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Photo-To-Sketch Matching Using Gabor Wavelet Transform

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Abstract: ***Face photo-to-sketch synthesis has helpful applications on each digital entertainment and law enforcement. This paper presents an efficient algorithm formatting sketches with a face images. in order to get the transformed sketch(synthesized sketch) that is in the same modality with the original sketch we use Roberts detection technique, extract features from both the sketch and the transformed sketch(output from edge detection technique) ,and finally the matching step achieved by using three methods that will be illustrated in section 6. The experiments achieved maximum accuracy of 94.3% and with an excellent execution time for the sketch synthesis process of a photo about 5.5 seconds on a computer with 2.13GHz CPU.***

Keywords: LDA (Linear Discriminant Analysis), Gabor Wavelet Transforms, Feature Fusion, SVM (Support Vector Machine), Combining Classifiers.

1. Introduction

Automatic face recognition systems is a successful application of computer vision in industry that has widely used been in law enforcement and security in recent years, but, it is difficult to directly match photo and sketch since they are in different modalities so the starting point of our algorithm is to transform photo into sketch so that recognition can be performed in the same modality.

Hong Zhao, Yao Lu and Zhengang Zhai [7] started by a feature extracting that form the feature pyramid for every face image, then, realizing the nearest matching pixel from the training face pictures for every pixel within the input image based on the features defined within the extracting stage, then the optimization stage within which they synthesize the “initial sketch” and optimize it to get the finally hallucinated sketch. Liang Chang, Mingquan Zhou [9] divided photos and sketches into overlapped regions then compute the sparse representation coefficient for each image patch.

The sketch synthesis process of a photo takes less than a minute on a computer with 2.99GHz CPU. Arif Muntasa [10] use Two Dimensional-Discrete Cosine Transform that extract one frequency from the image region and bring the training (photo) and testing (sketch) set toward new dimension by using the first derivative followed by negative process; the accuracy was 93%.Xinbo Gao, Nannan Wang, Dacheng Tao and Xuelong Li [11] propose an automatic sketch–photo synthesis and retrieval algorithm based on sparse representation with 93.7% accuracy for pseudosketch-based. Weiping Chen and Yongsheng GAO [12] recognize faces with partial occlusions of arbitrary shapes and locations by using every piece of non-occluded region, regardless of shape in the recognition process.

This paper is divided into 8 sections organized as follows: section 1 gives a literature survey, section 2 gives the methodology of feature extraction methods, section3 gives the classifiers techniques used, section 4 gives the classifier fusion, section 5 introduces the proposed algorithm, section 6 matches the transformed sketch and the sketch, section 7 introduces the experimental results. Finally, the paper’s conclusion introduced in section 8.

2. Methodology

We will explain two techniques: (1) feature extraction, (2) dimensionality reduction.

2.1 Feature Extraction

Feature extraction methods are used to represent images in another space. In the following sections we will explain the feature extraction methods used in this paper.

2.1.1 Gabor Wavelet Transform

Wavelet Transform extracts both the time and frequency data (features) from a given image. this nice property makes wavelet transform appropriate for applications such as image compression, edge detection, filter design, and few types of image object recognition, etc [11].

2.1.1.1 Gabor Features

To extract texture features from gray scale images we use Gabor filter-base method. It is an effective method in texture analysis used in many applications such as segmentation and biometrics. However, it is precise to changes in scale and orientation of the texture patterns. Thus, Gabor filter feature extraction method achieves a relatively small accuracy when the patterns have different scales and orientation [11].

The detailed algorithm can be summarized in algorithm (1).

Algorithm 1: Gabor Filter-Base Method

1	A 2D Gabor function $g(a,b) = \frac{1}{2\pi\sigma_a\sigma_b}\exp\left[-\frac{1}{2}\left(\frac{a^2}{\sigma_a^2}+\frac{b^2}{\sigma_b^2}\right)+2\pi jWa\right]$, Where σ_a and σ_b characterize the spatial extent and frequency bandwidth of the Gabor filter, and W represents the frequency of the filter.
2	A set of various Gabor functions $g_{m,n}(a,b)$ can be generated by rotating and scaling $g(a,b)$ to type Associate in a virtually complete and non-orthogonal basis set, that is $g_{m,n}(a,b) = x^{-2m}g(a',b')$, where $a' = x^{-m}(a\cos\theta_n + b\sin\theta_n)$, $b' = x^{-m}(-a\sin\theta_n + b\cos\theta_n)$, x > 1, $\theta_n = n\pi/K$, m 0,1, …, $S-1$, and $n = 0,1,\ldots,K-1$. Parameter S is the total variety of scales, and parameter K is the total variety of orientations. Thus S and K represent the whole variety of generated functions.
3	A Gabor-filtered image is $G_{m,n}(a,b) = \sum_{a_1}\sum_{b_1} I(a+b_1)\, g_{m,n}(a-a_1, b-b_1)$

2.1.1.2 Feature Fusion

Feature level fusion is used to improve the performance of the systems if the features are independent. Fusion of features is achieved through concatenating two or more different feature vectors into one feature vector.

Assume $f_1[a_1,\ldots,a_r]$, $f_2[b_1,\ldots,b_s]$, $f_3[c_1,\ldots,c_t]$ and $f_4[d_1,\ldots,d_o]$ are four feature vectors with four different sizes r, s, t, and o respectively. f_{new} = $[a_1,\ldots,a_r, b_1,\ldots,b_s, c_1,\ldots,c_t, d_1,\ldots,d_o]$, represents the concatenation of the four feature vectors f_1, f_2, f_3 and f_4[4].The problem that will appear due to the concatenation of more different vectors into one feature vector is the compatibility of different features. Thus, normalization techniques are used to solve this problem before concatenation .Zscore normalization is the most common method. This method maps the input scores to distribution with mean of zero and standard deviation of 1 as follows:

$$f_i' = \frac{f_i-\mu_i}{\sigma_i} \quad (1)$$

Where f_i are the i_{th} feature vector, μ_i and σ_i are the mean and standard deviation of the i_{th} vector, respectively, f_i' is the i_{th} normalized feature vector.

The fusion of all features occurs through concatenating the normalized feature vectors as shown in 2 as follows:

$$f_{new} = [f_1' f_2' f_3' f_4'] \quad (2)$$

$$f_{new} = [a_1,\ldots,a_{p1},\ldots,b_1,\ldots,b_{p2},\ldots,c_1,\ldots,c_{p3},d_1,\ldots,d_{p4}]$$

2.2 Dimensionality Reduction

The dimension of the feature vectors are too large due to using fusion method thus, we use the dimensionality reduction method to reduce the dimension of the feature vectors [14][15].

2.2.1 Linear Discriminant Analysis (LDA)

LDA is one amongst the most famous dimensionality reduction technique utilized in machine learning [14]. LDA tries to search out a linear combination of features that separates two or more categories. To point out the benefits of LDA, we will follow the subsequent algorithmic program detailed in algorithm (2).

Algorithm 2: Linear Discriminant Analysis method

1	Collect all sketches $I_1, I_2, \ldots, I_k$,where $I(M \times N)$.
2	Represent each sketch as a vector $\Gamma_i = N^2 \times 1$, so, Γ is $\mu(N^2 \times 1)$.
3	Compute the mean of each class $\mu_i(N^2 \times 1)$.
4	Compute the mean of all data $\mu(N^2 \times 1)$.
5	Compute the class-dependent scatter matrix is $(N^2 \times N^2) = S_i = \frac{1}{P}\sum_{i=1}^{K}(\Gamma_i - \mu_i)(\Gamma_i - \mu_i)^T$, Where P the number of images of each class is, Γ_i is the class data matrix, K is the number of classes, and S_i is the scatter matrix.
6	Compute the within –class scatter matrix $S_w(N^2 \times N^2) = S_w = \sum_{j=1}^{c}\sum_{i=1}^{N_j}(x_i^j - \mu_j)(x_i^j - \mu_j)^T$, Where x_i^j is the i^{th} sample of class j, μ_j is the mean of class j, c is the number of classes, and N_j is the number of samples in class j.
7	Compute The between-class scatter matrix $S_b(N^2 \times N^2) = S_b = \sum_{i=1}^{c}(\mu_i - \mu)(\mu_i - \mu)^T$, Where μ is the mean of all classes.
8	Compute the matrix W that maximizing Fisher's formula $W = \max\frac{\lvert W^T S_b W\rvert}{\lvert W^T S_w W\rvert} = \max\frac{S_b}{S_w}$.
9	Calculate the eigen values (λ) and eigen vectors (V) of the fisher's formula $S_b V = S_w V\lambda$.
10	Project all training images (Γ) onto Fisher's basis vectors $Y = V\Gamma$.
11	project the test image onto Fisher's basis vectors $r = VT$.
12	Match test image after projection (r) with all training images after projection (Y).

3. Classifier

Here we apply two classifiers to achieve a good performance with our approach. An over view of these classifiers are given below:

3.1 The minimum Distance Classifier

The minimum distance classifier is one of the oldest known methods. Its idea is extremely simple as it does not require learning. Despite its simplicity, Euclidean and Cityblock Distance has been successful in a large number of classification and regression problems. To classify an object I, first we need to find its closest neighbor X_i among all the training objects X and then assigns to unknown object the label Y_i of X_i. Euclidean Distance classifier works very well in low dimensions. The distance can in general be any metric measure .In this paper we used Euclidean and Cityblock classifiers [15].

3.2 Support Vector Machine(SVM)

SVM is one among the classifiers that deal with a problem of high dimensional datasets and offer good results. SVM tries to find out an optimum hyperplan separating 2-classes based on training Cases [15].

Given a training dataset $\{x_i, y_i\}$where $i = 1,2,3, \ldots, N$, wherever $N$is the number of training samples, $x_i$is a features vector, and $y_i \in \{-1, +1\}$is the target label, $y = +1$, for samples belong to class $C_1$and $y = -1$denotes to samples belonging to classC_2. Classes $C_1$and $C_2$are linearly separable classes. Geometrically, the SVM modeling algorithm tries to find an optimum hyperplane with the maximum margin to separate two classes, which requires solving the optimization problem in equation (3).

$$\text{Maximize} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j . K(x_i, x_j) \quad (3)$$

Subject to: $\sum_{i=1}^{n} \alpha_i y_i \; 0 \leq \alpha_i \leq C$

Where, $\alpha_i$is the weight assigned to the training samplex_i(if $\alpha_i > 1$, then x_i is named a support vector); $C$is a regulation parameter used to find a trade of between the training accuracy and also the model complexity in order that a superior generalization capability will be achieved, and $K$is a kernel function, which is used to measure the similarity between two samples.

4. Classifier Fusion

We can also combine more than one classifier (combining classifiers or fusion) to increase the recognition rate. A good result will be achieved when the classifiers are diverse and independent. In the other researches the combination is achieved through many levels such as the outputs of different samples, the outputs of one classifier using different parameters, or the outputs of classifiers using different feature extraction methods. But here we used abstract classifiers technique that combined the outputs of the nearest neighbor(Euclidean and Cityblock) and SVM classifiers trained by different regions on a face image.Here we use the majority voting[4] Many researches focus on producing a pool of classifiers and select the most diverse classifiers such as the most diverse ensemble [4]. the double fault measure (DF) [2] and the Q statistics [1]. The Other abstract level fusion methods are clustering and selection [3], and thinning the ensemble [6].

5. Photo-To-Sketch Transformation

In our proposed algorithm, starting by transforming the photo to sketch by using Roberts Edge Detection Technique that uses the object which finds edges in an input image by approximating the gradient magnitude of the image. The gradient is obtained as a result of convolving the image with the Roberts kernel as shown in Figure (1) that shows the original photo, the hand drawn sketch and the transformed sketch after applying Roberts Edge Detection Technique.

After the transformation step, we have three scenarios for matching, the first scenario is matching using single Feature Extraction Method, the second scenario is matching using Feature Fusion Method and the third scenario is matching using Classifier Fusion Method.

6. Matching the Sketch and the Transformed Sketch

There are three different methods to match the sketch and the transformed sketch.

6.1 Matching Using Single Feature Method

The first method for matching is the single feature extraction method. After the photo- to- sketch transformation, as shown in figure (2), we extract the features of the two images (the sketch and the Transformed sketch). Gabor wavelet transform is used because Gabor Wavelet Transform it is more suitable for applications such as image compression, edge detection, filter design, and some kinds of image object recognition. Then, we apply Euclidean Distance, Cityblock Distance SVM classifiers for matching that achieve an accuracy as shown in Table 1 .Our algorithm consists of two phase: Training and Testing phase are detailed in algorithm(3).

Algorithm 3: Training and Testing phases using single Feature Extraction Method

1	Training phase
2	Collecting all training transformed sketches
3	Resize the transformed sketches into four different scales (32, 64,128 and 256).
4	Using Gabor Extraction method to extract features from training transformed sketches
5	Each training transformed sketch is representing by one feature vector.
6	Apply LDA that useis used as a dimensionality reduction to reduce the number features in the vector.
7	Testing phase
8	Collecting all testing sketches..
9	Resize the testing sketchs into four different scales (32, 64,128and 256).
10	Using Gabor Extraction method to extract features from testing sketches.
11	Project the feature vector on LDA space.
12	Matching or classifying the testing feature vector with training feature vectors to identify final decision (i.e. whether the person is identified or not).

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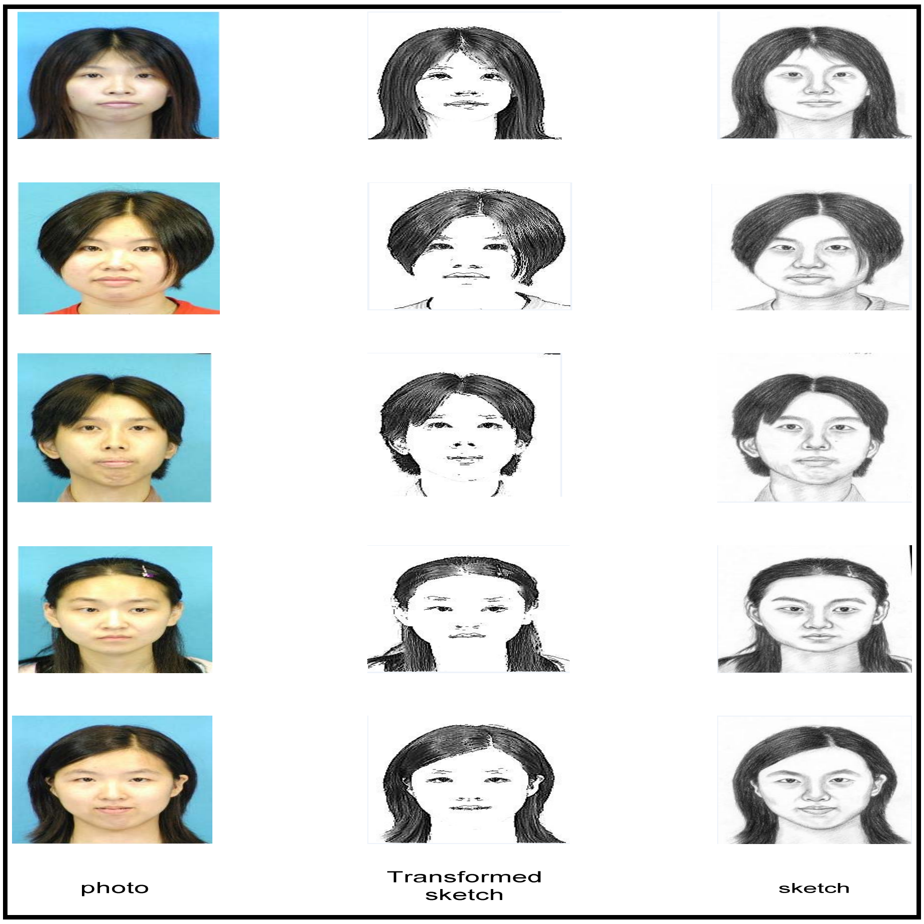

Figure 1 : Photo-Transformed Sketch(synthesized sketch) -Sketch

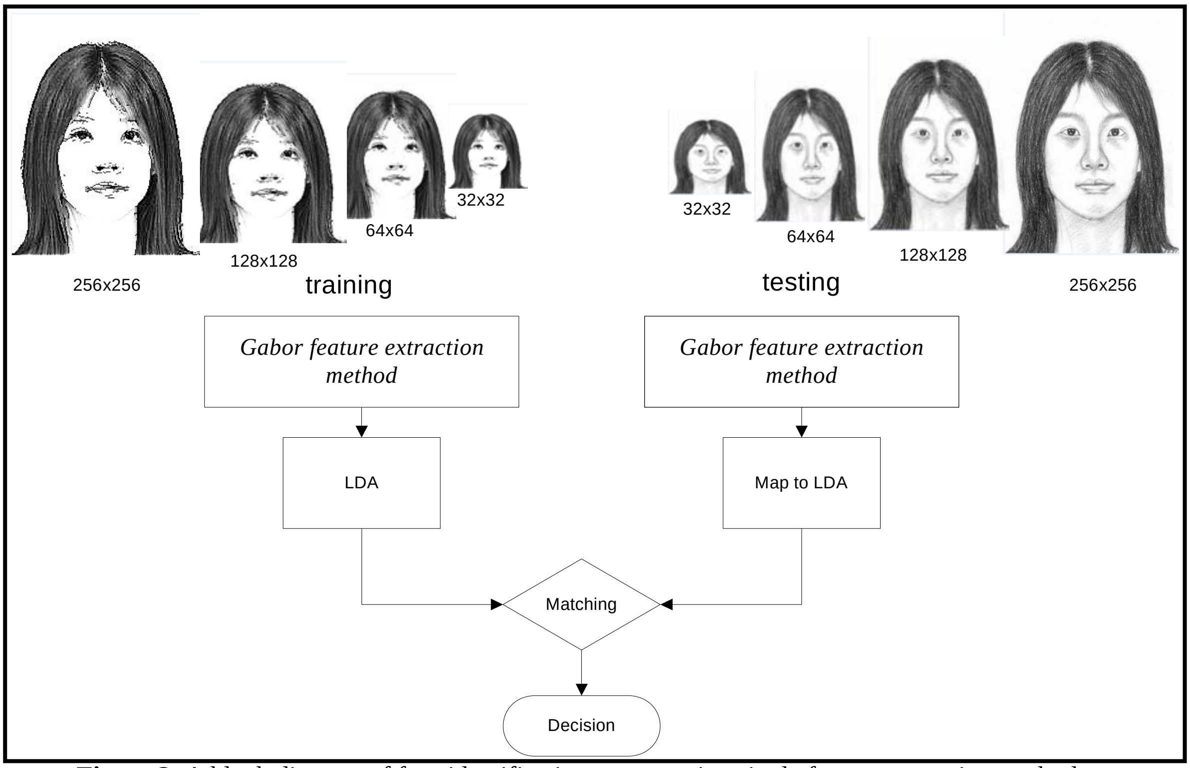

Figure 2: A block diagram of face identification system using single feature extraction method

6.2 Matching using Feature Fusion Method

The second method for matching is the feature fusion method as shown in Figure (3) that consists of 2 phases: training and testing phases.

Training Phase: the training phase is detailed in Algorithm (4).

Algorithm 4 : Training Phase in Feature Fusion Method

1	Collecting all training transformed sketches.
2	Resize the transformed sketches into four different scales $I_{256} = 256 \times 256$, $I_{128} = 128 \times 128$, $I_{64} = 64 \times 64$, $I_{32} = 32 \times 32$
3	Using Gabor feature extraction method to extract the features from each transformed sketch (I_{256}, I_{128}, I_{64} and I_{32}).
4	Each transformed sketch is Represented by one feature vector then LDA is used to reduce the number features in the vector.
5	Normalize each feature vector after LDA using Zscore normalization (I_{256}, I_{128}, I_{64} and I_{32}).
6	Concatenate the four normalized feature vectors into one new feature vector $f_{new} = [I'_{256}, I'_{128}, I'_{64}, I'_{32}]$

Testing Phase: the testing phase is detailed in algorithm (5).

Algorithm 5 : Testing Phase in Feature Fusion Method

1	Collecting the testing sketches.
2	Resize the sketches into four different scales $T_{256} = 256 \times 256$, $T_{128} = 128 \times 128$, $T_{64} = 64 \times 64$, $T_{32} = 32 \times 32$.
3	Using Gabor feature extraction method to extract the features from each sketches (Testing images) (T_{256}, T_{128}, T_{64} and T_{32}).
4	Each feature vector is projected on LDA space.
5	Concatenate the four normalized feature vectors into one new feature vector T_{new}.
6	Classifying the testing feature vector T_{new} with training feature vectors f_{new} to identify final decision (i.e. whether the person is identified or not).

6.3 Matching using Classifier Fusion Method

The third method of matching is classifier fusion method shown in Figure (4) that also consists of two phases: training and testing phases.

Training Phase: the training phase is detailed in algorithm (6).

Algorithm 6 : Training Phase in classifier Fusion Method

1	Collecting the testing sketches
2	Resize the sketches into four different scales $I_{256} = 256 \times 256$, $I_{128} = 128 \times 128$, $I_{64} = 64 \times 64$, $I_{32} = 32 \times 32$.
3	Using Gabor feature extraction method to extract the features from each sketches (Testing images) (T_{256}, T_{128}, T_{64} and T_{32}).
4	Each feature vector is projected on LDA space.
5	Classifying the testing feature vectors using different scales with training feature vectors to identify final decision in each scale D1, D2 and D3.
6	Combine the output of the four classifiers (decisions) D1, D2 and D3 in abstract level fusion (Voting) to get the final decision (i.e. whether the person is identified or not).

Testing Phase:Represented the testing phase is detailed in Algorithm (7)

Algorithm 7: testing Phase in classifier Fusion Method

1	Collecting the testing sketches
2	Resize the sketches into four different scales $I_{256} = 256 x 256, I_{128} = 128 x 128, I_{64} = 64 x 64, I_{32} = 32 x 32.$
3	Using Gabor feature extraction method to extract the features from each sketches (Testing images) (T_{256} , T_{128}, T_{64} and T_{32}).
4	Each feature vector is projected on LDA space.
5	Classifying the testing feature vectors using different scales with training feature vectors to identify final decision in each scale D1, D2 and D3.
6	Combine the output of the four classifiers (decisions) D1, D2 and D3 in abstract level fusion (Voting) to get the final decision (i.e. whether the person is identified or not).

7. Experimental Results

In order to compare our proposed methodology to published strategies on sketch matching, we evaluated our methodology using viewed sketches from the Chinese University of Hong Kong (CUHK) student database [8]. A database containing 188 pairs of photos and sketches of 188 people is used for the experiment. Each of these sketch images was drawn by a creative person while looking at the corresponding photograph of the subject. We perform three experiments: the first experiment is matching using single feature extraction method which resizing the images (sketch and the transformed sketch) into four different scales: $(32 \times 32, 64 \times 64, 128 \times 128 \text{ and } 256 \times 256)$ and applying Gabor feature extraction method to extract the features from each image individually. In these experiments we used Euclidean, Cityblock Distance and SVM classifiers for matching .A summary of this experiment is shown in Table 1.

Table 1: Accuracy results (in %) when applying Gabor feature extraction method

Dimension of the image	*Classifiers*	*Accuracy*	*Execution Time*
Gabor(32x32)	SVM	73. 8%	2.7s
	Euclidean Distance	69. 3%	0.7s
	Cityblock Distance	70.9 %	0.9s
Gabor(64x64)	SVM	81.8 %	3.2s
	Euclidean Distance	81.8 %	1s
	Cityblock Distance	81.8 %	1.2s
Gabor (128x128)	SVM	93.2 %	3.6s
	Euclidean Distance	93.2 %	1.3s
	Cityblock Distance	93.3 %	1.4s
Gabor (256x256)	SVM	82. 9%	4.7s
	Euclidean Distance	82. 9%	1.4s
	Cityblock Distance	83 %	1.5s

As shown in Table 1, can be seen the accuracy of matching the sketches and the transformed sketch .applying Gabor feature extraction method achieves a good result. We note that for Gabor(32×32), the accuracy of SVM classifier is better than the accuracy of Euclidean and Cityblock Distance classifier but for the others scale (64×64),the accuracy of SVM is the same as the accuracy of Euclidean and Cityblock Distance and for $(128 \text{ and } 256)$the accuracy of Cityblock classifier is better than SVM and Euclidean distance classifier. The best accuracy (93.3%) is achieved when the size of the image is (128×128) and the worst accuracy (69. 3%) is achieved when the size of the image $(32 \times 32)$with Euclidean Distance.

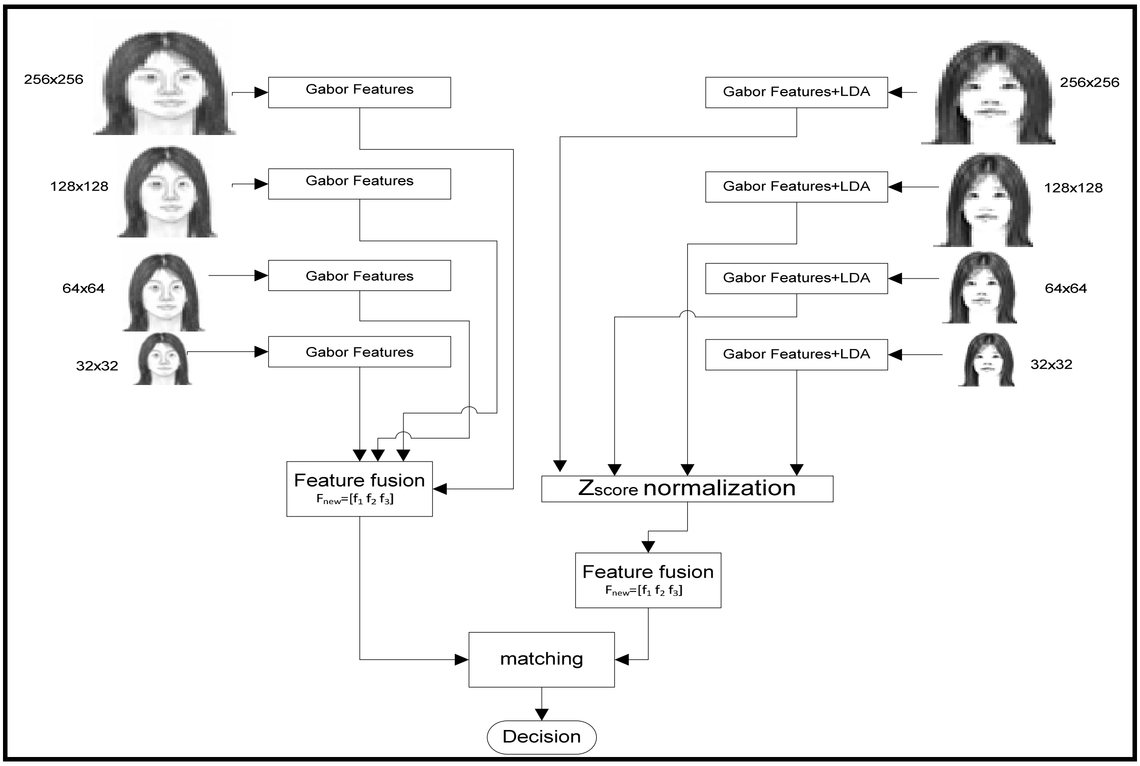

Figure 3 : A block diagram of face identification system using feature fusion

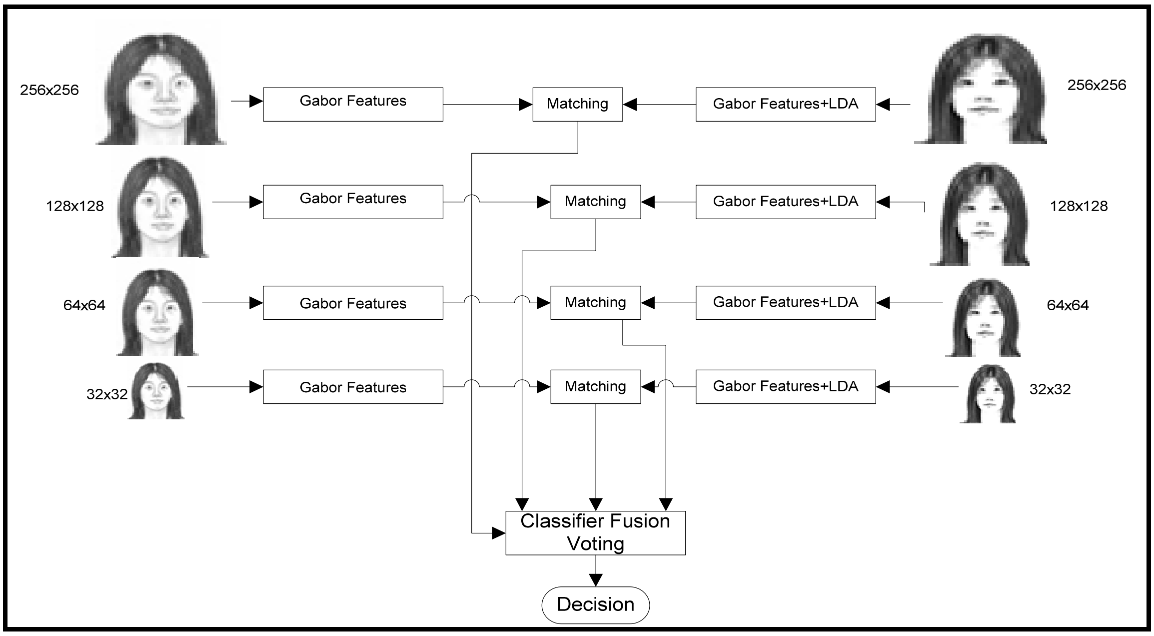

Figure 4 : A block diagram of face identification system using classifier fusion

We also note that the execution time of matching when using SVM is higher than the execution time for both the Euclidean and Cityblock classifiers. As the dimension increased, the execution time also increased. The second experiment was matching using feature fusion method which resizes the images (sketch and transformed sketch) into four different scales: $(32 \times 32, 64 \times 64, 128 \times 128 \text{ and } 256 \times 256)$, extract the features from each image using Gabor feature extraction method, normalize each feature vector after LDA using Z_{score} normalization and finally concatenate the four normalized feature vectors. In this experiment we used Euclidean, Cityblock Distance and SVM classifier for matching. A summary of this experiment is shown in Table 2.

Table 2: Accuracy results (in %) when applying Gabor Feature Extraction Method Feature Fusion

Fusion Method	*Classifiers*	*Accuracy*	*Execution Time*
Feature Fusion	SVM	94. 3%	5.6s
	Euclidean Distance	93. 2%	1.7s
	Cityblock Distance	93.2 %	1.9s

Table 2 shows the result of applying features fusion method. We note that the accuracy of SVM classifier is better than the accuracy of Euclidean and Cityblock Distance classifiers but the execution time for matching using Euclidean Distance is lower than the execution time of both SVM and Cityblock classifiers. From Table 1 and 2, we note that the feature fusion method increased the accuracy of matching. The third experiment was matching using classifier fusion method which resizes the images (sketch and transformed sketch) into four different scales:

$(32 \times 32, 64 \times 64, 128 \times 128, 256 \times 256)$, extract the features from each image using Gabor feature extraction method, each image represent by one feature vector and, use LDA To reduce the number features in the Vector, matching the testing feature vectors using different scales with training feature vectors to identify final decision in each scale D1, D2 and D3, finally combine the output of the three classifiers (decisions) D1, D2 and D3 in abstract level fusion (Voting) to get the final decision. In this experiment we used SVM, Euclidean Distance and Cityblock distance for matching .A summary of this experiment is shown in Table 3.

Table 3: Accuracy results (in %) when applying Gabor feature Extraction Method using Classifier Fusion

Fusion Method	*dimension of the image*	*Accuracy*	*Execution time*
Classifier Fusion	(32x32)	73.9%	7.3s
	(64x64)	82.4%	9.7s
	(128x128)	93.2%	11.4s
	(256x256)	85%	12.8s

Table 3 shows the result of applying features fusion method. We note that the accuracy of image of size (128×128) is the best accuracy and the execution time has increased as the dimension of the image increased.

8. Conclusion

In this paper, we have proposed a system for identifying images using Gabor filter-based method that has been used to extract both the time (spatial) and frequency information (features)from a given image; This great property makes wavelet transform suitable for applications such as image compression, edge detection, filter design, and some kinds of image object recognition. Extracting Gabor features from four different scales and combining the results of the four scales in Two levels of combination or fusion are used (feature and classifier fusion) to increase the accuracy. The dimension of feature vectors, calculated using Gabor, leads to dimensionality reduction problem. So, LDA is used to reduce the number of features and solve the dimensionality problem and at the same time to discriminate between different classes and improve the accuracy of our proposed system. The classifiers used in our proposed system are Nearest Neighbor (Euclidean and Cityblock) and SVM classifiers. The experiments succeeded to match the drawn sketch with the photo after transforming it to a sketch (transformed sketch or synthesized sketch) and achieving accuracy (93.3%) for single feature extraction method ,accuracy(94.3%) for feature fusion method and (93.2%)for classifier fusion method for the image of dimension (128×128). The feature level fusion achieved accuracy better than that of classifier fusion. In the implementation using Matlab, the transformation process (photo to synthesis sketch) of a photo takes 5.5 seconds on a computer with 2.13GHz CPU. In a future investigation, we will study how to use the experiments on matching using Images based on rotated images in different angels.

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