system become ready to identify the new signature, if the new signature is identical with any signature in dataset the classifier system will be predict ID of the signature and the cloud will get the personal information for this ID from database and send it to client, if the signature is not identical to signatures in dataset which the system trained on it previously, the cloud will reply (unknown) to the client.

The overall objective, is developing an offline signature system and applied on cloud environment. it consider ; novel (according to the fact that the method used in this thesis is greatly distinct from methods utilized in current systems) , and on the other hand accurate and efficient .

In 2016 [11] presented Open Handwritten Signature Identification System by Curvelet Transform (CT) and Principal Component Analysis (OC-PCA) , which used Curvelet Transform CT to explored for feature generation , where it efficient characterization of curves contained into the local orientations within the signature images. And One-Class classifier Principal Component Analysis OC-PCA is used for its effectiveness for absorb the high feature size generated by the Curvelet Transform CT and allows achieving at the same time an open system. And when few signatures are available, to improve the robust of system, proposed a novel combination approach by using Choquet fuzzy integral to combine multiple individual OHSIS. And the results on CEDAR dataset is 97.99%, and on GPDS dataset is 94.96% correction identification rate [11]. In 2004 [12] presented an innovative method for verification and recognition signatures system, with the use of a GSC ("Gradient, Structural and Concavity") for extracting features for signature images. Examining signature verification and recognition as off-line handwriting verification and recognition tasks. Both cases using the same steps in (Data acquisition, Preprocessing and Feature extraction) but the deferent in classification step where, use the weighted k-nearest neighbor classification When the aim is Identification, is to recognize the writer of a questioned piece of document considering a set of writing examples of a number known writers. And the accuracies results were 93% for identification on CEDAR dataset [12]. Also , In 2014 [13] proposed offline signature system for identification and verification based on feature extraction fractal approach , using same (pre-processing and feature extraction approach)for both verification and identification but the different in classification step. In this system used multi fractal approach for that applied 3 approaches for computing fractal dimensions, used a supervised classifier which is KNN. By using a large database, namely, "FUMPHSDB", those experiments illustrate a recognition percentage of 95% [13]. In (1996) [14] proposed handwritten signature retrieval and identification, which a group of geometrical and topological properties are considered to map a signature image into a couple of streams of finite symbols. The geometrical properties include horizontal and vertical bars in addition to loops obtained from the skeleton image of the signature with the use of the 4-connected elements labeling approach. The horizontal and vertical bars are obtained from the binary image of the signature with the use of morphological hit-or-miss process. The group of topological properties include endpoints, branch points, convex points, concave points and cross points. And in classification used a 2D string for matching two signatures in order to take under consideration the 2D spatial relations of the various properties contained in a signature. The Longest Common Subsequence (LCS) matching criterion is utilized in a form of a measure of similarity between the questioned and the reference signatures, for the retrieval and identification. The reference signature yielding the longest LCS is considered as the most identical to the questioned one [14]. In (1998) [15] proposed the use of a revolving active deformable model for obtaining the distinctive properties of the whole signature structure. In addition, a polygonal approximation algorithm is applied to smooth excessive information gathered at certain signature parts (for example, small fluctuations of nearly straight lines that could be meaningful for the purposes of verification, but are somehow disadvantageous for the purpose of recognition). And proposed a novel Synchronized String Matcher (SSM) algorithm in order to match accurately the questioned and reference signatures, which is derived from the error recovery approaches in compiler design. Basically, the Synchronized String Matcher approach attempts resynchronizing the matching procedure between the reference and the questioned signature strings. And the test results 78.89% is correct identification [15]. In (2000) [16] presented a system of a couple of separated stages for signature identification and verification. Followed this successful path to improve the handwritten signature identification by introducing a proper combining of distinctive and effective global properties (such as width and base-line) and local properties (such as critical points and gradients) , and developed multistage classifier is used in which a pre-classification phase for a set of identical slant signatures is applied in the beginning. After that, an identification approach is applied for resolving specific recognition in a set. In the subsequent phase, the distances between the global property vector of the input and the average of every class in the set are calculated and undergo comparison sequentially for selecting the optimal 3 candidates. In the third phase, the local central points are utilized for choosing the optimal candidate deciding whether the sample isn't identified. The choice depends on the corresponding threshold of every one of the candidate classes. And the accuracy is 91.82% for correct classification [16]. In (2000) [17] proposed a feature generation method based on different types of moments, and then a canonical variable analysis is carried out for reducing the number of features , Either in the classification stage through a comparison of several statistical methods. The obtained results show that the linear discriminant analysis performs better in terms of accuracy and computational cost than other classifiers, such as principal components regression, partial least square, quadratic discriminant analysis, KNN, fuzzy logic and two neural networks methods including back propagation and the radial basis model [17]. In (2006) [18] proposed a sufficient offline signature identification system, in their research they utilized 2 methods to the issue; generate every property vector with the use of a collection of global geometrical and moment-based properties from every signature and constructed the property vector with the use of the bitmap of the corresponding signature. For each of the two cases utilizing SVM and performs a comparison of its efficiency to a conventional classification method, multi-layer perceptrons (MLP). An approach for capturing the intra-personal variability of every one of the users with the use of a single original signature has been presented. Experimental results showed that support vector machines that achieve up to 71% true identification rate, is of higher efficiency that the MLP [18]. In (2014) [19] suggested using the adaptive window positioning method as an efficient feature ex- traction for offline handwritten signature identification. The pro- posed technique mainly, employs the division of signature images into 13 ×13 windows, where this size has to be sufficiently large to contain a big amount of information concerning the style of the author and sufficiently small for ensuring an efficient recognition performance. In addition, this technique creates some new clustering patterns for every one of the windows when classified to sets of identical features. Empirical results showed that the adaptive window positioning method established itself as a sufficient and dependable approach for precise signature property extraction for identifying off-line hand-written signatures [19]. in(2008) [20] presented an innovative method for off-line signature identification, in the presented method local points of interest are found in signature images, afterwards, local descriptors are calculated around those points, then, those descriptors are compared with the use of local and global matching processes. The last verification is performed with the use of a Bayesian classifier. The proposed system is validated with the use of GPDS signature data-base, in which it reached a FRR equal to 16.4% and a FAR equal to 14.2% [20]. In (2014) [21] an innovative method for addressing the issue of off-line hand-written signature verification. This approach incorporates both kinds of properties: finer intensity-based properties and global geometry-based properties. Specifically, the finer properties are calculated for each of the sample points of a signature with the use of intensity histogram, and the geometry based properties are obtained with the use of an adaptation of the shape context descriptor. Those properties are utilized for computing the score of similarity, after which comes a score calibration procedure for the estimation of the corresponding score of confidence (i.e., the use of log likelihood-ratio). In this system used (SignComp2011) dataset and the performance were pretty good [21]. In (2013) [22] presented Off-line Signature Verification system , in this system the four-directional chain code histogram of every one of the grids on the edge of the signature image is obtained. The Laplace of Gauss filter is utilized for the enhancement of the obtained properties of every signature sample. Therefore, the obtained and improved properties of each signature sample of the offline signature data-set produce the knowledge base. After that, the classifier of the SVM is utilized as a tool for verification. Extensive experiments were conducted for exhibiting the efficiency of the presented method on the publicly present data-sets which are: GPDS-100, MUKOS and CEDAR, a regional language data-set [22]. In (2013) [23] proposed an off-line signature verification system, which utilizes three distinct pseudo-dynamic properties based on grey level: local binary pattern (LBP), gray level co-occurrence matrix (GLCM) and histogram of oriented gradients (HOG), with two different classifiers; SVM and Global Real Adaboost approach, and two datasets; GPDS , CSD. The collaboration of all properties produces the optimal outcome of 7.66% and 9.94% equal error rate in GPDS while 7.55% and 11.55% equal error rate in CSD [23]. In (2011) [24] presented offline signature verification system, in this system, the signature is split to areas with the use of each of the Cartesian and polar coordinate systems and a couple of various histogram properties are computed for each area: of oriented gradients (HOG) and of local binary patterns (LBP) histograms. The classification is carried out with the use of the SVM, where a couple of various methods for training are researched, which are global and user-dependent support vector machines. The collaboration of all classifiers (global classifier and user-dependent classifier trained with every property type), reached a rate of error equal to15.41% in skilled forgery test, in the GPDS 160 signature data-base without the use of any skilled forging in the training [24]. In 2017 [25] presented offline signature identification system , after size fixing and noise reduction processes on signature's images used Histogram of Oriented Gradients (HOG) for feature extraction, In order to prevent the waste of processing time and to eliminate the redundant features, PCA is applied to the dataset. Obtained dataset is used to train the GRNN. And obtained 98.33% in test accuracy [25]. In 2013 [26] proposed a system for hand-written signature recognition and verification according to Shape Context Descriptors. The property vector is constructed from Shape Context Descriptors calculated for chosen points on skeletonized line of signature. The recognition procedure was based on KNN Classifier with a distance measurement that depends on Shape Context Descriptors, and the rate of precision obtained on the GPDS data-set is 96% [26].

## II. Methodology

Our proposed system contain client and cloud. Briefly; client Just to upload a signature image to be identified through the cloud and send its personal information to the client. The personal information has been store in “oracle” database in the Cloud. The identification process and sending information in cloud depend on the classifier because this classifier identify the ID of signature. There are two main steps in building the classifier system; training and testing. For this we followed the steps below;

### *2.1 Feature Extraction using SIFT:*

Signatures are consist of distinctive characteristics, therefore most of the signatures can be not clear to read, Also interpersonal differences Lead us to treating the signature as complete image and not as letters or words written together, and When the quantity of data is too large and may be notoriously redundant, must be transform data into a set of specific features which describe this image, for that use "feature extraction" method. The image property extraction has been described in the year of 1999 by D. G. Lowe, This approach is called the Scale Invariant feature Transform (SIFT). It is an approach invariant to scale, rotation, and illumination conditions. This method converts the image to a large set of local property vectors, every one of them is invariant to image translating, scaling, and rotation, and is partly invariant to lighting variation and affine or three-dimensional projecting. The produced properties are highly distinctive [8]. The main steps of computing utilized for generating the group of image properties is:

- **Step 1: scale-space Extrema Detection :**
  It is possible to calculate the local maxima across the scale and space, and that provides a set of $(x,y,\sigma)$ values, meaning that there’s a possible keypoint at (x,y) at $\sigma$ scale.SIFT utilizesdifference of Gaussian (DoG), obtained as the difference of Gaussian blurring of an image that has 2 various $\sigma$, for instance, $\sigma$ and $Z\sigma$. This procedure is performed for various image octaves in Gauss Pyramid. As soon as this difference of Gaussian is obtained, images are searched for local extrema through scale and space. For instance, one pixel in an image is compared to its 8 neighboring pixels, in addition to 9 pixels in following scale and 9 pixels in preceding one. In the case where it’s a local extrema, it is a possible keypoint. It typically refers to the fact that keypoint is optimally represented in that scale [3].
- **Step 2 : Keypoint Localization:**
  As soon as the possible key-points positions are detected, they must be refined in order to obtain more precise results. They utilized Taylor series expansion of scale space in order to gain more precise position of the extrema, DoG has better response for edges, therefore, edges have to be eliminated as well. It removes any low-contrast and edge keypoints and what is preserved is strong interest points.
- **Step 3 : Assigning Orientations:**
  In this stage orientations are assigned for every key-point in order to obtain invariance to image rotation. A neighborhood is selected surrounding the key-point position according to the scale, and the gradient magnitude and orientation is computed in that area. It creates keypoints that have same position and scale, but with different orientations. It takes part in the matching stability.

- **Step 4 : Key-point descriptor:**
  That key-point descriptor has been calculated, a 16×16 neighborhood surrounding the key-point is selected. It's divided into 16 sub-blocks of 4×4 size. For every one of the sub-blocks, 8 bin orientation histogram is produced. It is represented in a form of a vector to produce key-point descriptor. Moreover, numerous measurements are taken for the achievement of robustness against lighting variations, rotation and so on [27].

Now SIFT vector is free from the effect of geometrical transformations like the scale variations and rotation.
SIFT properties can describe well the unique features in the image with a 128-dimensional for every key-point. Thus, these properties may easily distinguish each other. At the end of SIFT we get feature vector from the signature image.

### *2.2 Bag Of Word model (BOW) to Histogram construction:*

The "bag-of-words" model (BOW) is one of the most widely known representation approaches for object categorizing. The main concept is quantizing every obtained keypoint into one of visual words, and afterwards represent every image with a histogram of the visual words [28]. The BOW gives an encoding approach to count the visual word redundancy in the signature image. It resulted in a histogram which becomes an innovative and reduced image representation. This histogram generated a basis to train a classifier and for the image classification itself. BOW produces vocabulary which may be utilized for explaining every unique image as histogram with the implementation of clustering approach in property extraction. We need to determine set of features (especially features which marked by words) that provides an identical relationship with signature (being trained) a set of features. In this case "words" does not have to necessarily be of a meaning like the "eyes", or "car wheels", nor is there a single optimal option of vocabulary. Instead, the objective is using a vocabulary allowing a good categorizing efficiency on a specified training data-set. the descriptors obtained in the (SIFT features extraction) step have to be invariant to variations which are irrelevant to the categorizing task (image transforming, illumination changes and occlusion) but sufficiently rich to hold a sufficient amount of information to be discriminative at the level of category. The vocabulary that has been utilized in this stage has to be sufficiently large for distinguishing useful variations in image parts, however, not large enough for distinguishing irrelevant changes like noise.
NOW, after detection and description features (keypoints descriptor) in feature extraction step by SIFT, basically this steps are followed in bag of word model;

- **Step 1:** Create a "visual vocabulary" – a list of common features.
- **Step 2:** Grouping keypoints descriptor (features) to the set of clusters, to construct a histogram – for each feature, find the closest visual word (centroid) in the dictionary.

Practically, in bag of word model we used two algorithms to this mission, with determine cluster's center we used K-means algorithm; we determined the Kmeans parameters such as (iterations, error rate) to select the best centers in order to clustering correctly, and used K nearest neighbor to clustering the features to constructing histogram; after centers determination in previous step, clustering process will applied by calculate Nearest Neighbors center for features. Features will represented as a histogram for signatures.
Optimally, those stages are modeled for maximizing the classification precision simultaneously minimizing the computation effort.

### *2.3 classification by Support Vector Machine (SVM):*

A Support Vector Machine (SVM) is a supervised learning approach which has been successful to prove itself as a sufficient and precise text classification method. SVM is used in this paper for signature image classification. Combined with the radial basis function (RBF) kernel that comes with its own SVM. The attempt is the histogram intersection kernel function that has established itself relevant in image classification. It also should be noted that the kernel function type is capable of directly affecting the efficiency of the Support Vector Machine classifier [10]. Similar to other supervised machine learning algorithms, Support Vector Machine operates in a couple of steps. In the first one —i.e. training— it learns a decision boundary in input space from previously classified training data. In the second one — i.e. classification— it classifies input vectors with respect to the previously learned decision boundary.

- **Step 1: training step**: The hypothesis space is represented using the functions $f(x) = \mathrm{sgn}(wx + b)$ in which w and b represent the parameters that have been learned in the training stage and those parameters decide the class that separates hyper-plane. The constraints require that every training example is classified properly, which allows for some outliers symbolized with the variables of stack. The factor C is a parameter allowing to trade off the training error against the complexity of model. In the limit $C \rightarrow \infty$ training errors are not permitted. This setting is known as hard margin support vector machine. A classifier with finite C is known as a soft margin SVM as well. Each training example with at the solution is known as support vector. The Support vectors are placed right at the margin and define the hyper-plane. The definition of a hyper-plane by the support vectors is quite beneficial in high dimensional property spaces due to a comparatively small number of parameters.

- **Step 2:** In the stage of **classification**: a term-frequency vector which not labeled is estimate to belong to the class ŷ = sgn (wx+b) …. (1)
  Heuristically the estimated class membership ŷ is corresponding to whether x is a part of the lower or upper side of the decision hyper-plane. Therefore, the estimation of the class membership using equation (1) includes a loss of information due to the fact that only the algebraic sign of the right-hand term is evaluated. Nevertheless, the value of v = wx + b is a real number and may be utilized for voting agents, which means that a separate support vector machine is trained for every one of the modalities that have resulted in three values vspeech ,vvideo and vaudio . Rather than computing the equation (1) we compute ŷ = sgn(g(vspeech ,vvideo ,vaudio )) .

It is common that the selection of the kernel function is highly important to the performance of the SVM. Thus, the data transformations that have been described previously were combined with kernel functions.
The Radial basis function kernel, known as the RBF kernel as well, or the Gauss kernel, is a kernel which is in the form of an RBF (more specifically, a Gaussian function). The Radial Basis Function kernel is identified as;

$$K(x_i, x_j) = exp\left(-\gamma \, \|x_i - x_j\|^2\right)$$

Radial basis kernel function is most popular and most widely used from all. Different Kernel Functions will generate different confusion matrix. Generally, the RBF kernel is a logical first option. This kernel non-linearly maps samples to a space of higher dimension, therefore it, in contrast to the linear kernel, is capable of handling the case in which the relation between the class labels and the attributes is non-linear.
Practically, we used SVM classification method to predict the ID of signature, and we did that by set the parameters for SVM and choosing the kernel type (RBF). [29]

After trained and tested the classifier system depending on the previous steps (SIFT for feature extraction, BOW model for construct histogram, SVM for classification), classifier system will be able to predict the ID for the new signature. And depending on this ID the cloud will get the personal information from the database for the person who signed and send it to the client.

## III. Experiments Result

The results of the proposed system has been carried out inside ; Visual Studio2013 by using C++ programming Language to build main system (feature extraction process , histogram construction and classification by SVM) , NetBeans IDE by using java programming language to build (graphic user interfaces) and Oracle 10g to store the personal information of each person signed in dataset.
Before going through these measurements, the process of the overall system were illustrated in figure 1, 2 and 3. These results were obtained by using a personal computer worked with Intel (R) Core (TM) i7-6700HQ , CPU 2.60 GHz and installed memory (RAM) of 16.00GB (15.8 GB usable) windows 7 64 bit .

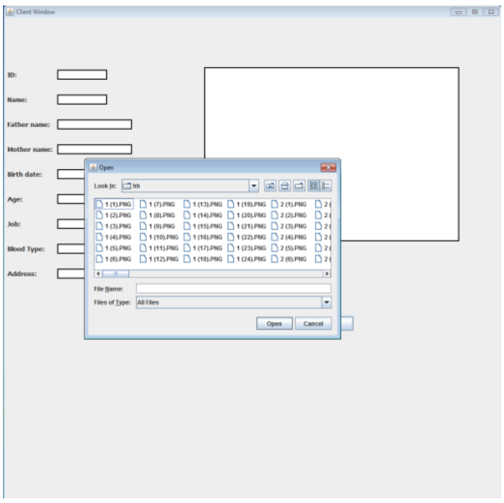

**Fig (1) upload signature by client**

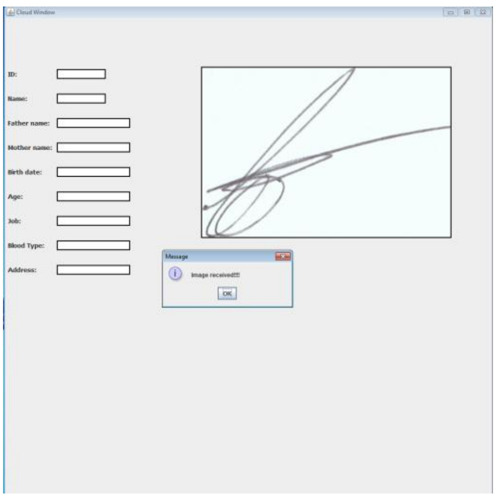

**Fig (2) Cloud received a signature**

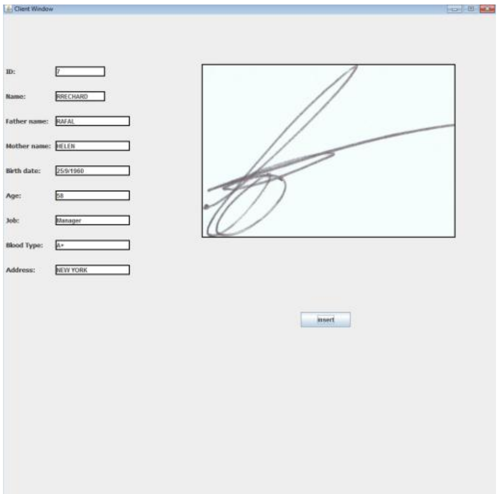


**Fig (3) Client retrieved personal information**

In fig (1) client was uploaded the offline signature (image) to the cloud, in fig (2) cloud received signature from client to perform identification process to retrieve personal information for person's signature, and in fig (3) the client displayed the personal information after receiving it from cloud .

The overall result of proposed system is depending on the identification process (classifier) that shown in fig(4), the steps to build this classifier started with feature extraction by using SIFT , after that histogram construction by using Bag Of Word model , and the classification step by using SVM with RBF kernel . .these steps were working on a sample of (SigComp2011) [31], which contain Dutch and Chinese Genuine signatures for 10 persons (each Nationality), each person 24 signature , and divided in 16 for training , 8 for testing , and choose the 24 randomly forged signatures from this dataset to train the system to classify the strange signature as an unknown .

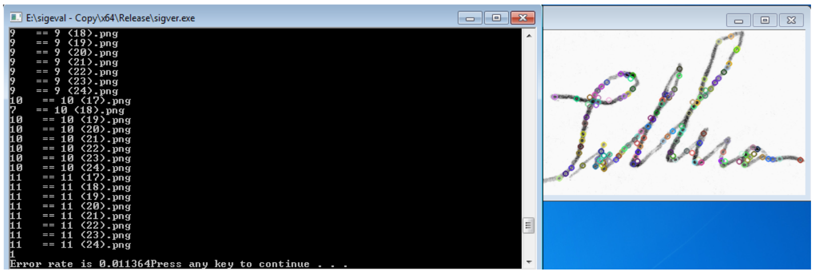


**Fig (4) Training and Testing SVM classifier**

In order to test the quality of the system, we applied accuracy and error rate. And this measures calculated by (1) (2); [30]

Identification Rate, Accuracy = $\frac{No.of\ correct\ identification}{\text{Total number of test signatures}} \times 100\%$ …. (1)

Misidentification Rate, Error Rate = $\frac{No.of\ incorrect\ identification}{\text{Total number of test signatures}} \times 100\%$ …. (2)

It can be seen from table (1), the test accuracy is obtained by using (SigComp2011) dataset, for Dutch and Chinese signatures, with various number of features detects.

In general the high result of system performance have been achieved during to set the parameters of SVM classifier (C, gamma), with (300, 400 and 500) features detects by SIFT. The best test accuracy is obtained is (98.8%).

| SIFT feature detect | Accuracy with Dutch signatures | Accuracy with Chinese signatures |
|---|---|---|
| **100** | **88.63%** | **85.22%** |
| **200** | **94.31%** | **89.77%** |
| **300** | **98.86%** | **96.95%** |
| **400** | **98.86%** | **98.86%** |
| **500** | **98.86%** | **98.86%** |
| **600** | **96.59%** | **95.45%** |
| **700** | **97.77%** | **94.31%** |
| **800** | **92.04%** | **94.31%** |

**Table (1) Test Accuracy for Identification with Dutch and Chinese Signatures** (SigComp2011)

It can be seen from table (2), the comparison of accuracy with other algorithms which (has been) used for signature identification.

| REFRENCE | Feature generation | classification | Identification Accuracy |
|---|---|---|---|
| **[18]** | **global geometric** | **SVM** | **71%** |
| **[16]** | **Combination (global and local features)** | **Multi stage** | **91.8%** |
| **[12]** | **GSC** | **KNN** | **93%** |
| **[13]** | **Fractal dimensions** | **KNN** | **95%** |
| **[11]** | **(CT)** | **(OC-PCA)** | **97.9%** |
| **[25]** | **HOG** | **GRANN** | **98.3%** |
| **Proposed Method** | **SIFT** | **SVM** | **98.8%** |

**Table (2) Comparison of test accuracy with other algorithms.**

## IV. Conclusion

The Spite of the identification importance, but it has very little attention in comparison with verification. In a matter of fact the identification can be considered a major preprocessing stage for verification. In other words, a correct verification depends on a correct identification. In this paper, the novel signature identification system has been applied with SIFT (feature extraction) and SVM (classification) to retrieve personal information from cloud. The main advantage of the proposed system is the ability of the classifier to recognize the strange signature and classify it as unknown, by training it on forgeries signatures. Also, the proposed System proved that has great test accuracy.

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