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Offline Signature Identification System To Retrieve personal information from cloud

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ABSTRACT

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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. In this thesis we present the cloud system allows to retrieve user information depend on offline signature identification , this identification process by using image process to classify the signature , we will use SIFT (Scale-Invariant Feature Transform) to features extraction and converts the image into a feature descriptors , Bag Of Word model (BOW) to present signature image by its histogram , and Support Vector Machine (SVM) classifier that had been successfully applied in different classification applications.

Keywords: Offline signature, Identification, cloud, SIFT, BOW, SVM.

ÖZET

İmza, kişisel kimlik doğrulama işlemleri için çok kabul gören ve yaygın kullanılan biyometrik bir yöntemdir; bu da her kişinin kendine özgü davranışsal ve karakteristik özellikleri ile kendi benzersiz imzaları bulunduğuna bağlı inanılmaktadır. Bu nedenle imzanın kendisinin tanınması son derece önem arz etmektedir. İmza sistemi davranışsal biyometrik bir yöntem olup, çevrimiçi imza sistemi ve çevrimdışı imza sistemine bölünmüştür. Birincisi, yazım esnasında zaman, uygulanan basınç ve hız gibi dinamik özellikleri yakalarken ikincisi imzaların durağan görüntülerini analiz eder, yazı işlemini çözümlemeye yöneliktir. Çevrimdışı sistemde dinamik bilgi edinmediğinden çevrimiçi sisteme göre daha zor ve karmaşık bir prosedürdür. Çevrimdışı imza, imzaların yalnızca basılı kopyalarının bulunduğu, özellikle birçok belgenin doğrulanması gereken durumlarda yer almaktadır. Bu yüzden, kişisel bilgileri tahsil etmek amacıyla Novel Offline İmza Tanımlama Sistemini uygulamayı öneride bulunduk. Bu sistem, istemci (müşteri?) tarafından alınan girdi türüne göre bulut sunucusu kullanılarak uygulanabilir. İmza, istemci tarafından yüklenen bulut üzerinde tanımlandıktan sonra kullanıcı bilgileri elde edilebilir. Bu tezde, çevrimdışı imza tanımlamasına bağlı olarak kullanıcı bilgilerini elde etmeyi sağlayan bulut sistemini tanıtlıyoruz; bu imza tanımlama işleminde imza özelliklerini çıkarma ve görüntüyü bir özellik tanımlayıcılarına dönüştürmek ile sınıflandırma yapmak için SIFT (Scale-Invariant Feature Transform/ Ölçek-Değişken Özellik Transformu) ve bir görüntü işleme programını kullanacağız. İmza imgesini histogram ile sunmak için Bag Of Word modeli (BOW) ve farklı sınıflandırma uygulamalarında başarı gören Support Vector Machine (SVM; Destek Vektör Makinesi) sınıflandırıcıyı kullanacağız.

Anahtar kelimeler: Çevrimdışı imza, Tanımlama, Bulut, SIFT, BOW, SVM.

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1. INTRODUCTION

1.1 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 identification 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 (K. Jain, 2004).

1.2 Statement of the Problem

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.

1.3 Statement of Study

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) (Lowe, Sept. 1999)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) (Zhou, 1998)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) (VAPNIK, 1995), 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.

1.4 The Objectives of study

The overall objective, is developing an offline signature identification 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 .

1.5 Related work

In 2016 (Bilal Hadjadji, 2017) 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 (Bilal Hadjadji, 2017). In 2004 (MEENAKSHI K. KALERA, 2004) 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 (MEENAKSHI K. KALERA, 2004). Also , In 2014 (Ramzi Zouari, 2014) 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% (Ramzi Zouari, 2014). In (1996) (Ke Han, 1995) 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 (Ke Han, 1995).In (1998) (I. Pavlidis, 1998) 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 (I. Pavlidis, 1998).In (2000) (M.A. Ismail, 2000) 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 (M.A. Ismail, 2000). In (2000) (Jordi-Roger Riba, 2000)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 (Jordi-Roger Riba, 2000). In (2006) (E. Frias-Martine, 2006) 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 (E. Frias-Martine, 2006). In (2014) (Ghazali Sulong, 2014) 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 (Ghazali Sulong, 2014). in(2008) (Javier Ruiz-del-Sola r, 2008) 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% (Javier Ruiz-del-Sola r, 2008). In (2014) (Do, 2014)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 (Do, 2014). In (2013) (R.K.Bharathi, 2013)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 (R.K.Bharathi, 2013). In (2013) (Juan Hu, 2013)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 (Juan Hu, 2013). In (2011) (Mustafa Berkay Yilmaz, 2011)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 (Mustafa Berkay Yilmaz, 2011).In 2017 (Murat Taskiran, Offline Signature Identification via HOG Features and Artificial Neural Networks, 2017) 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 (Murat Taskiran, Offline Signature Identification via HOG Features and Artificial Neural Networks, 2017). In 2013 (Marcin Adamski, 2013) 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% (Marcin Adamski, 2013).

1.6 Thesis Structure

Chapter 1 - Introduction: This chapter shown the general introduction related description of the topic of the research. The chapter proceeds with the statement of the problem then the selected research methodology, the overall objective for the research, and review number of previous researches which related to our research.

Chapter 2 - Background: This chapter shown the background description of the topic of the research.

Chapter 3 -Methodology: This chapter shown the research methodology is described in detail.

Chapter 4 - Result and Conclusion : This chapter shown the tools which used to implement the system , system result's , performance measure , make simple comparison in algorithms used and system accuracy with other researches , in the end of this chapter present the Conclusions and what is suggest for future works.

2. BACKGROUND

2.1 Introduction

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. (Sushma Jaiswal, 2011)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 verification situation, a signature). (YILMAZ, February 2015) Signatures are a behavioral biometrical property, which is influenced by physiological and emotional state of the signatory (K. Jain, 2004). 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, (Sushma Jaiswal, 2011) and they have been accepted in governmental, legal, and commercial transactions as an approach of identification (K. Jain, 2004).

The Previous researches in the signatures system divide in two type, known as offline and online systems. (Coetzer, 2006)

2.2 Online and offline signature systems

In offline systems, a signature is a static signature image, is the only input to off-line systems. Identification 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 (YILMAZ, February 2015).

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 systems are of quite less reliability than online ones. (Coetzer, 2006) 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 (Coetzer, 2006).

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 (Bilal Hadjadji, 2017).

2.3 Identification and verification

Identification differs significantly from verification. Identification can be defined as the operation comparing a person to a biometrical pattern or data-base.

Biometric Verification is a procedure that validating one’s ID through a comparison of their biometrical data with previously collected biometrical data stored in a system (Sushma Jaiswal, 2011). A verification system simply determines whether or not a specific entity is a part of a particular class. While a identification system has the task of deciding which of a certain number of classes the entity belongs to.

Identification is when the device asks and tries answering the question, —”Who is X?” When biometrics are utilized for identifying a person, the biometrical device reads a sample and performs a comparison of that sample with each template in the data-base. This is known as —”one-to-many”.

Verification is when the device asks and tries answering the question, —”Is this X?” after the user claims to be X. When biometrics are utilized for verifying the claimed identity of a person, the biometrical device at first asks for input from the user.

Identification may generate a one to many matches, whereas verification produces a one to one match (Coetzer, 2006) .

2.4 Cloud computing

2.4.1 Definition

Different Researchers gave a plenty of cloud computing definitions, one of them were given through Barkley RAD as:

“Cloud Computing refers to both the applications delivered as services over the Internet and the hardware and systems software in the datacenters that provide those services (Armbrust, 2009).

2.4.2 Crucial Features of Cloud Computing

There are five crucial features of the Cloud-Computing that clarify their differences and relations from common computing.

· **On demand self service**

Services could be unprovisioned or provisioned by the user when there is need, outside any interaction between the provider of the service and the user.

· **Broad Network Access**

It is accessed over a standard technique; also it has efficiency over network.

· **Resource-Pooling**

Provider’s computing resource are gathered to be at service for more than one user which are utilizing multitenant model, with many virtual and physical resources assigned in a dynamic manner, depending on user request.

· **Rapid-Elasticity**

The Services could be rapidly and elastically go under provision.

· **Measured Service**

The systems of Cloud Computing control in automatic way and make best of the resource-usage by supplying the services with a metering ability, types of these services:(e.g. active user accounts, bandwidth, processing, storage) .

2.4.3 Cloud-Service-Models

There are 3 Cloud Services Models; those important classifications could be referenced as the "SPI model" in other words. Platform, software, or infrastructure as a services.

• **Cloud-Software as Service**

It is the ability where that the user could utilize the applications of the provider that is functioning on cloud. (Alliance, 2009)

• **Cloud-Platform as Service**

In a service of this kind, the user is able to deploy, the applications that were acquired or created by the user are built by utilizing tools or programming languages supplied by the provider, over the cloud framework.

• **Cloud-Infrastructure as Service**

It is the ability that supplied to user when utilized, it helps the user to provision network, storage, processing, and other important computing- resource that the user can run and deploy software (in other words. applications, operating systems).

2.4.4 Cloud-Deployment-Models

• **Public-Cloud**

The framework of the cloud is accessible to the public.

• **Private-Cloud**

The kind of cloud, that is available merely for single organization.

• **Community-Cloud**

In this sort of the cloud deployment model, the infrastructure of the cloud is shared among a few organizations, also support particular group with shared interests.

• **Hybrid-Cloud**

It is an infrastructure of a cloud which is a combination of 2 or more than 2 clouds in other words. public, community or private. (Alliance, 2009)

2.4.5 Advantages of Cloud Computing

The above-mentioned features can suggest different benefits for the possible users. The following are the greatest in importance benefits of Cloud Computing:

Cost-reduction is accomplished by evading large initial investing for hardware and software acquisition. The training and maintenance cost also is reduced. Resources can be allocated by the organization for other activities example of that: R&D, integration of services. (Hamid R Motahari-Nezhad, 2009), (Mahmood, 2011)

Scalability and the agility of Business are accomplished by adopting Cloud based resolutions, producing alteration capacity and innovation for organizations (Mahmood, 2011).

The ability to access fresh Information Technology services that alternatively it is impossible to be acquired by small company. In this way the competition rules are changed. (Mahmood, 2011)

The on-premise Information Technology systems are improved in a manner to play supportive role in peak capacity, meaning that the most of computation strength stays idle. When talking in numbers, 85 percentage of computation ability sits idle whilst the rates of utilization are between 12% and 18%. Solutions based on Cloud supply effective power utilization that lead to cost-reduction. (Mahmood, 2011) The Cloud Ecosystems supply continuity of business and disaster recovery.

Cloud-services are greatly ready for use, as consumers can get their resources accessible in ubiquitous way. Data and applications can be accessed anywhere there is an internet connection (Duipmans, 2012).

2.5 TCP IP

The TCP/IP model, also called the Internet protocol suite, is a group of communication protocols which perform the protocol-stack that commercial networks and the Internet run in. The suite is named after the 2 protocols greatest in significance within the suite: Transmission-Control-Protocol (TCP) and the other one is the Internet-Protocol (IP).

The TCP/IP protocols suite much like the OSI suite is described as a group of layers. The user is much closer to the Upper layers and transact with abstract information, depending on the lower-layer protocols to perform date translation to forms that transmitted over network in physical way.

2.5.1 TCP/IP and the OSI Reference protocols

The TCP/IP model developed ahead of the OSI-model. Such that it doesn't map to the 7th-layer of the OSI suite. The TCP/IP suite has merely layers that can be relatively mapped to OSI stack

Application-Layer

It matches the application layer of the OSI reference model. Few examples of the entities of application level in the TCP/IP scope: (Fujitsu Network Communications)

- **Telnet FTP/ /SSH**
- **SNMP**
- **HTTP/Secure HTTP (SHTTP)**
- **POP3/SMTP**

Transport-Layer

This layer of the TCP/IP suite corresponds very closely to Transport -layer in the OSI protocol suite. The most protocols used in the transport layer are: Transmission Control protocol (TCP) and User-Datagram-Protocol (UDP)

Internet-Layer

The TCP/IP Internet layer corresponds to OSI network layer, Sometimes Internet layer mentioned as network layer. Internet Protocol (IP) is the main component of Internet layer. Much of TCP/IP suite gets also considered as part of Internet-layer.

Network-Access-Layer

The TCP/IP's lowest layer is the network access layer. It consists of 2 sub -layers, The first is the media access control (MAC) layer and the second is the physical layer. The MAC map relatively close to the data link layer of the OSI protocol suite, also it is occasionally mentioned by that name. (Fujitsu Network Communications)

2.6 Feature Extraction

Flourishes and special characters are the special characters which Signatures are composed of, that is why they may be frequently unreadable. Furthermore interpersonal differences and intrapersonal variations make it crucial to analyze them as whole images not as words and letters that were put with each other.

For that reason the image processing methods are utilized to extract the features from the signature images. As a lot of the features have familiar properties of intensity, then correlations and geometric features are utilized to differentiate between them.

While input-data is doubted to be notoriously-redundant or it is too large to undergo processing. Thus the input data shall be turn into minimized representation of the group of features. The process of transformation of the input data to the group of features is called the feature extraction. Also it is called dimensionality-reduction. When the features that were extracted are chosen neatly, then the expectation is that the group of features will get the related information from the input data so as to execute the preferred task by utilizing reduced-representation rather than the full size input. By utilizing considerable and relevant features a different classes should undergo representation, so as to arrange the input-image.

In this section, the feature extraction techniques that are utilized in the problem of offline signature identification are being summarized.

2.6.1 SURF features: In computer vision Speeded up Robust Features (SURF): it is a well-known algorithm made for describing and detecting image's local features. By using the keypoints local features (known as keypoints descriptors), it supplies feature description for the image also It captures the keypoints in image. The process of selecting the keypoints is done by utilizing Hessian blob detector and by utilizing the total value of Haar wavelet response around interest point, and then the feature descriptors are acquired. For any interest-point, the SURF descriptor vector which length is of 128 is acquired. Thus, dimension of the SURF -descriptors. (P M Panchal, April 2013) (Pedersen, 2014)

2.6.2 HoG features: In computer vision and image processing the Histogram of Oriented Gradients known as (HoG), is a well-known feature -descriptor for the purpose of detection of objects. It calculates the number of appearances of various gradient orientations in the localized section of image. Images are divided for 32_32 size blocks; the histogram of the size 31 is calculated for each one of the blocks. For that reason, the HoG descriptor's dimension for each one of the images is: the number of blocks _ 31. (Murat Taskiran, Offline Signature Identification via HOG Features and Artificial Neural Networks, 2017)

2.6.3 LBP features: The Local Binary Patterns (LBP) founded to be as robust as the local descriptors of texture classification. LBP descriptor is string of bits, and one bit for each neighborhood pixels, where that each bit is 0 or 1 and that depends on if the equivalent neighborhood pixel have intensity greater than central-pixel. The features of LBP are obtained from the patches of local image of the size 32 by 32, identical to the HoG; however feature-length for each single patch is "58". Thus each image's feature matrix is of the size: the number of patches _ 58. (Pietikäinen, 2011) (AbdurRahim, 2013)

2.6.4 SIFT features: The Scale Invariant Feature Transform Is an algorithm for generating the image's features, In this method the image is transformed into a large group of the local-feature vectors, and each one of them is invariant to processes such as scaling, rotation and image translation, plus it is slightly invariant to the illumination alterations and 3D or affine projection. The output features are greatly distinctive. (Lowe, Sept. 1999) Next are main phases of computation utilized to the process of generating the group of the image's features:

1. **Keypoints localization:**

We desire to recognize the locations in the image scale space which are constant with respect to rotation, scaling and image translation, and are least influenced by small distortions and noise. The only single potential smoothing-kernels used for analyzing scale space is Gaussian kernel and its derivatives.

To accomplish great efficiency-level and rotation invariance, we have selected key-locations at the maxima and minima of a variation of the Gaussian function utilized in scale-space. It can be calculated in a very efficient way by constructing image pyramid with resampling among each one of the levels. Moreover, it finds keypoints at scale of high variation and regions, leading to stable locations for characterizing image. (Lowe, Sept. 1999)

SIFT technique utilizes scale space “Difference of Gaussian” abbreviated as (DoG) to find the interest points within the image, (L. Zhang, 2008)

Let i (x, y) is an input image, L(x, y,σ) It is the scale space known as function

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (2.1)$$

where G(x,y, a) is a Gaussian-function:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)}/2\sigma^2 \quad (2.2)$$

DoG function D(x,y,σ) could be produced by the subtraction of each of the images from the direct neighbors k as a multiplicative factor : (L. Zhang, 2008)

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \quad (3.3) \end{aligned}$$

This process is done for different octaves of the image in Gaussian Pyramid. It is represented in below image (Open Source Computer Vision, 2017) :

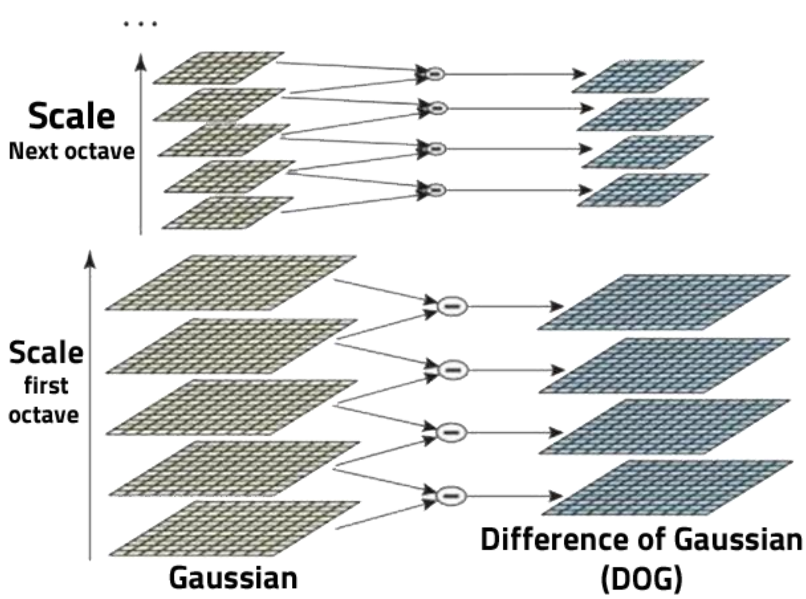


Figure 1: Different octaves of the image in Gaussian Pyramid

2. **keypoints stability:**

The process of detecting the candidates of keypoints is accomplished by the comparison between each single point to its eight neighbors on the same scale, also each one of its nine neighbors one the scale up and down. Each point which smaller or bigger than all of neighbors is a keypoint candidate (L. Zhang, 2008). One can examine the stability of the resulted keys when the natural images undergo brightness and contrast alterations, affine projection, also the addition of noise. (Lowe, Sept. 1999) Each key's location learned in the 1'st image could be recognized in transformed image by knowing the transform parameters. (Lowe, Sept. 1999)

The candidates which have low-contrast or found on the edge will be canceled. Rather than utilizing this detection technique, each other detector providing scale and location could be used. (L. Zhang, 2008)

3. **Assigning rotation:**

The image's descriptors are invariant to the process of rotation because every key location is given a canonical orientation. To make it as stable as can be against contrast or lighting alterations, Orientation is specified by the peak in a the histogram of local-image gradient orientation (Lowe, Sept. 1999)

Orientation ϴ(x, y) and Gradient magnitude m(x, y) are calculated by utilizing the pixel differences in Equ. (2.4), (2.5). (L. Zhang, 2008)

$$m(x,y)= \sqrt{\left(L(x+1,y)-L(x-1,y)\right)2+\left(L(x,y+1)-L(x,y-1)\right)2} \tag{2.4}$$

$$\Theta(x, y) = \tan^{-1}\left(\frac{L(x+1,y)-L(x-1,y)}{L(x,y+1)-L(x,y-1)}\right. \tag{2.5}$$

Then an orientation histogram with 36 bins (L. Zhang, 2008) covering the 360 (Lowe, Sept. 1999) degree is calculated of image gradients around the keypoints. Maximum orientation is allocated to the keypoint. A fresh keypoint with this orientation is generated (L. Zhang, 2008) for each another orientation in 80 percent of the maximum orientation. Each every one of the keypoints will undergo rotation in the same direction of its orientation then it will be normalized. (L. Zhang, 2008)

4. Keypoint Descriptor :

Given a scale, orientation and stable location for each one of the keys, there is possibility for local image region description in a way invariant to those alterations. Moreover, it is desired to make the representation firm against little shifts in the local geometry. (Lowe, Sept. 1999)

Area around keypoint is divided into 4 by 4 sub-regions. After that orientation histogram of eight bins built for each one of the sub-regions, also by utilizing Gaussian window, the corresponding gradient values are weighted. That will result in vector of 128 dimensions (4 by 4 by 8). Vector will be normalized to the length of unit, and that will give invariance to the multiplicative alterations in lighting condition.

In addition to that, few measurements were taken to give the ability to maintain robustness against rotation and illumination changes, etc. (L. Zhang, 2008)

2.7 Histogram Construction by Bag of Word model (BOW)

This is one of the most well-known representation techniques for the purpose of categorization of objects. The main thought is to quantize each one of the keypoints that were extracted to one of the visual words, after that representing each one of the images by a histogram of visual words. Utilized for the reason of representing the content of image and it has been applied successfully to categorization. The main thought is to quantize each one of the extracted keypoint to one of the visual-words, thereafter present each one of the images by histogram of visual-words. The vector quantization steps allow the representation of each image by a histogram of visual-words that is regularly pointed to a bag of words representation (Zhou, 1998).

BOW is an example of supervised learning. It's always better to keep a mapping of which images belong to what classification label (a label can be defined as a key/value for identifying to what class/category does the object belongs).We need to define set of words (essentially the features marked by words) that provides an analogous relation of an object (being trained) a set of features.

Extrapolated the similar features from the set of signature images, to make it more easily understandable. Because every image has certain discernable features, patterns with which can describe as to what in this image.

When you see a image of some object; let's say a motorbike - significant features are being extrapolated. This features together help in deciding whether what is being seen is actually a motorbike. The collection as well as frequency of particular features is what helps in estimating what object does the image contain. After extrapolated the similar features, will generate a dictionary that registers corresponding mappings between features and their definition in the object. (Csurka G, 2004)

Clustering procedure (for example. KNN) is frequently applied to a set of keypoints from the training images to big number of clusters, and the center of each one of the clusters (K-Means) is corresponding to a distinct visual word.

Yet, as far as we can tell, there are no academic analyses on the statistic features of vector quantizing for the categorizing (Zhou, 1998).

The main thought is to quantize each and every extracted keypoint to one of the visual words, then represent the image with the use histogram of visual words. For that reason, clustering method (as example. Knn, K-means), is in general utilized for the generation of visual words. In the clustering procedure use k nearest neighbor algorithm, and with center for each cluster using K-means algorithm.

K-means Algorithm

A traditional clustering analysis method that uses iterative partitioning training dataset for learning a part of a specific data space, learning a partition on a dataset for producing numerous non-empty clusters (typically, the number of clusters that is given previously). It is a popular approach for vector quantization, typically implemented in data mining, such as, image classification and voice recognition. It includes organizing a multi-dimensional space to a specific number of clusters, every one of which is entirely defined by its centroid. A specific vector in the space is part of the cluster in which it is of the minimum distance from the centroid. The clustering is ideal when the summation of the distances of each point to the centroid of its cluster is minimal. (Paula Camus, 2011)

This approach defines the centroid of a cluster as the average value of the points inside the cluster. This method operates according to the following steps. First, it arbitrarily chooses k objects in D, every one of which at this point is considered as the cluster mean or centroid. For every one of the rest of the objects, an object is assigned to the cluster to which it is closest, according to the Euclidean distance between the object and the cluster average.

Then, the algorithm performs improvement in an iterative manner within-cluster variation. For every one of the clusters, it calculates the new average utilizing the objects that have been assigned to the cluster in the preceding iteration. Each object is afterwards re-assigned with the use of the new average values as the new cluster centroids. The iterations are repeated to the point where the assignment is stable, where that, the clusters which were produced in the present round are as the same as the clusters were produced in the preceding one.

The k-means procedure may be utilized when the average of the group of objects is put to definition. Which could not be applicable in some of the applications like the case involving data with nominal attributes. The k-modes procedure is different from k-means that extend k-means paradigm to cluster nominal data via using modes instead of the means of clusters. It utilizes new variation measurements to handle nominal objects and a method based on frequency for the purpose of updating modes of the clusters. The k-modes and the k-means approaches may be integrated to the cluster data with mixed nominal and numeric values.

The k-means procedure is not adequate to discover clusters of very different size or with clusters with no convex shapes. Furthermore, it is sensitive to outlier date points and noise and the reason is that a small number of that data may significantly influence the average value (Jiawei Han, 2012).

One way to make k-means procedure operate more efficiently on large datasets is to utilize an efficiently sized group of examples in the clustering process. One other way is to deploy a filtering process which employs a spatial hierarchical data index for saving the costs when computing ways. A third way is to explore the micro-clustering idea, that first group the near objects into "micro-clusters", after that, implement k-means clustering on the micro-clusters. (Jiawei Han, 2012)

K-Nearest Neighbor Algorithm

A simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions; Euclidean distance) (Jiawei Han, 2012).

$$\text{Euclidean distance} = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

Assuming that K =1, then the case is directly allocated to the class of it's the nearest neighbor.

The process of data inspection will lead to choosing optimal value for K. generally, when the K value is large, then it is more accurate as it minimizes the total noise but there is no assurance for that (Jiawei Han, 2012).

“How can I determine a good value for k, the number of neighbors?” By using experiments we can determine this value. Starting with k D 1, we employ a testing group to classifier’s error rate estimation. This procedure could be done continuously via the increment of k value for allowing an additional neighbor. The process of selecting k value with minimal error rate may be general, with the number of training tuples is large, then the value of k will also be (in order that numeric prediction decisions and classification can be based on a bigger part of the stored tuples). While the number of the training tuples approach infinity and k D 1, then the error rate could not be worse than twice the Bayesian error rate (which is the theoretical minimum). In the case where k approaches infinity, then the error rate will approach the Bayesian error rate. (Jiawei Han, 2012)

KNN Is a classifier that discriminates classes with a distance measure between the feature vectors on the feature space. The classifier places an unknown class in the similar groups determined by the quantified closeness. In the K-NN based prediction, a future class is assumed to follow a similar posterior distribution of its nearest neighbors’ distributions, which is convincing for a circumstance that guarantees a sufficient scale of historical data containing various past traffic situations. The K-NN extracts k neighbors for a given input set by measuring its similarity to those neighbors, and the feature vector represents the description of a traffic situation. (Ahmed, 2017)

When talking about pattern recognition the K-NN is a non-parametric procedure deployed for the purpose of regression and classification. The input is made up of k closest training examples in feature space. While the output depends on if K-NN is utilized for regression or classification. The training samples are vectors in a multi-dimensional property space every one of which holds a class label. The training stage of the approach includes storing the class labels and property vectors of the training examples. The KNN classifier is used to reduce the computational load. There are two problems with practical exploitation of the power of the K-NN method. The first, whereas there is no time needed for parameters estimation from the training data, the time that is required to find the nearest neighbors in large training sets could be prohibitive.

The classification rule in KNN algorithm could be explained as decision that was taken according to assessments of the posterior possibilities from the data. The larger the number of the examples N, the smaller the impact of damage in spatial precision, permitting larger k values to be utilized. A lot of training samples, allow good estimates, (T. Cover, 1967)

However they demand large computation effort. The issue with the nearest neighbor method is the computation difficulty of the search for the nearest neighbors between the N training samples. Some strategies were studied for the purpose of improving performance, such as reducing the number of training samples utilized and efficient searches. (T. Cover, 1967)

2.8 Classification

Classification is one of data analysis forms which extract models that describe significant data classes. These models, known as classifiers, are capable of predicting categorical (unordered, discrete) class labels. As an example for that, it is possible to construct a classification model for the purpose of categorizing bank loans applications as risky or safe. (Jiawei Han, 2012)

There are many different classifiers that are used in offline signature identification. For basic feature types and relatively easier problems, the most classification methods used are presents following:

Inducting the Decision Tree

It is the process of decision trees learning from class labeled training tuples. Decision tree is a flowchart that is much like the tree structure, that every one of the internal nodes (i.e. the non-leaf nodes) indicate a test on attribute, every one of the branches represents test outcome, also that each one of the leaf nodes (or the terminal nodes) hold class label. The topmost node in the tree is the root node.

"How are decision trees used for classification?" Considering a tuple, X, where the related class label is unknown, attribute values of tuple are put to test with the decision tree. The path is tracked from the root to a leaf node that holds the class prediction for that tuple. It is easily to convert decision trees to classification rules.

"Why are decision tree classifiers so popular?" The process of constructing decision tree classifiers doesn't need parameter setting or domain knowledge thus it is suitable for exploratory knowledge detection. The decision trees have the ability for handling multi-dimensional data. (Jiawei Han, 2012)

The representation of obtained knowledge in the tree forms intuitive and mostly simple to picture by a human. The classification and learning phases of the decision tree induction are fast and easy. Generally, the decision tree classifiers are accurate.

Yet, successful usage could rely on the available data. The induction methods have been utilized for the classification in various fields like the molecular biology, manufacturing, medicine, financial analysis, production and astronomy. Decision trees are the basic portion of many commercial rule induction systems. (Jiawei Han, 2012)

Bayes Methods (Naive Bayesian Classification)

The bayesian classifiers are statistical classifiers. Those classifiers have the ability to anticipate class membership probabilities just as the probability that a specified tuple belong to a certain class. Bayes' theorem is the base of Bayesian classification.

Naive Bayesian classifiers presume that the impact of attribute value on a specified class is separate from the values of other attributes, that presumption is known as class conditional independence; its purpose is to facilitate the involved computation and is considered "naive."

"How effective are Bayesian classifiers?" Different researches concerning this classifier compared with neural network and decision tree classifiers found that it is comparable in several domains. Theoretically, Bayesian classifiers, when compared to other classifiers hold the least error rate. Yet, practically this isn't necessarily the condition, due to inexactness in the presumptions made for its usage, like class conditional independence, and shortage of available probability data.

Also, Bayes classifiers are beneficial in a way that they give a theoretical justification for the other classifiers which do not utilize Bayesian theorem explicitly. (Jiawei Han, 2012)

As an example for that, under specific presumptions, many curve-fitting algorithms and neural networks give output with the maximum posteriori hypothesis, so as the naive Bayesian classifier (Jiawei Han, 2012)

Support Vector Machines

Support vector machines (SVMs), a method for the classification of both linear and nonlinear data. It is statistical learning methods which have been founded to be widely successful in a many of classification actions. SVMs utilize a non-linear mapping to the process of transforming the original training data to higher dimensions. In the new dimension, it does search for linear optimal separating hyper-plane (it is the decision boundary that separate tuples of a class from

another one), the data taken from two classes could be separated via the hyper-plane when using appropriate non-linear mapping to adequate high dimension. SVM locate hyperplane by utilizing support vectors (“essential” training tuples) also using margins (defined via support vector).
In addition to that it recognizes the patterns and analyzes data. Thus, it can predict the specified input and makes both classes and shape the output. Each and every one of the training advantages are noticed as a belong to one of two categories. Lastly it constructs a model which assigns fresh features to one category of another. The classifier is being trained by supervised learning techniques. It is useful to recognize abnormal positions.
SVM is a robust technique for data classification and regression. SVM models search for a hyperplane that can linearly separate classes of objects. SVM is used to discriminate the various categories. SVM learning algorithm is employed to the content of the image can be distinguished to the different categories in term of designed support vector classifier. (Jiawei Han, 2012) (VAPNIK, 1995)
Support vector machines could be implemented to nonlinear classification via utilizing nonlinear kernel function to mapping the input data to higher dimensional feature space in which that the input data could undergo separation with linear classifier. The simplest case a two class problem in which classes are linearly separable. In fig below (Chih-Chung Chang, 2013) :

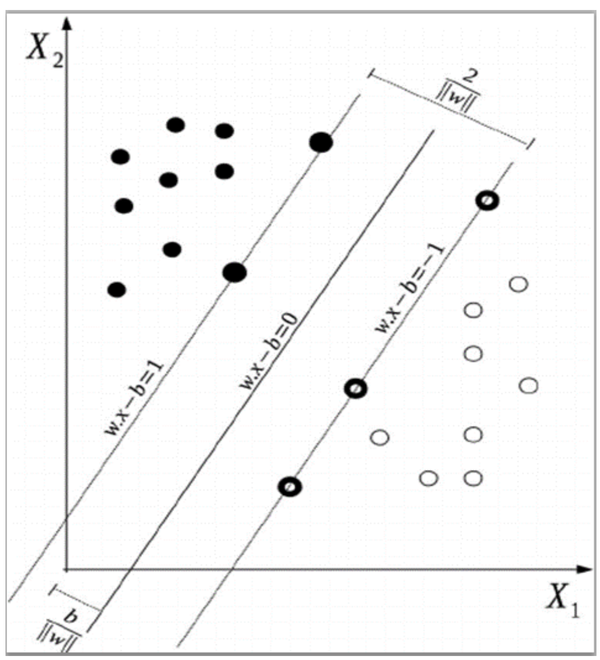


Figure 2: Simplest case a two class are linearly separate

In support vector machines, the classification function is a hyperplane that separate the various classes of the data, w.xi + b = 0 .

The notation (w,x) represent dot product of coefficient vector (w) and vector variable (x).

There is an unlimited figure of separating lines that may be drawn. We need to find the best one of them. Hyperplane refer to the decision boundary that we are seeking, regardless of the number of input attributes. (Jiawei Han, 2012) (Chih-Chung Chang, 2013)

An SVM approaches this problem by searching for the maximum marginal hyperplane. The expectation that the hyper-plane with larger margin have greater accuracy when it comes to classifying the future data tuples than hyper-plane with small margin.

That is the reason why (through the training or learning phase) SVM locates the hyper-plane which has the biggest margin, maximum marginal hyperplane (MMH). The biggest separation between classes is given by the associated margin. The margin is the smallest distance of a hyper-plane to one-side of its margin is equivalent to the shortest distance of the hyper-plane to other side of its margin, that the sides of margin are parallel to the hyperplane. Any of the training tuples that falls on the hyperplanes (the "sides" describing margin) satisfy, also called support vectors. Support vector are surrounded with thicker border as shown in fig (3) (Jiawei Han, 2012). Basically, the SVMs are the most difficult tuples when it comes classifying and give the most information concerning classification.

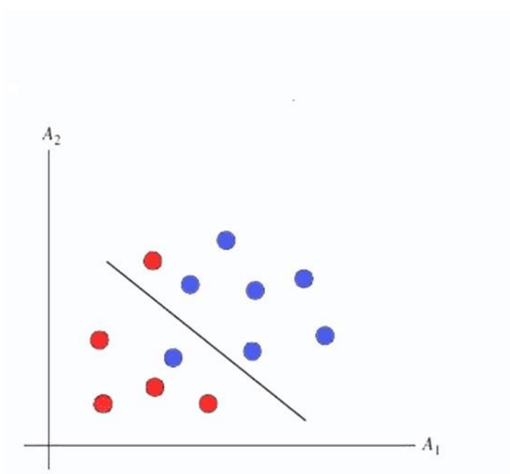


Figure 3: Not possible to draw a straight line to separate the classes

Linear Support Vector Machines could undergo extending process to make non-linear SVMs for classification of data that is linearly inseparable (in addition to that it is referred to as non-linearly separable data, or non-linear data for short). Those Support Vector Machines are able to find non-linear decision boundaries in the input space. In 1’st phase, the original input data goes into transformation to a higher dimensional space utilizing a non-linear mapping. Few common non-linear mappings could be utilized in this phase; first the data goes into transformation for the new higher space, second phase tries to find a linear separating hyper-plane in the new space. Then we again finish up with a quadratic optimization problem which could be solved by utilizing linear support vector machine formulation. Maximal marginal hyper-plane is found in new space match to a non-linear separating hyper-surface in the original space. (Chih-Chung Chang, 2013) (Jiawei Han, 2012)

Rather than computing dot output on the transformed tuples, it becomes eventually that it is mathematically equivalent to, Rather than Appling kernel function as shown in figure (4) (Berwick, 2013), K(Xi , Xj), to the original input data.

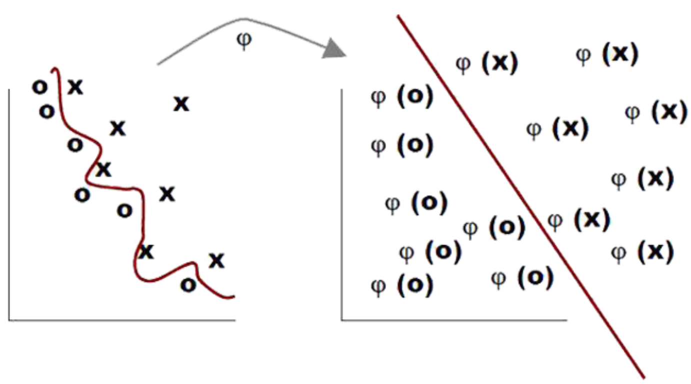


Figure 4: Transformation to separate

Three transform kernel functions are:

- Polynomial kernel of degree.
- Gaussian radial basis function kernel.
- Sigmoid kernel.

Radial basis function (RBF Kernel)

Generally, RBF kernel is sensible first choice. The kernels non-linearly map samples to higher dimensional space, therefore it is, unlike linear-kernel, is capable of handling the situation in which the relationship between attributes and class labels is nonlinear.

Moreover, linear-kernel is special situation of RBF due to the fact that the linear-kernel that their penalty parameters “C” have the same execution as the radial basis function kernel with some parameters “C”. Moreover, for certain parameters sigmoid-kernel behaves like RBF.

The 2nd cause is number of hyperparameters that in uences the complexity of the selection of model. Polynomial-kernel has more hyperparameters than RBF-kernel.

Lastly, there are few conditions where RBF-kernel isn’t suitable. Specifically, when the number of characteristics is quite large, one may just utilize linear-kernel. (Chih-Wei Hsu, 2010)

3. METHODOLOGY

3.1 Introduction

Signature is still the most socially and legally accepted means, and in many transactions (e.g vouchers and bank cheques) Depends on signatures for identification, and modern systems has become increasingly dependent on sharing data by using common database. For this reasons we proposed to build a system to retrieve the personal information from cloud based on signature system.

Our system (represent in fig (5)) 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 system;

The database contain the basic information of each person, who are signed in dataset. we used oracle database and this database has a table (SIG) contain (ID , Name , Father Name , Mother Name , Age , Address , Blood Type , Occupation , Birth Date). And the classifier was trained by dataset sample and tested by the other part from this dataset, the dataset we used is (SigComp2011). Training the classifier start with SIFT, We extract Interest points with the use of SIFT detector in each signature image and describe every local property with the SIFT descriptor. The visual dictionary is generated with a K-means method and KNN algorithm in form of bag of word model, KNN algorithm to clustering the features while determined the center by K means algorithm, signature images is then represented by its histogram onto the visual vocabulary. When the histogram is ready, we classify the signatures with SVM as the number of ID per each signature class. Our aim of building this classifier is predict the personal by using signature. After training the classifier system we tested by test dataset. And the classifier become ready to predict the ID of signatures. Now when Cloud receive the offline signature from the client the classifier system predict the ID of this signature and the cloud get the personal information of this signature from database and send it to client .

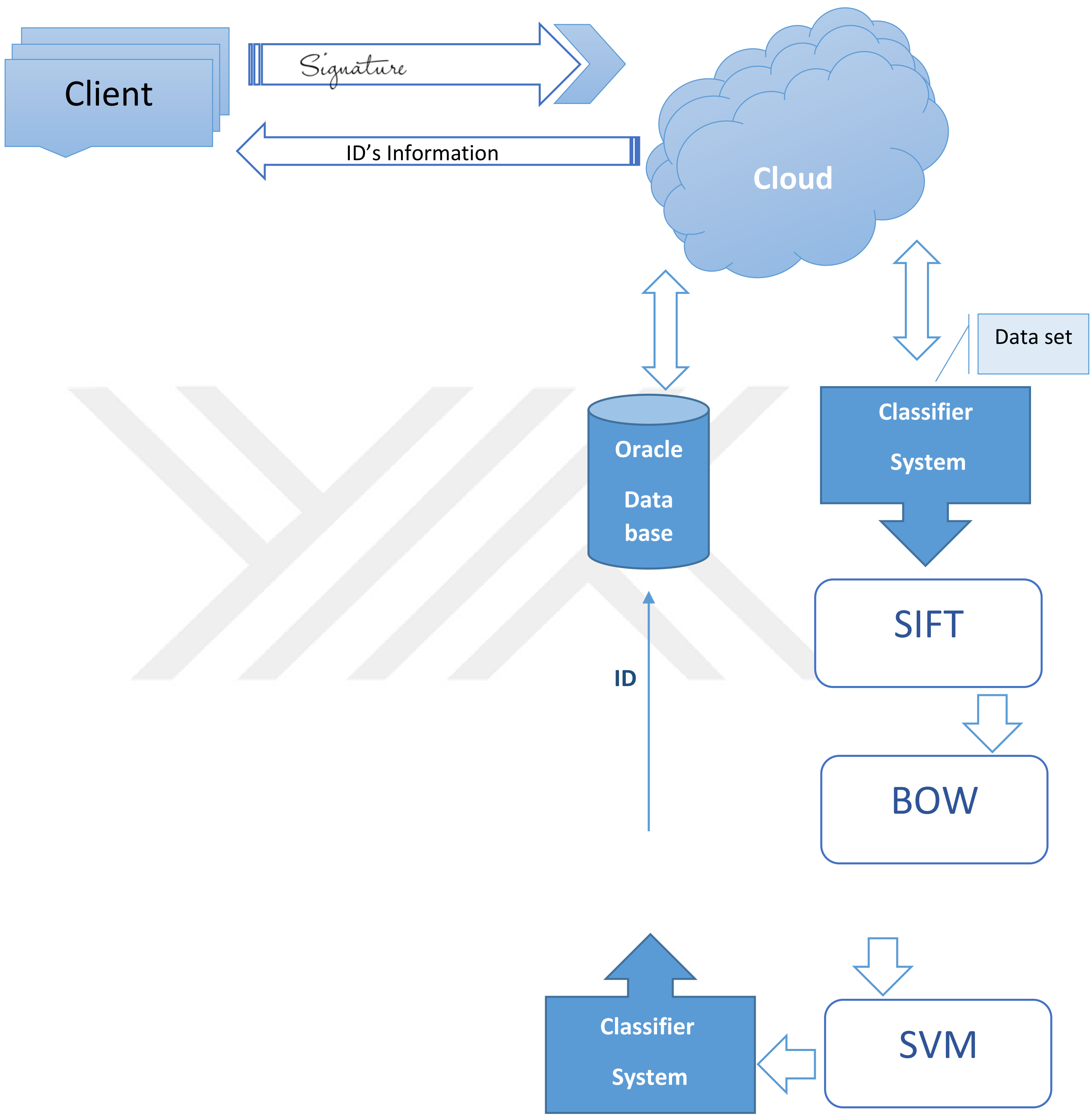


Figure 5: Shown retrieve information based on signature system

3.2 Dataset

We used SigComp2011 dataset (Marcus Liwicki, 2001) ; Fig (6)

- The set includes simultaneously obtained on-line and off-line samples.
- The set includes off-line and on-line samples of signatures. The off-line data-set includes PNG images, scanned at 400 dpi, RGB color. The on-line data-set includes ASCII files of the format: X, Y, Z (per line).
- Each of offline and online samples contain Dutch dataset and Chinese dataset, and each of them contain a Genuine and Forgeries signatures.

We used a sample from this dataset, 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.

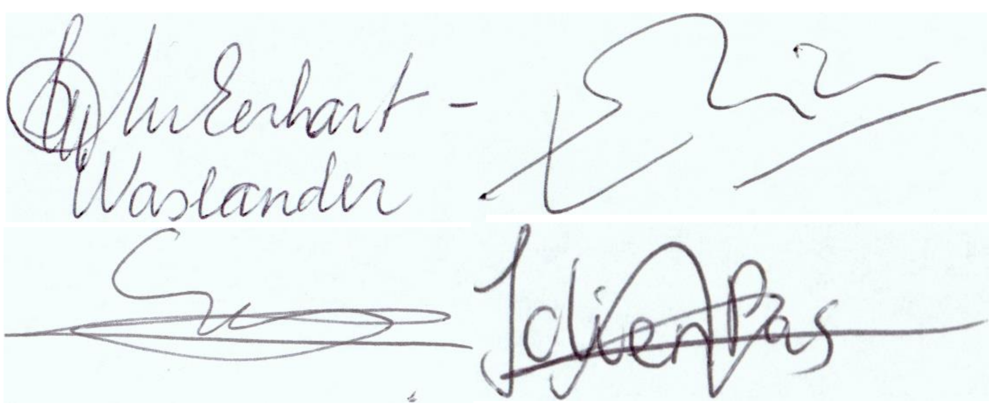


Figure 6: Samples of dataset (SigComp2011)

3.3 System design

Our system is designed to retrieve personal information after recognize the signature from cloud, when the client request this information by uploading the offline signature. This system contain client and cloud. Client this framework to upload signature image to the cloud. And the cloud has the classifier and database. We used to designed this system ;

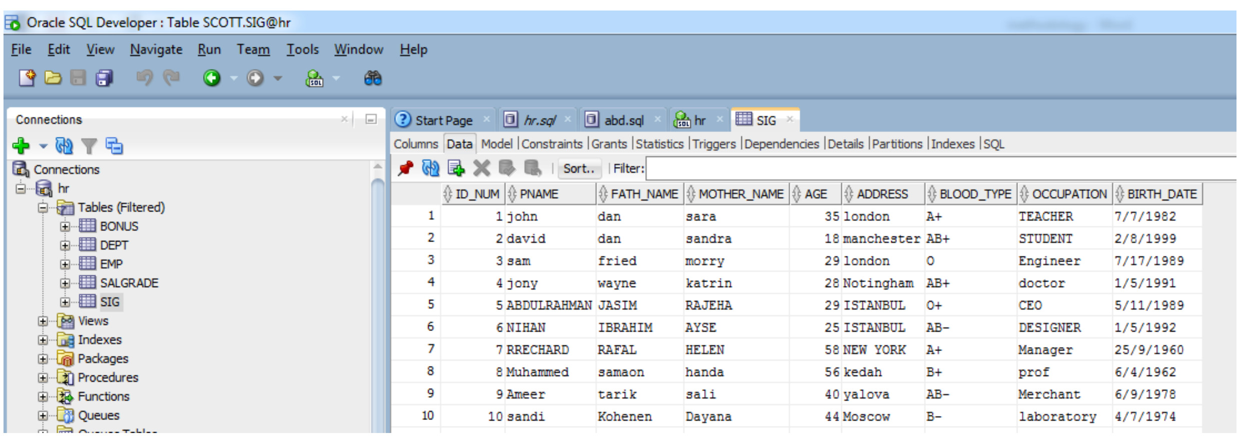
Programming Language: Jave , C++

Environment: Netbeans IDE ,Visual Studio 2013

Database: Oracle 10g

3.3.1 Database

We used oracle 10g database to store the personal information for persons, who are signed in dataset. We create a Table with name SIG this table contain (ID , Name , Father Name , Mother Name , Age , Address , Blood Type , Occupation , Birth Date). Fig (7)



	ID_NUM	PNAME	FATH_NAME	MOTHER_NAME	AGE	ADDRESS	BLOOD_TYPE	OCCUPATION	BIRTH_DATE
1	1	john	dan	sara	35	london	A+	TEACHER	7/7/1982
2	2	david	dan	sandra	18	manchester	AB+	STUDENT	2/8/1999
3	3	sam	fried	morry	29	london	O	Engineer	7/17/1989
4	4	jony	wayne	katrin	28	Notingham	AB+	doctor	1/5/1991
5	5	ABDULRAHMAN	JASIM	RAJEHA	29	ISTANBUL	O+	CEO	5/11/1989
6	6	NIHAN	IBRAHIM	AYSE	25	ISTANBUL	AB-	DESIGNER	1/5/1992
7	7	RRECHARD	RAFAL	HELEN	58	NEW YORK	A+	Manager	25/9/1960
8	8	Muhammed	samaon	handa	56	kedah	B+	prof	6/4/1962
9	9	Ameer	tarik	sali	40	yalova	AB-	Merchant	6/9/1978
10	10	sandi	Kohenen	Dayana	44	Moscow	B-	laboratory	4/7/1974

Figure 7: Sample of oracle database which used

3.3.2 Classifier system

The classifier system is designed to predict ID for the new signature, which uploaded from client. This classifier worked as identification system, which it can be recognize the signatures. There are two main steps in building the classifier system; training and testing. For this steps we used SIFT , Bag Of Word , and SVM . it is represented in figure below ;

Figure 8: Algorithms are used to build classifier system.

3.3.2.1 Feature Extraction using SIFT

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). (Lowe, Sept. 1999) It is an approach invariant to scale, rotation, and illumination conditions.

This method converts the image to a large set of local property vectors, fig (9), 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 (Lowe, Sept. 1999).

Figure 9: SIFT feature extraction

As mentioned previously, 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,σ) values, meaning that there's a possible keypoint at (x,y) at σ scale.

SIFT utilizes DoG, obtained as the difference of Gaussian blurring of an image that has 2 various σ, for instance, σ and kσ. 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 (Open Source Computer Vision, 2017).

- 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, and in the case where the intensity at this extrema is bellow a threshold (0.03 in this paper), it is declined. 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

Now 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. (Open Source Computer Vision, 2017)

Briefly; this approach is designed for the extraction of local properties which are capable of describing different signatures types. For details SIFT start to detect extrema values in scale space for locating the location of key points on image. The pixel will be tested and compared, which are eight neighboring pixels in the same scale and 9×2 neighboring pixels in the prior and following scales. SIFT is categorized to numerous parts: find and eliminate bad key-points, which are edges and low contrast areas by fitting 3-D quadratic functions, at the same time this stage will make algorithm strong and sufficient. Every one of the key-point directions and magnitudes will be evaluated by the orientation of gradient of its surrounding pixels. Afterwards, select and detect the most prominent direction in the area as the area of the key-point. This efficiently removes the effect of orientation, making it invariant to rotations.

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, As shown in Fig (10).

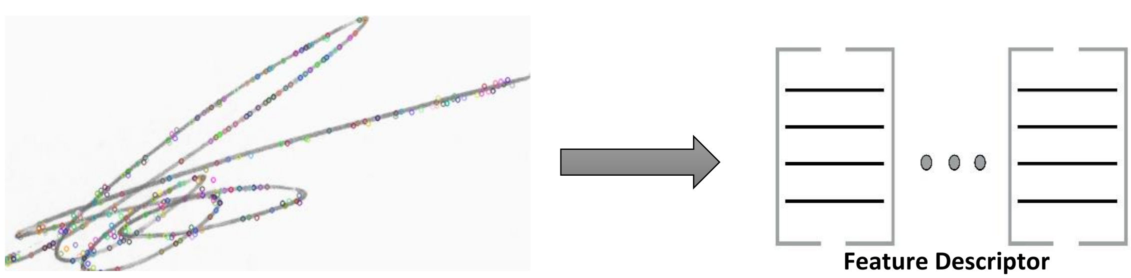


Figure 10: Convert signature image to feature vector by SIFT

3.3.2.2 Histogram constructing using Bag of Word model

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. (Zhou, 1998)

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 define set of words (essentially the features marked by words) that provides an analogous relation of an object (being trained) a set of features.

In the case of this research "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.

NOW, after detection and description features (keypoints descriptor) in feature extraction step by SIFT, basically this steps are followed in bag of word model (fig2.9)

1- Create a "visual vocabulary" – a list of common features.
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.

Optimally, those stages are modeled for maximizing the classification precision simultaneously minimizing the computation effort.

Therefore, 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.

Practically, in bag of word model we used two algorithms to this mission, with determine cluster center we used K means algorithm, and used K nearest neighbor to clustering the features to constructing histogram.

3.3.2.2.1 K means algorithm

K-means clustering aims to divide a collection of data points into K clusters. The number of clusters, K, must be given, it is not determined by the clustering: thus it will always attempt to find K clusters in the data, whether they really exist or not. (Shimodaira, 27 January 2015) In K-means, the optimization criterion is to minimize the total squared error between the training samples and their representative prototypes. This is equivalent to minimizing the trace of the pooled within covariance matrix. The main steps for k-means algorithm is:

- Step 1: Select cluster center (c, centroid) randomly.
- Step 2: calculate the distance between each datapoint and centroid using Euclidian distance.
- Step 3: assign datapoint to centroid (has minimum distance of all centers).
- Step 4: re-calculate centroid by equation (3.1) ;

$$z_i=(1/c_i)\sum_{j=1}^{c_i} x_i \tag{3.1}$$

Where X = $\{x_1,x_2,x_3,........,x_n\}$, set of datapoints .

Z = $\{z_1,z_2,z_3,........,z_c\}$, set of centers .

c_i= number of datapoints in i cluster.

- Step 5: Re-calculate distance between each datapoint and centroid (which calculated in step - 4).
- Step 6: If datapoint was not reassigned then stop, else; repeat from assign datapoint to centroid (step-3) to be achieved this condition.

The algorithm converges since after every iteration, the objective function is not increasing.

One of the shopping criteria is if the user observes the assignment functions in the two iterations are completely identical. In the case where the assignment function does not vary anymore, after that, the prototypes will not vary either (and the other way around).

Practically, we often terminate as soon as the decrease in the objective function becomes small. It gives the ability of computing the ratio between the decreasing and the objective function value in the preceding iteration. In the case where the ratio is less than a threshold, such as 0.0001, the iteration is terminated.

3.3.2.2.2 K Nearest Neighbor algorithm

A simple approach which stores every available case and classifies new ones according to a similarity measurement (for example, distance functions). If K = 1, then the case is assigned to the class of its nearest neighbor (Ahmed, 2017).

The main idea is to detect the k training samples for determining the k-nearest neighbors based on a distance measurement. After that, most of these k nearest neighbors determine the category of the following instance.

The main steps for KNN clustering is :

- Step1: determine K , where K , estimator parameter .
- Step2: compute the distances between the new input and all the training data
- Step3: sort the distance and decide k nearest neighbors according to the k-th minimal distance.
- Step4: collect the categories of these neighbors.
- Step5: decide the category according to the majority vote.

The objective of this approach is separating the data according to the presumed similarities between different classes. Therefore, the classes could be distinguished from each other via searching for similarities between the provided data.

A distance is given between all points and identified as the Euclidean distance between a couple of points .

From those distances, a distance matrix is generated between all possible pairings of points (x, y). Every data point has a class label in the group, C={c1,...,cn}.

The data points', k-closest neighbors (k being the number of neighbors) are then detected by the analysis of the distance matrix.

At the end of this step represent the image signature with histogram fig(11) to make classification by SVM .

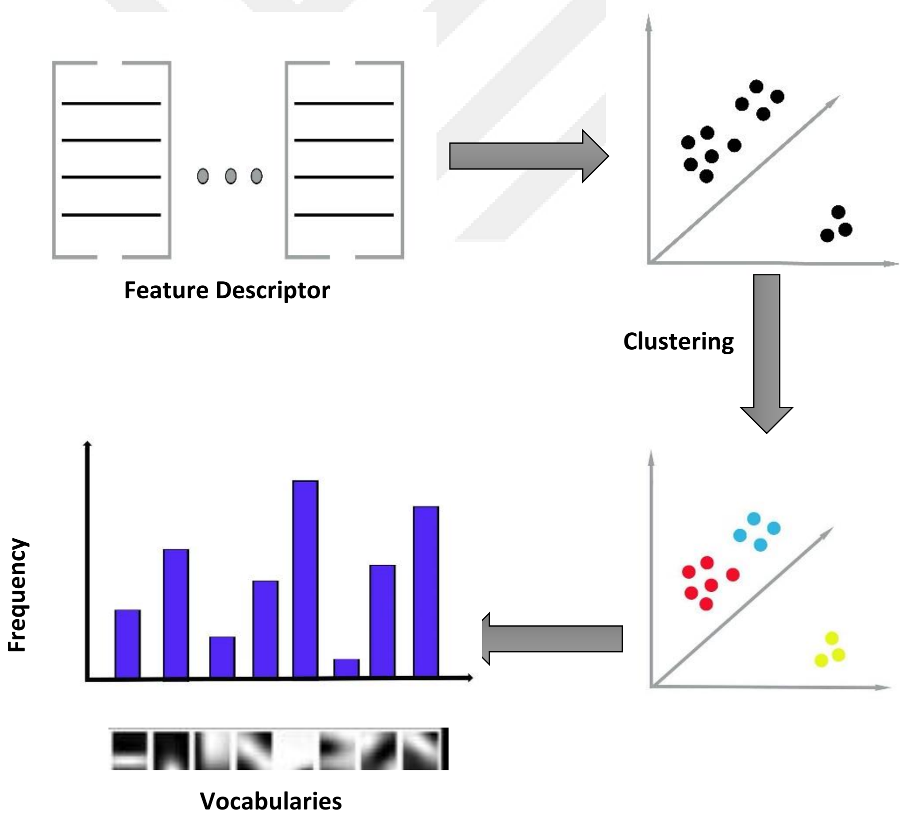


Figure 11: The steps to represent signature image in a histogram

3.3.2.3 Classification - 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 thesis 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.

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: an unlabeled term-frequency vector is estimated to belong to the class

$$\hat{y} = \mathrm{sgn}\,(wx+b) \tag{1}$$

Heuristically the estimated class membership $\hat{y}$ 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 $\hat{y}$ = sgn(g(*vspeech* ,*vvideo* ,*vaudio*)) .

In this thesis there have been experiments with various settings of this type but with a small degree of success. 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; $K\left(x_i, x_j\right) = exp\left(-\gamma \parallel x_i - x_j \parallel^2\right)$

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).

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.

4. RESULT AND CONCLUSION

4.1 Introduction

In this chapter, we present the results of the steps in our system which leads to building and identifying the offline signature in the cloud depending on the classifier system, and retrieving personal information after the identification process.

The system is implemented by using:

1. Visual C++ under Visual Studio version 2013, including the Microsoft Visual C++ Redistributable software platform that permits the user to run content written in the C++ programming language, and the latest supported Visual C++ redistributable package for Visual Studio 2015, 2013 and older.
2. Open CV version 2.4.8, which is released under a BSD license; thus it is free for commercial and academic use. It has C++, Java, C, and Python interfaces and supports Mac OS, Windows, Android and Linux. Open CV was prepared for computational efficiency, with a powerful focus on real-time applications.
3. For the database, we used Oracle 10g, which is an object-relational database management system in which data are stored on to a logical drive which cab be made secure by creating a backup for an organization or even for a small corporation. Oracle 10g is one of the best software packages that can help in database management.
4. Java SE version 8, in which the graphic user interfaces were built by using the Java programming language. Java is one of the top choices for software developers battling for supremacy with the C and C-based languages. Its features are used on most electronic equipment worldwide, including mobile terminals, media players and PCs.
5. NetBeans IDE 8.0.2 is famous for the Java Integrated Development Environment (IDE). It is easy to combine language support with other features into any of the default packages, and the NetBeans Marketplace allows for virtually unlimited customization and extension.

4.2 System design

The results of the proposed system have been processed inside Visual Studio 2013 using the C++ programming language to build the main system “classifier” (feature extraction process, histogram construction and classification by SVM), and NetBeans IDE using the Java programming language to build graphic user interfaces and Oracle 10g to store the personal information of each person signed in the dataset.

The processes of the overall system are illustrated in Figures 12, 13, 14 and 15. A signature is required to be identified and to retrieve personal information. Figure 12 shows the client interface and the (insert) button, which used to select the signature image, In Figure 13, the client uploads the offline signature (image) onto the cloud. In Figure 14, the cloud receives the signature from the client to perform the identification process with the classifier system to retrieve personal information and the person’s signature from the database. In Figure 15, the client is displayed his personal information after receiving it from the cloud.

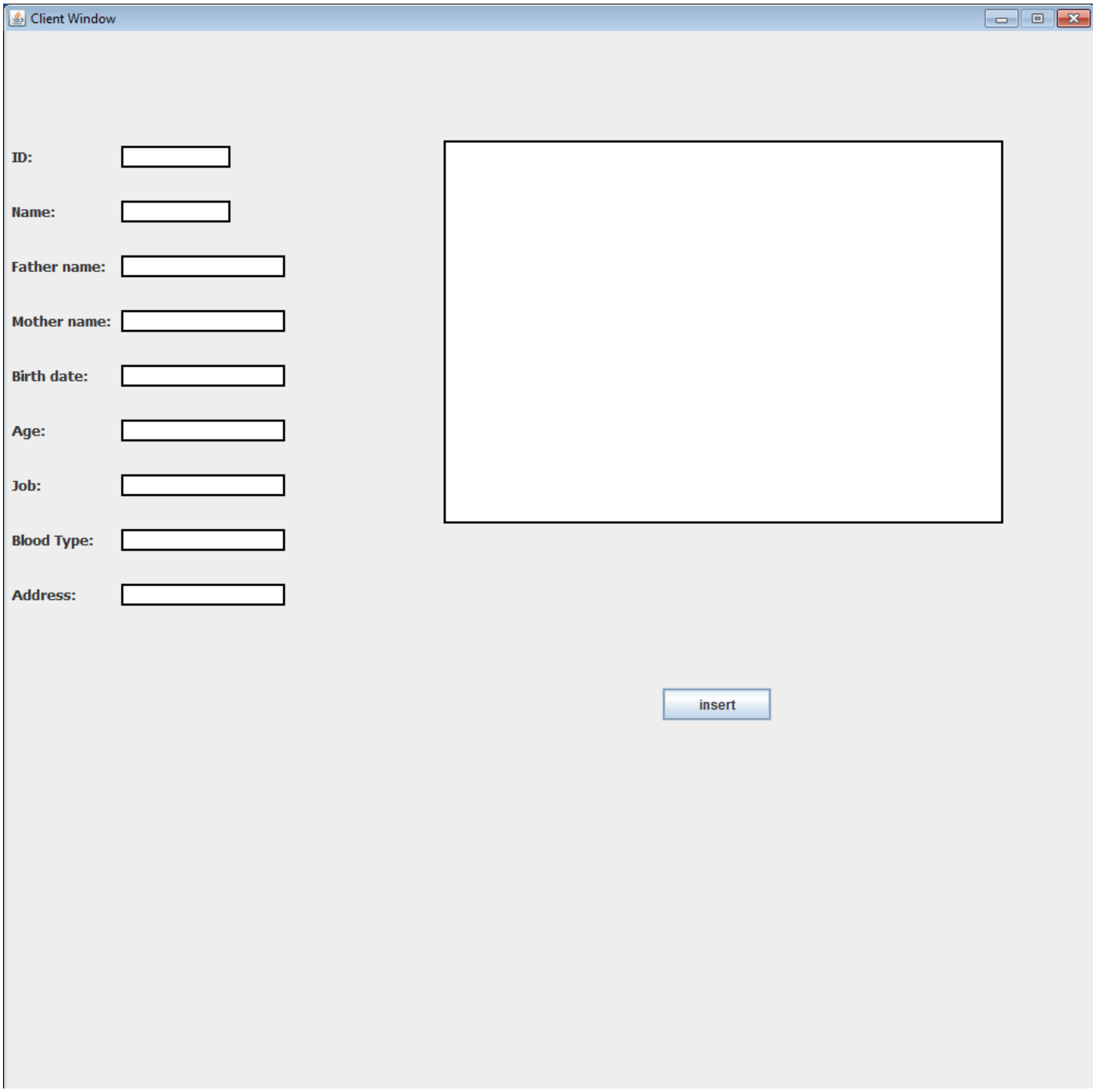


Figure 12: Client interface

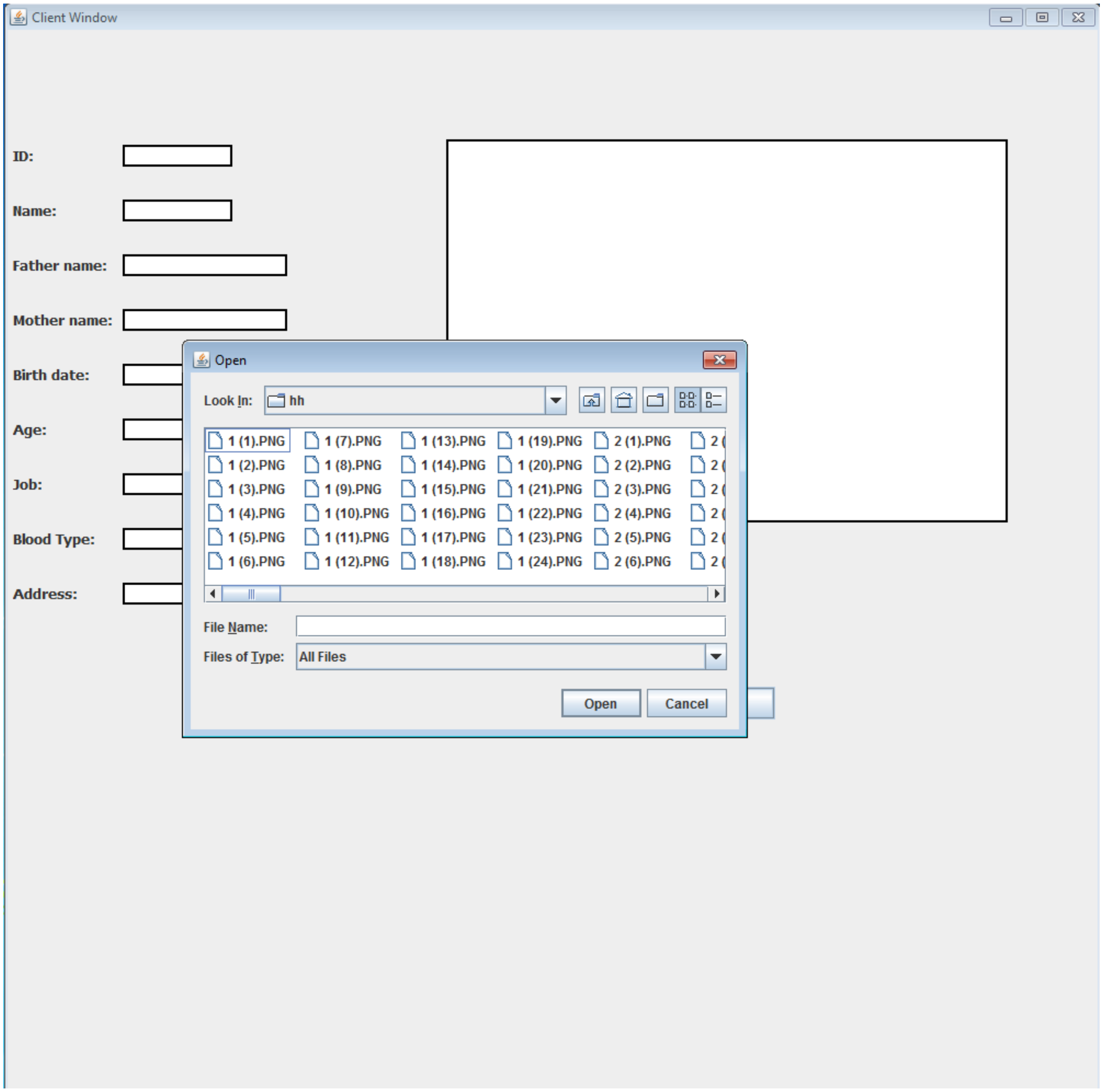


Figure 13: Upload signature by client

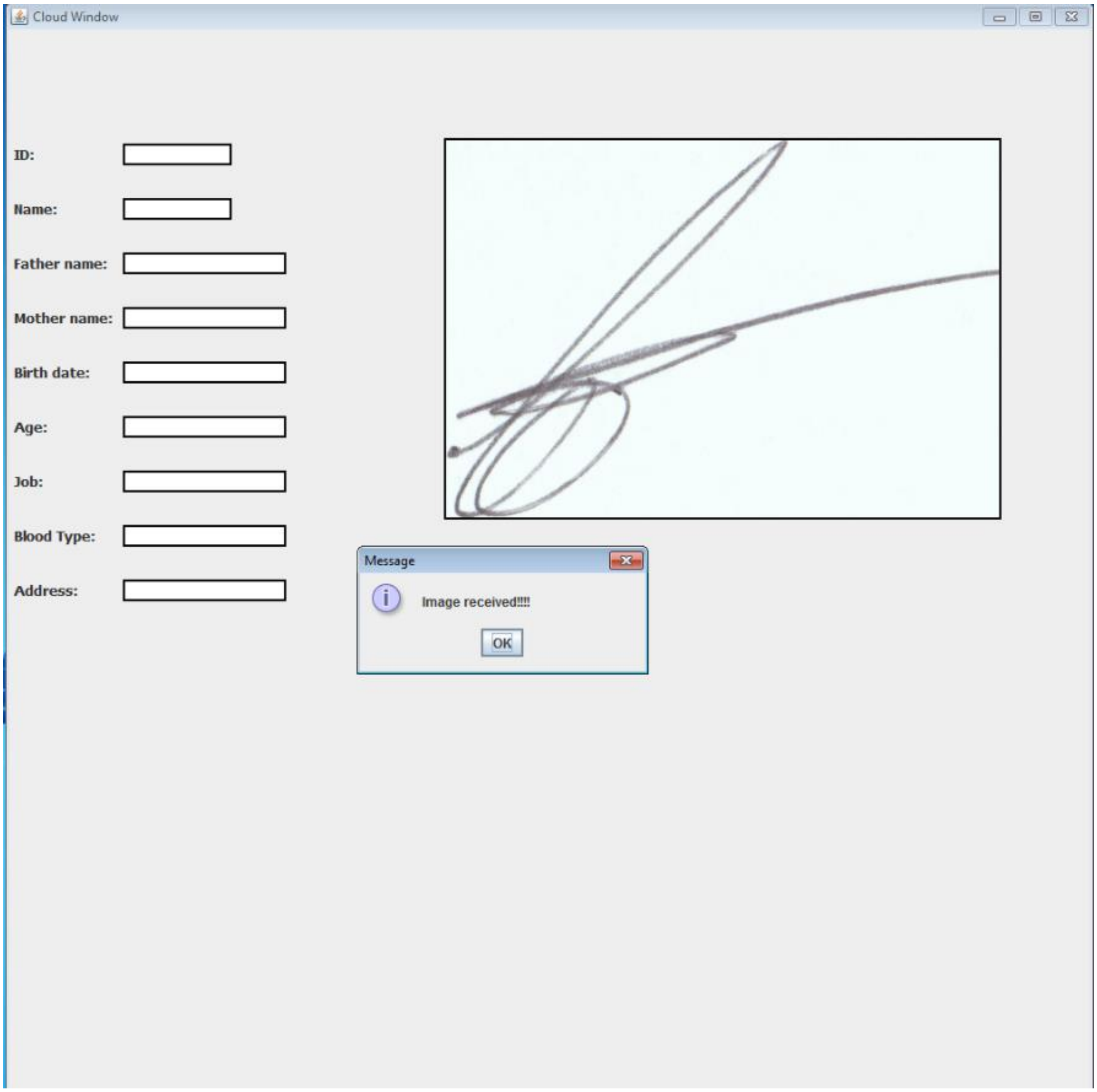


Figure 14: Cloud received a signature

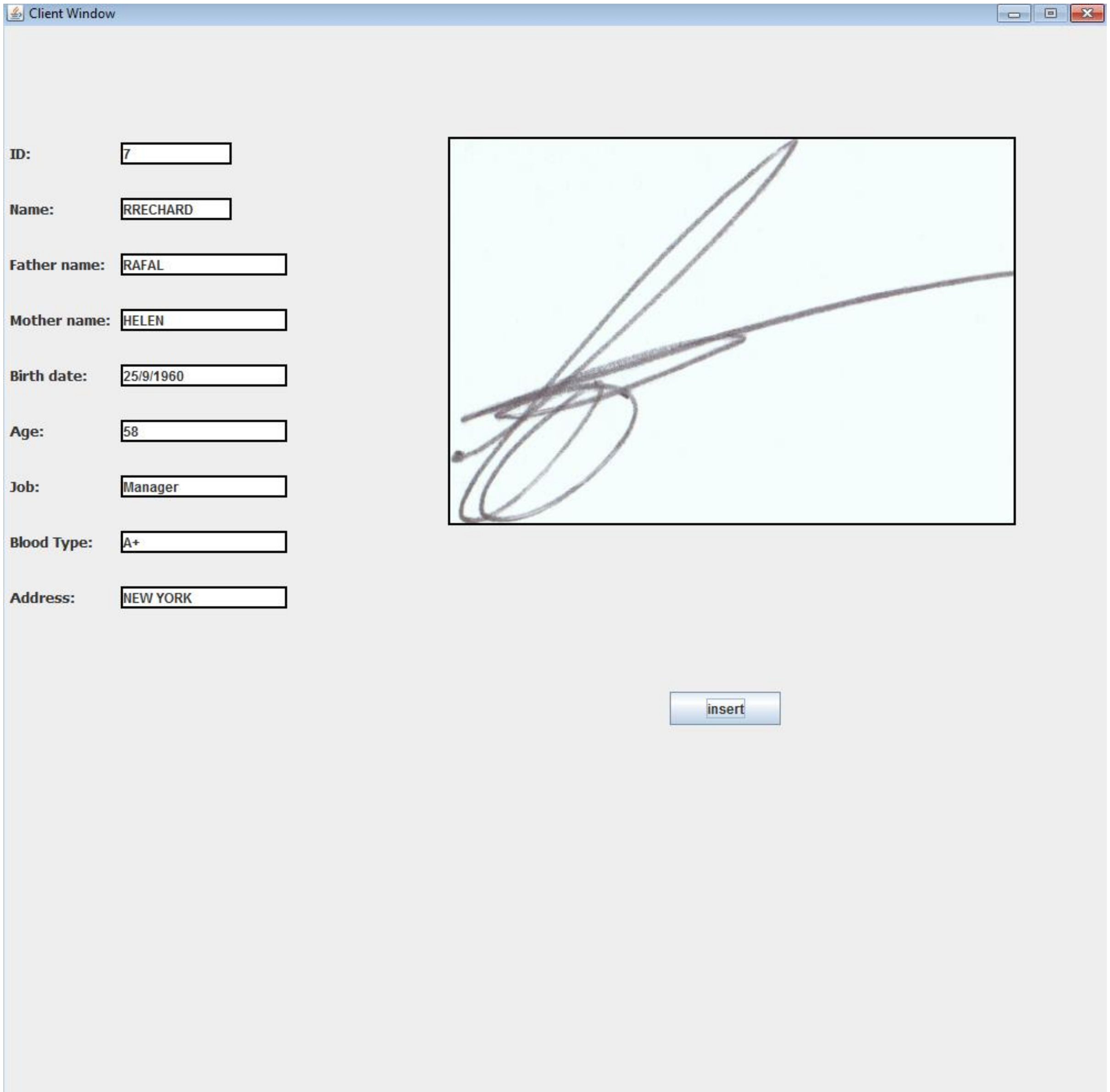


Figure 15: Client retrieved personal information

The overall results of the proposed system depend on the identification process (classifier) shown in Figures 16 and 17, which show the steps to build this classifier, starting with feature extraction using SIFT, followed by histogram construction using the Bag Of Word model and the classification step using SVM with the RBF kernel. These steps work on a sample of (SigComp2011) (Marcus Liwicki, 2001), which contains Dutch and Chinese (each separately) and genuine signatures for 10 persons (of 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 strange signature as unknown.

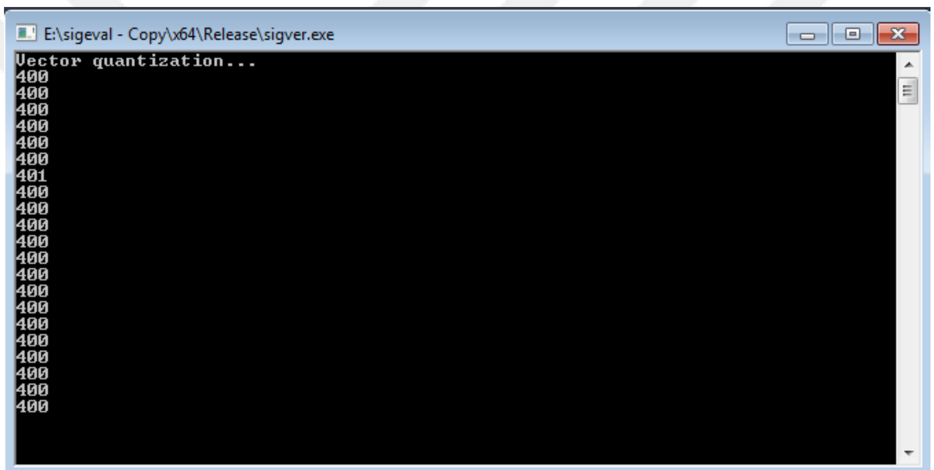


Figure 16: Features extraction by SIFT

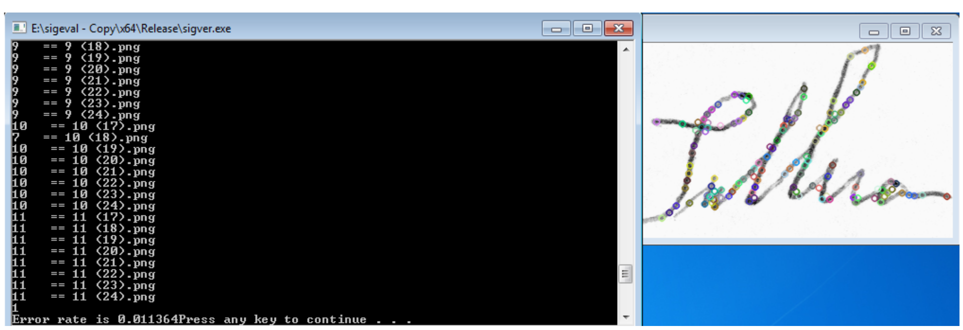


Figure 17: Training and Testing SVM classifier

4.3 Performance Measure

In order to test the quality of the system, we applied the accuracy and error rate which were calculated by (4.1) (4.2); (Jiawei Han, 2012)

$$\text{Identification Rate, Accuracy} = \frac{No.of\ correct\ identification}{\text{Total number of test signatures}} \times 100\% \tag{4.1}$$

$$\text{Misidentification Rate, Error Rate} = \frac{No.of\ incorrect\ identification}{\text{Total number of test signatures}} \times 100\% \tag{4.2}$$

It can be seen from (Table 1) that the test accuracy was obtained using the (SigComp2011) dataset for Dutch and Chinese signatures with various numbers of feature detected by SIFT.

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

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%**

In general, the high results of system performance had been achieved while setting the parameters of the SVM classifier (C, gamma), with 300, 400 and 500 features detected by SIFT. The best test accuracy and Error Rate obtained were 98.8% , 1.2% respectively .

4.4 Comparison

In (E. Frias-Martine, 2006) , (M.A. Ismail, 2000) , (MEENAKSHI K. KALERA, 2004) , (Ramzi Zouari, 2014) , (Bilal Hadjadji, 2017)and (Murat Taskiran, Offline Signature Identification via HOG Features and Artificial Neural Networks, 2017), also presented an offline signature identification system and (Table 2) shows that our proposed system provides a higher degree of accuracy in comparison to other proposed algorithms in these references. This means that our system helps to identify offline signatures at a very acceptable level of accuracy.

Table 2: Comparison of test accuracy with other algorithms.

REFRENCE	Feature generation	classification	Identification Accuracy
(E. Frias-Martine, 2006)	global geometric	SVM	71%
(M.A. Ismail, 2000)	Combination (global and local features)	Multi stage	91.8%
(MEENAKSHI K. KALERA, 2004)	GSC	KNN	93%
(Ramzi Zouari, 2014)	Fractal dimensions	KNN	95%
(Bilal Hadjadji, 2017)	(CT)	(OC-PCA)	97.9%
(Murat Taskiran, 2017)	HOG	GRANN	98.3%
Proposed Method	SIFT	SVM	98.8%

4.5 Conclusion

In spite of its importance, identification has received very little attention in comparison to verification. As a matter of fact, identification can be considered a major preprocessing stage for verification. In other words, a correct verification depends on correct identification. In this thesis, our novel signature identification system was applied with SIFT (feature extraction), Bag Of word (histogram construction) and SVM (classification) to retrieve personal information from the cloud according to the type of input taken by the client. The main advantage of the proposed system is the ability of the classifier to recognize unusual signatures and classify them as unknown, by training the proposed with forged signatures. Moreover, the proposed system proved to have great test accuracy.

4.6 Future work

As a future work , a new architecture based on the SIFT (scale-invariant feature transform) to extract features with BOW (bag of word) and choose the other classification algorithms like a neural network (supervised learning) , where SIFT has demonstrated its ability to extract features from signature images well , and on the other hand , suggest a offline signature verification system depend on proposed algorithms (SIFT , BOW and SVM) by learning the classifier on the more forged signatures and creating new classes to be able to classify the forgery signature as a forged .

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