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Ensemble of Log-Euclidean Kernel SVM based on Covariance Descriptors of Multiscale Gabor Features for Face Recognition

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A B S T R A C T

Face recognition (FR) is a challenging computer vision task due to various adverse conditions. Local features play an important role in increasing the recognition rate of an FR method. In this direction, the covariance descriptors of Gabor wavelet features have been one of the most prominent methods for accurate FR. Most existing methods rely on covariance descriptors of Gabor magnitude features extracted from single-scale face images. This study proposes a new method named multiscale Gabor covariance-based ensemble Log-euclidean SVM (MGcov-ELSVM) for FR that uses the covariance descriptors of Gabor magnitude and phase features derived from multiscale face representations. MGcov-ELSVM begins by producing multiscale face representations. Gabor magnitude and phase features are derived from the multiscale face images in the second stage. After that, the Gabor magnitude and phase features are used to generate covariance descriptors. Finally, Covariance descriptors are classified via a log-Euclidean SVM classifier, and a majority voting technique determines the final recognition results. The experimental results from two face databases, ORL and Yale, indicate that the MGcov-ELSVM outperforms some recent FR methods.

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1. INTRODUCTION

Face recognition (FR) is the process of recognizing an unknown face from a set of labeled face samples. FR has various applications in criminal screening, surveillance, military, mobile telephone, computer unlocking, and social media monitoring. As technology advances and data volumes increase, artificial intelligence techniques play an increasingly important role in automatic face recognition. Recognition of faces with machine learning techniques is challenging due to the various complex factors such as facial expression, image noise, head poses and illumination conditions, sensitivity to geometrical variations such as scale, rotation, and translation, the large volume of data, and small training sample size [1, 2].

The performance of the FR method depends on its robustness against the mentioned adverse conditions. Gabor textural filters inspired by the functioning of the mammalian visual cortices are robust under some adverse conditions [2]. Gabor textural features are usually generated by convolving the Gabor filters in the different scales and orientations with the original face image. Although resultant Gabor features vectors are discriminative, managing the high dimensionality of these vectors is challenging.

Tuzel et al. [3] proposed the covariance matrix as a novel image region descriptor and used it to detect objects and classify textures. The covariance matrix is a powerful image descriptor, with each diagonal element representing variance and each non-diagonal member representing covariance between two features. The rotation invariance is the most critical advantage of the covariance descriptor. In addition, covariance descriptor is the natural way to transform the high dimensional data to the new low dimensional matrix-based features, which contain discriminative second-order statistics.

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Most of the existing FR techniques rely on the single-scale representation of the faces; however, recently, different studies have shown that multiscale facial representation can increase the FR approach's performance [4]. In this work, motivated by the effectiveness of covariance descriptors and Gabor features in FR, we proposed a novel ensemble FR approach based on covariance descriptors of multiscale Gabor features. It seems that by using the ability of Gabor features and covariance descriptors, the proposed FR method can become more robust to adverse conditions such as illumination conditions and geometric variations. In addition, the proposed FR method can better manage the high dimensionality of Gabor features, leading to appropriate recognition rates in small sample size situations. The following is a summary of this study's contributions:

- We introduce a novel effective FR system that uses covariance descriptors of Gabor magnitude and covariance descriptors of Gabor phase information. It should be noted that the combined Gabor textural features gained a powerful tool for modeling the local characteristics of face images.
- We offer a novel ensemble FR system that integrates covariance descriptors of the Gabor feature generated from the multiscale face representation.
- The study demonstrated the efficacy of the proposed method over several new FR methods using two well-known face databases.

The organization of the study is as follows. Section 2 delves into the related works. section 3 introduces the proposed FR method. The benchmark FR databases are introduced in section 4. Section 5 contains an analysis of the experimental results. In section 6, we conclude this study.

2. RELATED WORKS

Generally, FR methods can be categorized into two major groups, holistic and local approaches. This section reviews some important recent approaches of mentioned two groups of FR.

The use of holistic methods has a long literature. The most well-known methods in this group are eigenface (based on principal component analysis) and fisherface (based on Linear Discriminant Analysis). Aliyu et al. [5] compared the performance of eigenface and fisherface for FR on the LFW dataset and proved that the FR with fisherface technique outperformed the eigenface technique. Other recent classifiers, such as extreme learning machines (ELMs), have lately been employed for FR in addition to traditionally used nearest neighbor and support vector classifiers. ELMs can handle the high dimensional data and commonly perform better than SVM for FR. In this direction, Abd Shehab and Kahraman [6] proposed an ensemble version of ELM for FR to address the problem of its randomization nature In another study, Dalal and Vishwakarma [7] used the optimized extreme learning machines with PCA transform for FR. Their results on various face datasets proved some merits of the proposed method against the standard extreme learning machines. As stated earlier, FR is a complex task due to the various adverse conditions. In addition, the high dimensionality of face feature vectors is another issue that leads to the poor performance of the traditional FR methods. To address this problem, Khalili Mobarakeh et al. [8] proposed a new method named supervised kernel locality-based discriminant neighborhood embedding. Using nonlinear kernel mapping, this method effectively represents the nonlinear and complex variations of face images while simultaneously preserving the local structure information of data from the same class as well as discriminant information from other classes. Although their method can achieve appropriate recognition results on some FR dataset such as ORL, their results on complex face databases such as Yale is not better than the recent state-of-the-art methods. In another study, Gao et al. [9] proposed the new FR method, named extendface, that uses the complex number data augmentation and collaborative representation to address the problem of the high dimensionality of face images. Like the previous method, their results on the complex Yale face dataset do not reach a high level of recognition according to the state-of-the-art methods.

Holistic methods do not consider local characteristics of the face image, so they do not lead to optimal accuracy. Different Recent researches suggest that incorporating local features can improve recognition rates of the FR [2]. In this direction, Zaaraoui et al. [10] proposed the new local descriptor for face recognition by dividing the face image into some regions and calculating the histogram of dictionary words in each region. Their final results show an average accuracy of about 91% on two ORL and Yale face databases. Although their proposed method outperformed other FR methods, such as PCA, it seems that the use of the histogram method to generate the final local features reduced the performance of the proposed method, especially in small training samples size. In another recent study, Asadi Amiri and Rajabinasab [11] used the local features of color and edge orientation difference histogram in the conjugation with Canberra measure for FR. Their final results demonstrated a recognition rate of below 80% on the Yale database in the situation of the limited training sample size, which is not in comparison to recent state-of-the-art methods. In another recent study, Zhang and Yan [12] proposed a new local FR method that uses the histogram of local image gradient feature compensation as the feature descriptors of the face. Although their experiment reported the appropriate results on the ORL face database, their recognition accuracy is commonly below 80% on the challenging Yale database.

Among all the mentioned methods, Gabor features have received the most attention from researchers [2, 13]. Gabor features can model facial texture using filters at different scales and directions. Although using Gabor features for FR can improve recognition rate, it is challenging to manage the high dimensionality of the generated features. Covariance descriptors can effectively solve this problem by compressing the high-dimensional Gabor data cube into a matrix. In addition, covariance descriptors contain information about second-order statistics that are useful in face recognition. In recent years, several studies, such as Pang et al. [14, 15], used the covariance descriptors of Gabor features for FR. Although Gabor feature covariance descriptors have been used in several studies for FR, it seems that the capabilities of these descriptors for FR have not been fully exploited due to the following points:

- The proposed covariance-based methods usually use only Gabor magnitude features and do not consider the valuable information of the Gabor phase features.
- Previous works have usually used a single-scale representation of faces, discarding the valuable information contained in different scales of face representation.
- The ability of some advanced matrix-based classification methods such as SVM with Log-Eclidean SVM for FR is less exploited. Log-Eclidean SVM is a powerful machine learning technique that can handle matrix-based descriptors such as covariances.

According to the mentioned points, this study proposes a new ensemble-based FR method that uses covariance descriptors obtained from multiscale Gabor magnitude and phase. In addition, this study's new ensemble-based FR method can effectively exploit the underlying information of multiple covariance descriptors.

3. METHODOLOGY

In this section, at first, Gabor features, covariance descriptors, and log-Euclidean kernel SVMs are reviewed, and finally, the proposed FR method is introduced.

3. 1. Feature Extraction with Gabor Filters

Gabor functions can accurately model a cell in the human visual brain. Gabor filters are commonly employed in image processing to extract texture information. Many FR approaches are based on Gabor features, which can describe the frequency content of images in different orientations. Gabor representation ($G_{\mu,v}$) of a face image (I) at each pixel ($z=(x, y)$, x and y are the coordinates of the pixel z) are produced by convolving the face image with the Gabor kernel ($\psi_{\mu,v}$) as following [16]:

$$G_{\mu,v}(z) = I(z) * \psi_{\mu,v}(\mathrm{z}) \quad (1)$$

$$\psi_{\mu,v}(\mathrm{z}) = \frac{||k_{\mu,v}||^2}{\sigma^2} e^{(-||k_{\mu,v}||^2||z||^2/2\sigma^2)}[e^{ik_{\mu,v}z} - e^{-\sigma^2}/_2] \quad (2)$$

In which the parameters of the above equations are as follows [16, 17]:

- μ, v: are the orientation and scale
- $k_{\mu,v} = k_v e^{i\phi_\mu}$, $k_v = {k_{max}}/{f^v}$, $\phi = \mu \cdot \pi/8$
- f is the spacing between kernels in the frequency domain set to $\sqrt{2}$.
- k_{max} is the max frequency, commonly set to 0.25
- σ is commonly set to π.

The solution to Equation (1) for each pixel is a complex number with two parts: real (Re(z)) and imagery (Img(z)). From them, Gabor magnitude (mag) and phase features are defined as follows [16]:

$$Mag(z) = \sqrt{Re(z)^2 + Img(z)^2} \quad (3)$$

$$phase(z) = arctan\left({Img(z)}/{Re(z)}\right) \quad (4)$$

This work created Gabor magnitude and phase textural features using the MATLAB 2020b image processing toolbox. Eight orientations [0, 22.5, 45, 67.5, 90, 112.5, 135, 157.5] and nine wavelengths [from 2:1:10] are used to create these features. As a result, at each scale of the face representation, the numbers of Gabor magnitude and phase features are both equal to 72.

3. 2. Covariance Descriptors

Here, we calculate the covariance descriptors of the Gabor magnitude and phase features derived from each scale of faces. Each created Gabor feature has the same size as a single-scale face image with $m \times m$ pixels. We produced 72 Gabor magnitude and phase features for each facial image. As a result, the final feature vector of each Gabor feature for the i^{th} pixel is a (72+2)-dimensional feature vector (z_i), which is composed of two coordinate features (x_i, y_i) and 72 Gabor features [14]:

$$z_i^{mag} = [x_i, y_i, mag_i^1, mag_i^2 \ldots, mag_i^{72}] \quad (5)$$

$$z_i^{phase} = [x_i, y_i, phase_i^1, phase_i^2 \ldots, phase_i^{72}] \quad (6)$$

Covariance descriptors (C) of each Gabor feature with the size (72+2)×(72+2), which are symmetric, are computed by Pang et al. [14]:

$$C_{mag} = \frac{1}{(m\times m)-1}\sum_{i=1}^{m\times m}(z_i^{mag} - \mu^{mag})^T(z_i^{mag} - \mu^{mag}) \quad (7)$$

$$C_{phase} = \frac{1}{(m\times m)-1}\sum_{i=1}^{m\times m}(z_i^{phase} - \mu^{phase})^T(z_i^{phase} - \mu^{phase}) \quad (8)$$

where μ is the mean vector and T is the transposition operator. A regularization approach is used to make the covariance matrix strictly positively defined.

3. 3. Log-Euclidean Kernel SVM Covariance descriptors of Gabor features (C) are on a Riemannian manifold; therefore, the logarithm of matrix operator (*logm*) is used to C to transfer them from Riemannian to Euclidean space. The Log-Euclidean-based kernel function is then defined as follows [18]:

$$k_{logm}(C_i, C_j) = trace[logm(C_i) \cdot logm(C_j)] \tag{9}$$

In which C_i and C_j are the covariance descriptors of i^{th} and j^{th} face images. Since the Log-euclidean kernel of Equation (9) is symmetric and a positive defined function, it meets mercer's conditions; therefore, it can be applied to categorize data using SVM [19].

3. 4. Proposed FR System Figure 1 depicts a flowchart of the proposed multiscale Gabor covariance-based ensemble Log-euclidean SVM (MGcov-ELSVM) method. According to Figure 1, this method has five stages:

1) In the first stage, to incorporate information from the multiscale representation of faces, each original face image is resized to 30×30, 60×60, and 90×90 pixels using the bicubic interpolation method.

2) In the second stage, the magnitude and phase of the Gabor filter are calculated using Equations (3) and (4) for each face scale from the previous stage.

3) In stage 3, the covariance matrices of features are extracted for each obtained group of Gabor features from each scale of faces using Equations (6) and (7).

4) In stage 4, log-Euclidean kernel SVM is used to classify covariance matrices, and the recognition results of each branch in Figure 1 are obtained.

5) In the end, majority voting between the obtained results of each classifier determines the final recognition result.

4. FACE DATABASES

The proposed MGcov-ELSVM method was tested on the two challenging Face databases, ORL and Yale. The ORL face database contains ten separate image samples from 40 different people taken under various conditions such as illumination and lighting, facial emotions (natural and smiling), and head attitude. All of the images have dark backgrounds and are viewed from the front, and their original size is 92×112 pixels. Prior to further processing, a pre-processing stage based on median filtering with a kernel size of 5×5 is used to decrease noise and increase the accuracy of the proposed technique. Figure 2 illustrates several samples of the ORL face database.

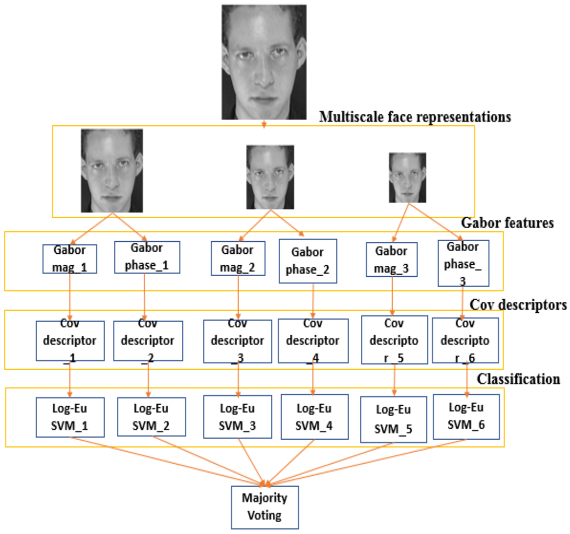

Figure 1. Flowchart of proposed MGcov-ELSVM method

Figure 2. ORL face database

The Yale database has 165 images at a resolution of 320 ×243 pixels from 15 different subjects, each with 11 images. These images display variations in lighting and emotions. To eliminate noise, a median filter with a kernel size of 5×5 is applied to each image. Figure 3 depicts several images from this database.

Figure 3. Yale face database

5. EXPERIMENTAL RESULTS

This section has the four subsection. First subsecrion analyzes the efficacy of the suggested ensemble technique. In the second subsection, the performance of the suggested method is compared with various existing cutting-edge FR approaches. Third subsection investigates the computational complexity of proposed method. Finaly in fourth subsection named, discussion, most important findings are presented along with some advantages and disadvantages of proposed method.

In the following experiments, for each face database, different sizes of training samples (T4=4, T5=5, and T6=6) are selected at random for each individual, and reminders are used as test samples for the method assessment. The experiment is repeated fifty times with different sets of training and test samples, and the mean recognition rate is reported.

5. 1. Efficacy of the Ensemble Strategy In the first experiment, we investigate the efficacy of the ensemble strategy used in the proposed method on both face databases. Figures 4 and 5 compare the recognition results of each branch of figure 1 based on the covariances of Gabor features and Log-Euclidean SVM from each scale of face images to the ensemble of results with the majority voting for both datasets. As a result, the proposed ensemble strategy can improve recognition rates. The superiority of the ensemble method is thought to lie in the integration of contextual information from multiple scales of faces.

5. 2. Comparison to Other Methods In this subsection, we compare the recognition results of our MGcov-ELSVM method with some recent FR methods on two face databases, ORL and Yale. We compare our proposed method to the following seven recent methodologies on both face databases: Mobarakeh et al. [8], Gao et al. [9], Zaaraoui et al. [10], Abd Shehab and Kahraman [6], Dalal and Vishwakarma. [7], Asadi Amiri

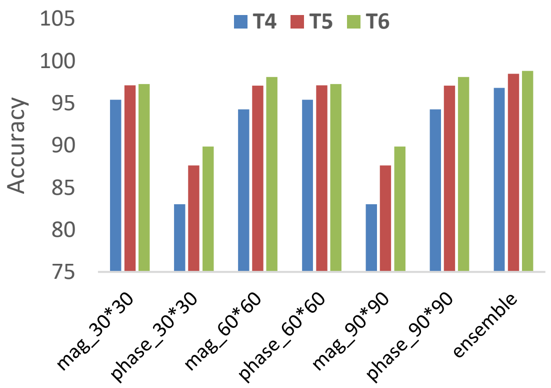

Figure 4. Recognition results for ORL database

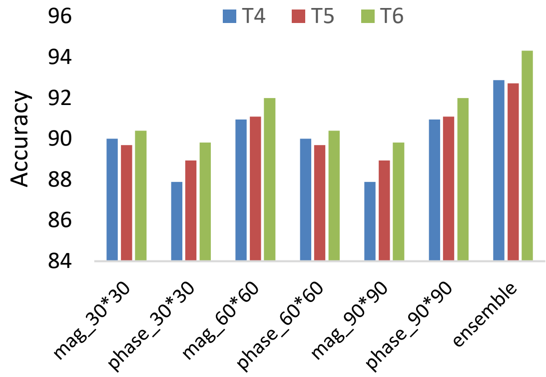

Figure 5. Recognition results for Yale database

and Rajabinasab [11] and Zhang and Yan [12]. The results of various comparing methods are all provided based on their original articles. In order to provide a fair comparison, all techniques use the same sample sizes during training and testing. Tables 1 and 2 summarise the mean recognition rate of each method on the ORL and Yale face databases, respectively.

Table 1 shows that for the ORL face database, MGcov-ELSVM achieves the average recognition accuracy of 98.04 on all sizes of training samples which is 1% higher than the recognition results of the very recent Zhang and Yan [12] method. Also proposed method performed 1.78% better than the new ensemble-based FR technique of Abd Shehab and Kahraman [6]. Table 2 shows that comparing methods can hardly achieve recognition accuracy higher than 90% in almost all cases on challenging the Yale face database. Whereas, the proposed MGcov-ELSVM has excellent performance (above 90%) on Yale databased, even when small numbers of training samples are provided (T4). Proposed MGcov-ELSVM achieves the best classification results

TABLE 1. Recognition results of different methods on the ORL face database

Methods	**Ref/ year**	**Training size**		
		T4	**T5**	**T6**
Mobarakeh et al	[8]/2019	93.33	94	96.87
Gao et al.	[9]/2020	---	92	---
Zaaraoui et al.	[10]/2020	---	92.5	---
Abd Shehab and Kahraman	[6]/2020	94.81	96.93	---
Dalal and Vishwakarma	[7]/2021	85.83	88.5	89.37
Asadi Amiri and Rajabinasab	[11]/2021	79.58	89	95.62
Zhang and Yan	[20]/2022	93.75	98	**99.38**
MGcov-ELSVM		**96.82**	**98.49**	98.83

***Result is not reported in the original paper**

TABLE 2. Recognition results of different methods on the Yale face database

Methods	Ref/ year	Training size		
		T4	**T5**	**T6**
Mobarakeh et al	[8]/2019	---*	---	85
Gao et al.	[9]/2020	---	88.89	---
Zaaraoui et al.	[10]/2020	---	90.66	---
Abd Shehab and Kahraman	[6]/2020	81.49	84.92	---
Dalal and Vishwakarma	[7]/2021	73.33	80	86.67
Asadi Amiri and Rajabinasab	[11]/2021	72.38	74.44	81.33
Zhang and Yan	[12]/2022	75.24	77.78	78.67
MGcov-ELSVM		**92.78**	**92.71**	**94.32**

***Result is not reported in the original paper**

for the Yale face database, with a 9.54% higher recognition rate than the ensemble approach of Abd Shehab and Kahraman [6]. Also, compared to the recent FR approach of Zhang and Yan proposed MGcov-ELSVM method achieved about 16% higher recognition accuracy.

In conclusion, the recognition rates can be improved by incorporating the local characteristics of the face. The performance of the proposed method on a complex Yale database can reveal that the proposed method is more robust than other recent methods under complex adverse conditions. In our view, the superiority of the proposed method can be explained by the ability of Gabor features to extract contextual information from multiscale face representations and the ability of covariance descriptors to model the relationship between Gabor features.

5. 3. Time Complexity

All experiments in this study are implemented in MATLAB 2020a on a computer with a Core i5 4590 CPU with 8 GB of RAM. Due to the unavailability of codes for almost all competing FR methods, in this experiment, we only report the execution time of our proposed method. In general, the proposed method has three steps: preprocessing (Pre), feature generation (FG), and classification (CL). The time complexity of each step of the proposed method on ORL and Yale face databases is shown in Table 3.

According to Table 3, it is obvious that most of the execution time of the proposed method is related to the feature generation stage. It is worth noting that the parallel processing technique can reduce the execution time of the proposed method in such a way that the processing of each scale is executed on a separate system and then the final results are combined.

TABLE 3. Running time (in second) of the proposed method

Dataset	Pre	FG	CL	Total
ORL	1.3	150	0.29	**151.59**
Yale	0.6	62	0.09	**62.69**

5. 4. Discussion

This study proposes a new ensemble strategy based on covariance descriptors of multiscale Gabor magnitude and phase feature for FR. We assess the proposed method in the three experiments. The first experiment proved that the decision fusion of covariance descriptors, derived from multiscale Gabor magnitude and phase features, can improve the recognition accuracy compared to the single-scale approach. In the second experiment, we compared the proposed method with seven states of FR methods. This experiment reveals that some recent competitor methods, such as Zhang and Yan [12], have a challenging performance on the complex Yale face database. This also shows that even recent approaches may not be invariant enough to FR under adverse conditions. The final results demonstrate that the proposed method outperformed the competitor methods in almost all experiments. Also, it can be concluded that the proposed method is more robust to the different challenges since it can achieve appropriate performance even when four samples are available for training. In the last experiment, we assess the performance of the proposed method in terms of computational cost. Final computational cost analysis shows that the feature generation stage consumes most of the time of the proposed method. Most advantages and disadvantages of the proposed method are listed as follows:

Advantages:

- The proposed method of this study has a simple but efficient structure that does not need expensive hardware to run, in contrast to many recent FR methods.
- The recognition rate of the proposed method is commonly above 92%, even when few training samples are available.

Disadvantages:

- The computational time of the proposed method is not as fast as some recent FR techniques. This issue should be solved in future studies.
- The performance of the proposed method degraded when only one training sample was available for each person. In future studies, we should propose an improved version of the proposed method, which is more robust to the training sample size.

6. CONCLUSIONS

We present a new ensemble classification approach for the FR in this study. This technique utilizes an ensemble of log-Euclidean kernel SVMs to recognize faces based on the covariance descriptors of Gabor magnitude and phase features obtained from the multiscale representation of faces. Experiments on the two well-known face databases, ORL and Yale, reveal that the suggested technique outperforms some current state-of-the-art FR methods. In the future study, we will combine covariance descriptors of various textual features for accurate FR.

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Persian Abstract

چکیده

تشخیص چهره به دلیل عوامل مختلفی مانند نویز، میزان روشنایی و شرایط محیطی یک کار چالش برانگیز در حوزه بینایی ماشین است. ویژگی‌های محلی تصویر نقش مهمی را در افزایش دقت شناسایی روش‌های تشخیص چهره ایفا می‌کنند. در این راستا، توصیفگرهای کوواریانس ویژگی‌های موجک گابور یکی از برجسته‌ترین روش‌ها برای تشخیص دقیق چهره بوده است. بیشتر روش‌های موجود در این دسته بر توصیف‌گرهای کوواریانس ویژگی‌های بزرگی گابور استخراج‌شده از تصاویر تک‌مقیاس چهره تکیه می‌کنند. در این مقاله یک سیستم طبقه‌بندی چندگانه جدید (به نام MGcov-ELSVM) برای تشخیص چهره پیشنهاد شده است که بر اساس توصیف‌گرهای کوواریانس به دست آمده از ویژگی‌های بزرگی و فاز گابور در مقیاس‌های گوناگون است. MGcov-ELSVM با تولید نمایش‌های چند مقیاسی چهره آغاز می‌شود. ویژگی‌های اندازه و فاز گابور از تصاویر چند مقیاسی چهره در مرحله دوم استخراج می‌شوند. پس از آن، ویژگی‌های بزرگی و فاز گابور برای تولید توصیفگرهای کوواریانس استفاده می‌شود. در نهایت، توصیفگرهای کوواریانس از طریق طبقه‌بندی‌کننده ماشین بردار پشتیبان با کرنل لگاریتم اقلیدسی طبقه‌بندی می‌شوند و رای‌گیری اکثریت نتیجه نهایی شناسایی چهره را تعیین می‌کند. نتایج تجربی بر روی دو پایگاه داده چهره، ORL و Yale، نشان می‌دهد که MGcov-ELSVM از برخی روش‌های اخیر تشخیص چهره بهتر عمل می‌کند.