Performance Analysis of Facial Expression Recognition Schemes

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Abstract
Face recognition plays an important vision task having many practical applications such as biometrics, video surveillance, image retrieval, and human computer interaction. Most recently facial expression recognition has been focused for biometric facial recognition system in various confidential and high secured operational areas. Information for biometric representation and recognition are available in image space, scale and orientation. Combinatorial analysis of space, scale and orientation provide enriched features for more accurate biometric facial recognition. Position, spatial frequency and orientation selectivity properties of facial feature components play major role in visual perception.

There are various methods have discussed for Facial Expression Recognition scheme for human biometric recognition. In this work we analyze current Facial Recognition schemes and provide an overview of the emerging Facial Expression Recognition methods and related research work done in this area. Also comparisons are done between the various schemes to clarify benefits and limitations. There are different measures on which performance of Facial Expression Recognition scheme depends, such as Recognition rate, Illumination variance, Expressional changes, Time differences, Facial color code, Size of feature components, False Positive and Negative and True Positive and Negative. Experimental Results shows that the performance analysis of the Facial Expression Recognition schemes on the basis of Recognition rate, Illumination variance, False Positive and True positive rate.

Keywords:
Face Recognition, Biometrics, Classification

1. Introduction
Facial expression is a visible manifestation of the affective state, cognitive activity, intention, personality, and psychopathology of a person; it plays a communicative role in interpersonal relations. Facial expressions, and other gestures, convey non-verbal communication cues in face-to-face interactions. These cues may also complement speech by helping the listener to elicit the intended meaning of spoken words. Facial expressions have a considerable effect on a listening interlocutor; the facial expression of a speaker accounts for about 55 percent of the effect, 38 percent of the latter is conveyed by voice intonation and 7 percent by the spoken words.

As a outcome of the information that they carry, facial expressions can play an important role wherever humans interact with machines. Automatic recognition of facial expressions may act as a component of natural human machine interfaces (some variants of which are called perceptual interfaces or conversational interfaces). Such interfaces would enable the automated provision of services that require a good appreciation of the emotional state of the service user, as would be the case in transactions that involve negotiation, for example. Some robots can also benefit from the ability to recognize expressions.

a) b) c) d) e) f) g)

Fig. 1 Facial Expressions a) Anger b) Disgust c) Fear d) Joy e) Sadness f) Surprise g) Neutral

Fig. 1 shows the various kinds of Facial Expressions. Automated analysis of facial expressions for behavioral science or medicine is another possible application domain. From the viewpoint of automatic recognition, a facial expression can be considered to consist of deformations of facial components and their spatial relations, or changes in the pigmentation of the face. Research into automatic recognition of facial expressions addresses the problems surrounding the representation and categorization of static or dynamic characteristics of these deformations or face pigmentation.

As one of the most important biometric techniques, face recognition has clear advantages of being natural and passive over other biometric techniques requiring cooperative subjects such as fingerprint recognition and iris recognition. To benefit from the non-intrusive nature of face recognition, a system is supposed to be able to identify an uncooperative face in uncontrolled environment and an arbitrary situation without the notice of the subject. This generality of environment and situations, however, brought serious challenges to face recognition techniques, e.g., the appearances of a face due to viewing (or photo shooting) condition changes may vary too much to tolerate or handle. Though many face recognition approaches, reported satisfactory performances, their successes are limited to the conditions of controlled environment, which are unrealistic in many real applications.

In recent surveys of face recognition techniques, pose variation was identified as one of the prominent unsolved problems in the research of face recognition. It gains great interest in the computer vision and pattern recognition research community. Consequently, a few promising methods have been proposed in tackling the problem of recognizing faces in arbitrary poses, such as tied factor analysis (TFA), 3D morphable model (3DMM), eigen light-field (ELF), illumination cone model (ICM), etc. However, none of them is free from limitations and is able to fully solve pose problem in face recognition. Continuing attentions and efforts are still necessary in the research activities towards ultimately reaching the goal of pose-invariant face recognition and achieving the full advantage of being passive for face recognition.

Although several survey works on face recognition have been published which gave very good reviews on face recognition in general, there is no review specific on this challenging problem of face recognition across illumination and pose. This work provides the survey on face expression recognition, with comprehensive and up-to-date reviews on existing techniques and critical discussions of major challenges and possible directions in this research area.

2. Literature Review

Automatic facial expression recognition involves two vital aspects: facial representation and classifier design. Wright, J. et al., 2009 exploit the discriminative nature of sparse representation to perform classification. Instead of using the generic dictionaries represent the test sample in an overcomplete dictionary whose base elements are the training samples themselves. Xiaozheng Zhang and Yongsheng Gao, 2009 provides a critical survey of researches on image-based face recognition across pose. The techniques are classified into different categories according to their methodologies in handling pose variations.

Wagner, A. et al., 2009 propose a conceptually simple face recognition system that achieves a high degree of robustness and stability to illumination variation, image misalignment, and partial occlusion. The system uses tools from sparse representation to align a test face image to a set of frontal training images. Caifeng Shan et al., 2009 empirically evaluate facial representation based on statistical local features, Local Binary Patterns, for person-independent facial expression recognition. Different machine learning methods are systematically examined on several databases.

Recently, there has been more interest in the automatic recognition of dimensional affect. H. Gunes and M. Pantic, 2010 presents Automatic, dimensional and continuous emotion recognition.

An example of an appearance-based approach that explicitly models a facial expression’s temporal dynamics is that of Koelstra et al., 2010. In their work, they propose a method that detects AUs and their temporal phase onset, apex, and offset using free-form deformations and motion history images as appearance descriptors and hidden Markov models as machine learning technique.

Simon et al., 2010 use both geometric and appearance-based features and include modeling of some of the temporal dynamics of AUs in a proposed method using segment-based SVMs. Facial features are first tracked using a person-specific AAM so that the face can be registered before extracting SIFT features.

Recently, considerable research work in face recognition (FR) has shown that facial color information can be used to considerably improve FR performance, compared to the FR methods relying only on grayscale information [J. Yang et al., 2010]. In particular, it has been reported by M. Rajapakse, J. Tan, and J. Rajapakse, 2010 that the effectiveness of color information can become significant for improving FR performance when face images are taken under strong variations in illumination, as well as with low spatial resolutions.

Jae Young Choi et al., 2011 introduces the new color face recognition (FR) method that makes effective use of boosting learning as color-component feature selection framework. The boosting color-component feature selection framework is designed for finding the best set of color-component features from various color spaces (or models), aiming to achieve the best FR performance for a given FR task. Zhen Lei et al., 2011 proposes a face representation and recognition approach by exploring information jointly in image space, scale and orientation domains. Specifically, the face image is first decomposed into different scale and orientation responses by convolving multiscale and multiorientation Gabor filters.

Wonjun Hwang et al., 2011 present a robust face recognition system for large-scale data sets taken under uncontrolled illumination variations. The face recognition system consists of an illumination-insensitive preprocessing method, a hybrid Fourier-based facial feature extraction, and a score fusion scheme. Initially, a face image is transformed into an illumination-insensitive image, called an “integral normalized gradient image,” by normalizing and integrating the smoothed gradients of a facial image.

Dinesh Chandra Jain and V. P. Pawar, 2012 present a new way to recognize the face using facial recognition software and using neural network methods. That makes a facial recognition system to protect frauds and terrorists. Michel F. Valstar et al., 2012 present a meta-analysis of the first such challenge in automatic recognition of facial expressions. It details the challenge data, evaluation protocol, and the results attained in two sub challenges: AU detection and classification of facial expression imagery in terms of a number of discrete emotion categories.

However, Facial Recognition with expression and color face components analyzed in the recent literatures lack in following aspects such as highly uncontrolled illumination, dynamic pose variation, variance in resolution of facial color feature components, expressions relativity to behavioral traits of human, acceptable and adaptable FAC sets and psychological effects of emotions in the face for recognition.

3. Methodology

A typical face recognition problem is to visually identify a person in an input image through examining his/her face. The first attempt to this task can trace back to more than 30 years ago. After that, a number of face recognition methods have been proposed, among which principal component analysis (PCA also known as Eigen faces), Fisher discriminant analysis (FDA, also known as Fisher faces, linear discriminant analysis, or LDA in short), self organizing map and convolution network, template matching, modular PCA, line edge maps (LEMs), elastic bunch graph matching (EBGM), directional corner point (DCP), and local binary patterns (LBP) are some of the representative works. All of these methods attempt to extract classification patterns (or features) from 2D face images and to recognize input face images based on these patterns against the known face images in the database.

3.1 Meta-Analysis in Automatic Recognition of Facial Expressions

Automatic facial expression recognition has been an active topic in computer science for over two decades, in particular facial action coding system action unit (AU) detection and classification of a number of discrete emotion states from facial expressive imagery. Standardization and comparability have received some attention; for instance, there exist a number of commonly used facial expression databases. However, lack of a commonly accepted evaluation protocol and, typically, lack of sufficient details needed to reproduce the reported individual results make it difficult to compare systems. This, in turn, hinders the progress of the field. A periodical challenge in facial expression recognition would allow such a comparison on a level playing field. It would provide an insight on how far the field has come and would allow researchers to identify new goals, challenges, and targets.

This work presents a meta-analysis of the first such challenge in automatic recognition of facial expressions. It details the challenge data, evaluation protocol, and the results attained in two subchallenges: AU detection and classification of facial expression imagery in terms of a number of discrete emotion categories.

3.2 Boosting color-component feature selection framework

This work introduces the new color face recognition (FR) method that makes effective use of boosting learning as color-component feature selection framework. The proposed boosting color-component feature selection framework is designed for finding the best set of color-component features from various color spaces (or models), aiming to achieve the best FR performance for a given FR task. In addition, to facilitate the complementary effect of the selected color-component features for the purpose of color FR, they are combined using the proposed weighted feature fusion scheme.

The effectiveness of our color FR method has been successfully evaluated on the following five public face databases (DBs): CMU-PIE, Color FERET, XM2VTSDB, SCface, and FRGC 2.0. Experimental results show that the results of the proposed method are impressively better than the results of other state-of-the-art color FR methods over different FR challenges including highly uncontrolled illumination, moderate pose variation, and small resolution face images.

3.3 Robust Alignment and Illumination by Sparse Representation

In this work, we show how registration and illumination can be simultaneously addressed within a robust sparse representation framework. We show that face registration, a challenging nonlinear problem, can be solved by a series of linear programs that iteratively minimize the sparsity of the registration error. This leads to an efficient and effective alignment algorithm for face images that works for a large range of variation in translation, rotation, and scale, even when the face is only partially visible due to eyeglasses, closed eyes and open mouth, sensor saturation, etc. We also propose a sufficient set of training illuminations that is capable of linearly representing typical indoor and outdoor lighting, along with a practical hardware system for capturing them.

We then demonstrate the effectiveness of the proposed new methods with a complete face recognition system that is simple, stable, and scalable. The proposed system performs robust automatic recognition of subjects from loosely controlled probe images taken both indoors and outdoors, using a gallery of frontal views of the subjects' faces under the proposed illuminations. An off-the-shelf face detector2 is used to detect faces in the test images. We conduct extensive experiments on the proposed system with both public databases and a face database that is collected by our own acquisition system. Our experimental results on large-scale public face databases show that our algorithm indeed achieves very good performance on these databases, exceeding or competing with the state-of-the-art algorithms. Additionally, our experimental results on our own database clearly demonstrate that our system not only works well with images taken under controlled laboratory conditions, but is capable of handling practical indoor and outdoor illuminations as well.

3.4 Recognition of Human Face Automatically Using Neural Network Method

Our technology is based on neural computing and combines the advantages of elastic and neural networks .Neural computing provides technical information processing methods that are similar to the way information is processed in biological systems, such as the human brain[4]. They share some key strength, like robustness fault-resistance and the ability to learn from examples. Elastic networks can compare facial landmarks even if images are not identical, as is practically always the case in real-world situations. Neural networks can learn to recognize similarities through pattern recognition.

A newly-emerging trend in facial recognition software uses a 3D model, which claims to provide more accuracy. Capturing a real-time 3D image of a person's facial surface, 3D facial recognition uses distinctive features of the face -- where rigid tissue and bone is most apparent, such as the curves of the eye socket, nose and chin -- to identify the subject[5-6]. These areas are all unique and don't change over time. Using depth and an axis of measurement that is not affected by lighting, 3D facial recognition can even be used in darkness and has the ability to recognize a subject at different view angles with the potential to recognize up to 90 degrees (a face in profile). Using the 3D software, the system goes through a series of steps to verify the identity of an individual.

1) Detection: Acquiring an image can be accomplished by digitally scanning an existing photograph (2D) or by using a video image to acquire a live picture of a subject .

2) Alignment: Once it detects a face, the system determines the head's position, size and pose. As stated earlier, the subject has the potential to be recognized up to 90 degrees, while with 2D, the head must be turned at least 35 degrees toward the camera.

3) Measurement: The system then measures the curves of the face on a sub-millimeter (or microwave) scale and creates a template.

4) Representation: The system translates the template into a unique code. This coding gives each template a set of numbers to represent the features on a subject's face.

5) Matching: If the image is 3D and the database contains 3D images, then matching will take place without any changes being made to the image. However, there is a challenge currently facing databases that are still in 2D images. 3D provides a live, moving variable subject being compared to a flat, stable image. New technology is addressing this challenge. When a 3D image is taken, different points are identified. For example, the outside of the eye, the inside of the eye and the tip of the nose will be pulled out and measured. Once those measurements are in place, an algorithm will be applied to the image to convert it to a 2D image. After conversion, the software will then compare the image with the 2D images in the database to find a potential match.

4. Performance analysis of various Face recognition schemes

In this section, we demonstrate performance analysis of various Face recognition schemes through experiments by examining the performance metrics. We have discussed recognition and classification as the driving force behind our analysis. Various Face recognition schemes are, Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition Using Neural Network Method and Boosting color-component feature selection framework.

Performance evaluation various Face recognition schemes is measured in terms of

I. False Positive rate
II. Execution Time
III. Recognition Rate
IV. Illumination variance

Face Recognition Rate

Face Recognition Rate is a ratio in which total number of faces that are correctly detected under random corruption.

False positive rate

A result that is erroneously positive when a situation is normal. An example of a false positive: a particular test designed to detect faces. The detector output is positive but it is false (there is actually no face).

Execution Time

Execution Time is defined as amount of time taken to recognize the faces in a given set. It is measured in terms of milliseconds (ms).

Table 4.1 Recognition Rate based on percent corrupted

Percent Corrupted	Recognition Rate (%)			
	Meta-Analysis in Automatic Recogn	Robust Alignment and Illumination by Sparse Representation	Face Recognition Neural Network Method	Boosting color-component featur selection framew
10	100	100	100	100
20	99.8	100	99.92	98.73
30	98.4	99.1	99.12	97.64
40	97.12	98.86	98.85	95.12
50	91.43	97.73	97.02	89.06
60	83.34	95.51	89.16	82.11
70	74.12	92.28	81.15	65.14

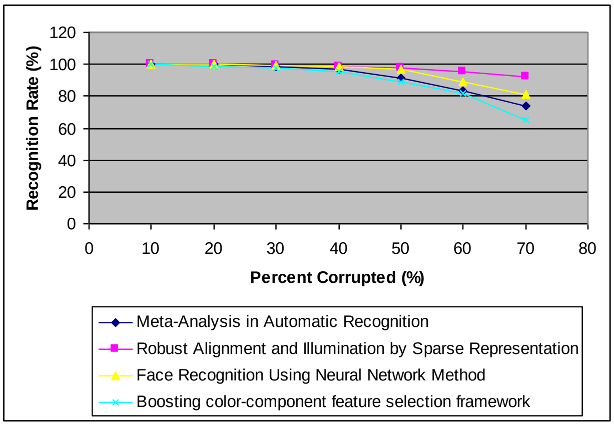

Figure 4.1: The results of Recognition rate when percent of corrupted face

In Fig. 4.1, the change of percent corrupted face has various impacts on the recognition rate of the four schemes such as, Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition Using Neural Network Method and Boosting color-component feature selection framework. As the Corruption percent increases, the recognition rate decreases automatically. From the above figure we can say, Robust Alignment and Illumination by Sparse Representation method achieves greater Recognition rate 81 to 100%.

Table 4.2: Recognition Rate for Illumination Variations

Illumination Variations	Recognition Rate (%)			
	Meta-Analysis in Automatic Recognition	Robust Alignment and Illumination by Sparse Representation	Face Recognition Using Neural Network Method	Boosting color-component feature selection framework
5	100	99.24	99.98	98.63
10	98.5	96.72	98.73	95.57
15	92.24	91.25	97.63	89.73
20	84.27	87.42	91.27	81.25
25	81.23	82.37	88.72	76.93
30	74.23	78.26	86.27	72.94
35	62.84	61.28	82.52	56.03

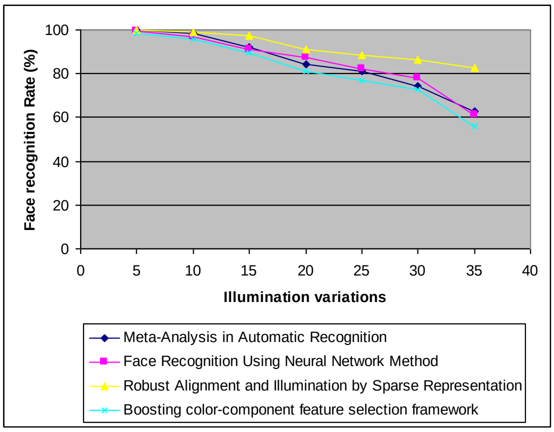

Fig. 4.2 Recognition Rate for Illumination Variations

In Fig. 4.2, the change of Illumination Variations has various impacts on the recognition rate of the four schemes such as, Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition Using Neural Network Method and Boosting color-component feature selection framework. As the Corruption percent increases, the recognition rate decreases automatically. From the above figure we can say, Robust Alignment and Illumination by Sparse Representation method achieves greater Recognition rate(averagely 87%).

Table 4.3: False Positive Rate of various Face Recognition methods

No. Of Faces	False Positive Rate (%)			
	Meta-Analysi inAutomatic Recognition	Robust Alignmen Illumination by Sparse Representation	Face Recogniti Using Neural Networ Method	Boosting color component feature selectic nework
5	0.023	0.013	0.017	0.01
10	0.052	0.031	0.04	0.02
15	0.087	0.052	0.064	0.034
20	0.12	0.064	0.093	0.067
25	0.13	0.124	0.14	0.1
30	0.18	0.13	0.16	0.12
35	0.23	0.16	0.187	0.14

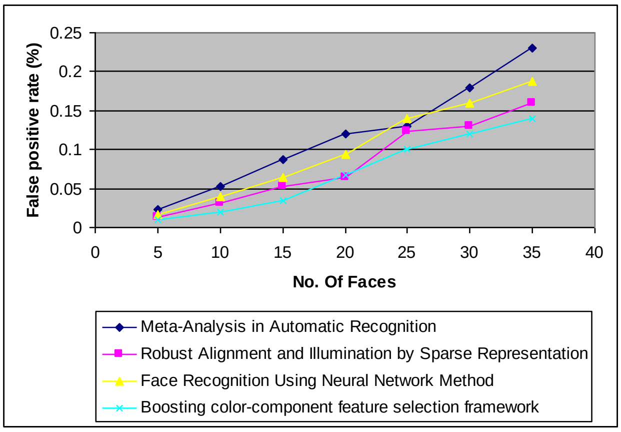

Fig. 4.3 False Positive Rate of various Face Recognition methods

In Fig. 4.3, the change of number of faces has various impacts on the False Positive Rate of the four schemes such as, Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition

Using Neural Network Method and Boosting color-component feature selection framework. As the number of faces increases, the False Positive Rate increases automatically. From the above figure we can say, Boosting color-component feature selection framework achieves less False Positive Rate (0.01 to 0.14%).

Table 4.4: Execution Time

No. Of Faces	Execution Time (ms)			
	Meta-Analysis Automatic Recognition	Robust Alignment and Illumination by Sparse Representation	Face Recognition Using Neural Network Method	Boosting color-component feature selection framework
5	28	32	12	45
10	45	64	24	73
15	47	87	35	86
20	69	104	54	125
25	121	115	83	148
30	145	142	106	173
35	173	168	142	189

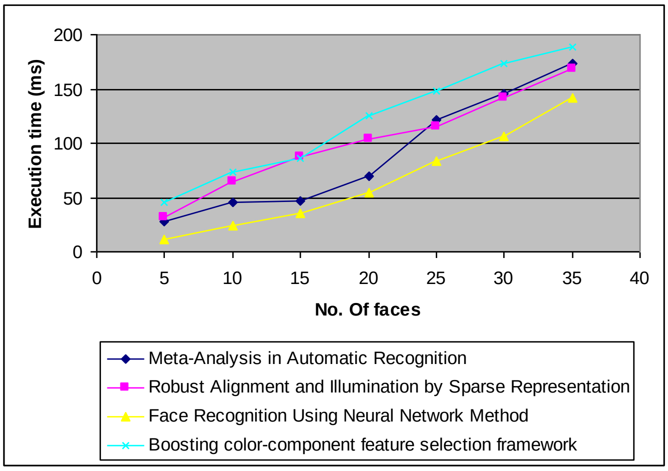

Fig. 4.4 Execution time

In Fig. 4.4, the change of number of faces has various impacts on the Execution time of the four schemes such as, Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition Using Neural Network Method and Boosting color-component feature selection framework. As the number of faces increases, the Execution time increases automatically. From the above figure we can say, Face Recognition Using Neural Network Method achieves less execution time (5 to 12%).

5. Conclusion

This paper has briefly discussed the various methods of Automatic Face Recognition. Identical architectures and processing systems are often used for facial expression recognition and face recognition, although the duality that exists between these recognition tasks. Comparisons are made to explain the advantages and limitations of different Face Recognition schemes. Performance analyses of these schemes are evaluated during the experiments. Various Automatic Face Recognition systems (Meta-Analysis in Automatic Recognition, Robust Alignment and Illumination by Sparse Representation, Face Recognition Using Neural Network Method and Boosting color-component feature selection framework) are examined and their performance is evaluated on four criteria: False Positive rate, Execution Time, Recognition Rate and Illumination variance. From the experimental results Face Recognition Using Neural Network Method performs well in Execution time, Boosting color-component feature selection framework performs well in False positive rate, Robust Alignment and Illumination by Sparse Representation performs well in Recognition rate.

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