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# Research on the Face Recognition in Color Picture Using Characteristic Extraction Based on the Kernel Algorithm

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Abstract

In this paper, the author researched on the face recognition in color picture using the characteristic extraction based on the kernel algorithm. A variety of methods are proposed in the frame of the sparse representation and dictionary learning to improved algorithms, essentially, which is an extension for the sparse representation to study the

problem of face recognition and under different conditions for imaging face. In fact, the sparse representation based classification model is the linear combination through training samples and has great reconstruction powers to represent unknown testing samples.
Keywords: FACE RECOGNITION, COLOR PICTURE, CHARACTERISTIC EXTRACTION, KERNEL ALGORITHM

**1. Introduction**

Advance in the management of identity is a result of the crucial role it plays in a number of applications in the field of Information Technology makes it is an inseparable part of it. Information Security is one of those applications, it includes for example restricting physical access to important facilities like nuclear plants or airports, controlling logical access to shared resources and information, regulating international border crossings, performing remote financial transactions, or distributing social welfare benefits, web-based services and decentralized customer service centers (e.g. online banking and credit cards). These applications need reliable identity management systems to reduce from concerns about national security and identity theft.

The determining relationship between individuals and their personal identities is the fundamental task in identity management. The task can be done by matching a person's identity or checking the allegations of an individual whenever required. Person recognition knows as the process that can identify a person based on the following three basic approaches: first adopts, the person has an exclusive knowledge of some secret information (e.g., password, personal identification number, or cryptographic key), this approach is what a person knows. The second proposes, the individual has an exclusive possession of the extrinsic token (e.g., identification card, driver's license, passport, physical key, or personal device such as a mobile phone), this approach is what a person possesses extrinsically. Third approach, who the person is intrinsically, determines the person's identity based on his\her inherent physical or behavioral traits and is known as biometric recognition.

Biometric recognition examines the unique physical and/or behavioral traits of the person either in a fully automated or a semi-automated manner that can be used to determine a person's identity. For many reasons the knowledge-based and token-based mechanisms become alone is not sufficient for reliable identity management, such as surrogate representations of identity like passwords or ID cards, which can be easily forgotten/lost, guessed/stolen, or shared, beside presenting forged or duplicate identification documents Individuals can also conceal their true identity. By using biometric recognition, or simply biometrics, it is possible to confirm or determine the identity of an individual. Since the biometric characteristics are inherent to a person, it is more difficult to manipulate, share, or forget these traits. That is, the user of the biometric system is the person who presents his biometric identifier to a system for the purpose of being recognized.

Biometric system extracts features set from the acquired biometrics data, and compares it with the template sets in the data [1] and for many decades it has been and still is an area of extensive research. The biometric traits includes, fingerprint [2], Palin print, the DNA information of an individual to determine or verify his identity [3], etc.

Cognitive biometrics refers to face recognition, where it has several advantages over other biometric methods, some of which are outlined here: More of these technologies require the user to do some voluntary actions, i.e., placing the hand on a hand-rest for fingerprinting or hand geometry detection, for iris or retina identification where a person should stand in a fixed position in front of a camera and the epidermis tissue of hands and fingers is damaged (i.e., bruised or cracked) prevents the interest of techniques that rely on it. In an Iris and Retina identification, these techniques needs expensive equipment and are highly sensitive to any body motion.

Voice recognition is vulnerable to background noise in public places and the vagaries of the audio on the phone line or tape recording. Signature scan be modified or forged. The case of capturing the biological characteristics, the equipment may become a transmitter of germs and impurities from users to another, because of multiple individuals using it, while, face recognition can be done passively without any action or explicit involvement of the user since the facial images can be easily obtained with a couple of inexpensive fixed cameras.

**2. Collaborative Representation for Face Recognition**

Face Recognition is an active research topic in computer vision and pattern recognition driven by its wide range of practical applications such as access

control, identification systems, surveillance, pervasive computing, social networks, etc. This is due to the fact that present methods perform well under relatively dominant environments but which also tend to suffer when there are variations in different factors (such as pose, illumination, etc.) exist.

The idea of performing recognition on face images is not new. In practice, face recognition is a very difficult problem due to a substantial variation in directions of light, different face pose and diversified facial expressions. A good Face recognition methodology should be considered is a representation as well as classification issues and a good representation method should require minimum manual annotations. Face recognition depends heavily on the particular choice of features, which used by the classifier. Therefore, the desired aim for a long time has been the achievement progress in obtaining more accurate recognition for such images. However, great attention has been devoted to recent developments in face recognition algorithms, which are to provide a surprisingly effective solution, although the face recognition methods show stunning improvement in successive contests. The success of these methods is due to two main reasons: first, it identifies common face parts that characterize the different faces within the class, and second, the parts are combined in a way that allows variations learned from the training data. This concept extends in the current work from the representation of faces to the representation its constituent parts.

Recent years witnessed substantial renaissance of interest in sparse representation, and have been shown promising results not merely in face recognition but as well in numerous visual recognition tasks, such as image super-resolution and classification, motion segmentation [4] and background modeling [5]. The aim of sparse representation is to find high fidelity representation and compression of a given signal by using predefined bases and reconstruct the signal by the seeking of only a few (or sparse) bases from the whole dictionary, with no any particular semantic meaning between individual base elements. The sparse representation-based classification (SRC) is vastly spread amid face recognition schemes. In the SRC method, face images in the training set form a dictionary matrix, and then a vectored test face image are represented under this dictionary matrix. The representation coefficients provide hints for recognition. (SRC) is robust and it can also achieve good performance in occlusion and noise environments.

Moreover, (SRC) became an eminent technique in face recognition, from which emerged a new approach, adopted by Lei Zhang et al. [6], they proposed classification scheme, and namely collaborative representation based classification (CRC) with regularized least square (CRC_ RLS), which is significantly less complex than SRC.

Sparse representation (or coding) codes a signal y over a dictionary p such that y is a sparse vector, while collaborative representation (CR) uses the training samples from all classes to represent the query sample y, although the (CRC_ RLS) based FR scheme proposed in [7] has encouraging results.

There is an issue that motivated us to benefit from it and propose an approach that is more creative and effective. In face recognition, selection the optimal features coupled with a particular classifier can be done by training and evaluating the classifier using all the combinations of available features and thus obtain better result. There is a variety of strategies for getting optimal features; in many situations, images suffer from contamination of mixed noise of impulsive noise and additive noise. Therefore, image denoising or filtering is necessary or even indispensable for any image application system and the image denoising or filtering is one of the strategies which is a fundamental image processing task to discover features or subset of features by replacing a pixel with an uniform or weighted average of its neighbors. Its computational complexity normally depends on the size and the complexity of the filter. The bilateral filter was first introduced and applied to noise removal in images by Tomasi and Manduchi [8].

The bilateral filter is a technique used to smooth images while preserving edges, the main concept underlying the bilateral filters is the definition of intensity proximity among pixels, the edge-preserving property comes from the use of a range kernel (along with the spatial kernel) to control the diffusion in the vicinity of edges. Bilateral filters have been used widespread in many computer vision and graphics tasks like denoising, texture editing and relighting.

A wide range of potential applications have motivated extensive studies efforts on face recognition. Many algorithms have been developed that aim to tackle the influence of a single factor or combination of factors of appearance variations for face recognition. For example, various techniques have been developed to handle sensitive of illumination conditions and tested on data sets that contain only illumination variations. Consequently, there exist many face databases that have been gathered under controlled settings and that contain facial appearance variations caused by a single factor or more a combination of factors. Valuable insights have been provided by

those studies about different aspects of performing face recognition and the databases are gathered to know the algorithms' robustness against specific sources of variations. It is necessary and important, that each face algorithm is tested on this standard face databases and even:

The variations of the facial appearance are created so that, facial image can be oriented and scaled differently and imaged under changing a single source or two sources of variation.

The facial appearance has separate variations, e.g. head poses is orientated at some specific angles. The person stays in front of the camera and he/she is aware that his/her image is being captured. It is collected collaboratively. The face is a universal feature of human beings. Face recognition is important not only because of the ability of a lot of potential applications in the areas of research, but also because of the ability to solve them and that would help solve the classification problems such as object recognition. Another recent technique for pursuit of face recognition is sparse representation based classification that has shown strong ability in solving computer vision problems and pattern recognition and this in turn has had the effect of encouraging more research in face recognition even when face is partly occluded. Wagner has proposed tools based on sparse representation to align and match the face image in the presence of registration errors. In the context of sparse representation classification (SRC), the face images in the training set form the dictionary matrix, and then a vectorized test face image is represented under this dictionary matrix.

**3. The Kernel Algorithm**

Although a great deal of works and researches have been presented in the field of face recognition (FR) it is still an open problem, and it has a wide range of applications in many fields such as human computer intelligent interaction, digital library, control access, real time matching of surveillance video images, building or office security, criminal identification and authentication in secure systems like computers or bank teller machines, this is attributed due to its being one of the most visible and active challenging researches since the human face image contains many variations such as facial expression, gesture, pose, variations of light, occlusion, aging and the imaging conditions.

It is well known that many techniques along this line have been used. Among these, principal component analysis (PCA), which is one of the techniques families for taking high dimensional data, and using the dependencies between the variables to be, represented it in a more tractable, lower-dimensional form, without losing too much information. PCA is one of the simplest and most robust methods of performing such dimensionality reduction.

The main idea of using PCA for FR is to express the large 1 D-vector of pixels constructed from 2D facial image into the Compact Principal Components of the feature space. Thereafter, several variants and developments of PCA have been explored and proposed. Despite the effective features of PCA, it can still be affected if outliers are present in the data and becomes unreliable. To avoid these effects, the goal of robust PCA methods is obtain principal components that are not influenced much by outliers. Moreover, several of natural approaches to robustify PCA have been explored and proposed in the literature.

If these two kernels are combined linearly, the new mixed kernel function is:

$$K = \alpha K_1 + (1-\alpha)K_2 \tag{1}$$

$K_1$ is the Gaussian kernel function, $K_2$ is the Polynomial kernel function. If $\alpha = 1$, $K$ is the Gaussian kernel function. If $\alpha = 0$, it is Polynomial kernel function.

The sample collection is

$$\{x_i, y_i\}_{i=1}^{N} \tag{2}$$

So we have the equation (3):

$$y(x) = \hat{y}(x) + e(x) = \sum_{i=1}^{M} \omega_i g_i(x) + e(x) \tag{3}$$

The model of kernel function can be concluded in the following equation (4).

$$g_i(x) = \alpha_i k_{1i}(x) + (1-\alpha)k_{2i}(x), \alpha \in (0,1) \tag{4}$$

The mixed kernel function is denoted as equation (5)-(9) as following.

$$\vec{y} = [y_1, y_2, y_3, \ldots, y_N]^T \tag{5}$$

$$\vec{e} = [e_1, e_2, e_3, \ldots, e_N]^T \tag{6}$$

$$\vec{\omega} = [\omega_1, \omega_2, \omega_3, \ldots, \omega_N]^T \tag{7}$$

$$\vec{G} = [g_1, g_2, g_3, \ldots, g_N]^T \tag{8}$$

$$g_k = \begin{bmatrix} g_k(x_1), g_k(x_2), \\ g_k(x_3), \ldots\ldots, g_k(x_N) \end{bmatrix}^T \tag{9}$$

Based on these function,

$$\vec{y} = \vec{G}\vec{\omega} + \vec{e} \tag{10}$$

$$\vec{G} = \vec{P}\vec{A} \tag{11}$$

$$\vec{y} = \vec{P}\vec{\theta} + \vec{e} \tag{12}$$

$$\vec{\theta} = [\theta_1, \theta_2, \theta_3, \ldots, \theta_N]^T \quad (13)$$

$$\vec{\theta} = \vec{A}\vec{\omega} \quad (14)$$

The MSE is

$$J = \vec{e}^T \vec{e} / N = \vec{y}^T \vec{y} / N - \sum_{i=1}^{M} \vec{p}_i^T \vec{p}_i \theta_i^2 / N \quad (15)$$

So

$$J_k = J_{k-1} - \frac{1}{N} \vec{p}_k^T \vec{p}_k \theta_k^2 \quad (16)$$

Then we can calculate the direction of the coefficient using the following formula (17)-(19):

$$D(X) = D + \frac{\partial D^T}{\partial X} X + \frac{1}{2} X^T \frac{\partial^2 D^T}{\partial X^2} X \quad (17)$$

$$m(x,y) = \sqrt{\begin{matrix}(L(x+1),y) - L(x-1,y)^2 \\ + (L(x,y+1) - L(x,y-1))^2\end{matrix}} \quad (18)$$

$$\theta(x,y) = \tan^{-1} \frac{L(x,y+1) - L(x,y-1)}{(L(x+1),y) - L(x-1,y)} \quad (19)$$

**4. The Experiment Result and Data Analysis**

Therefore, different methods seek to an optimal dictionary by learning from training data. A set of metagenes from the original gene expression data provides a more robust clustering of the samples via training it by using nonnegative matrix factorization.

As well as in image restoration, the learned dictionary has been used for image analysis by learning an over complete dictionary of atoms from natural images. The learning Meta faces has been learned from original images and then is used it as the dictionary to represent the input query image, and the learned metafaces will be more representative for sparse representation and more efficient in minimization. In the training set, each subject constitutes many images representing various lighting conditions, so that an inquiry image of certain illumination condition can be represented by a sparse linear combination of the training samples. However, in realistic applications it is hard for every enrolled user to have such varying lighting images. In order to tackle this basic issue in a unified framework, in this chapter, we introduce a new method for face recognition in which the preprocessing step is a Robust Principal Components Analysis (RPCA), and next step is using learned metafaces for learning from the original images and then used it as the dictionary to represent the input query image in general framework of sparse representation based classification (SRC), in which the minimization is more convenient for learned metafaces to be more representative and efficient.

Such test is run 10 times and we take the average of the recognition rates for comparison. In addition to our proposed method, we also tested the UDP and KUDP methods. Figure 1 shows the rate of three typical algorithms (UDP, KUDP and CKUDP). Figure 2 shows the rate of three typical algorithms (UDP, KUDP and CKUDP) on the Bridgeman database in the standard experiment database.

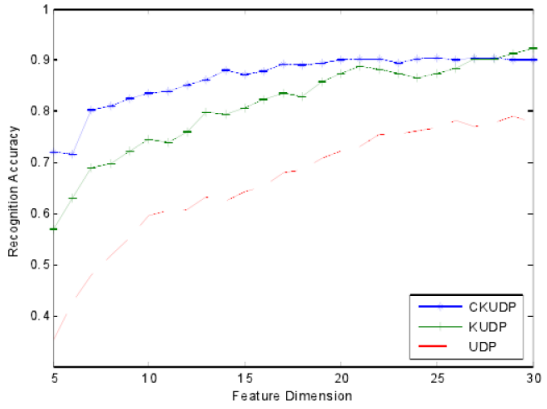


**Figure 1**. The rate of three typical algorithms (UDP, KUDP and CKUDP)

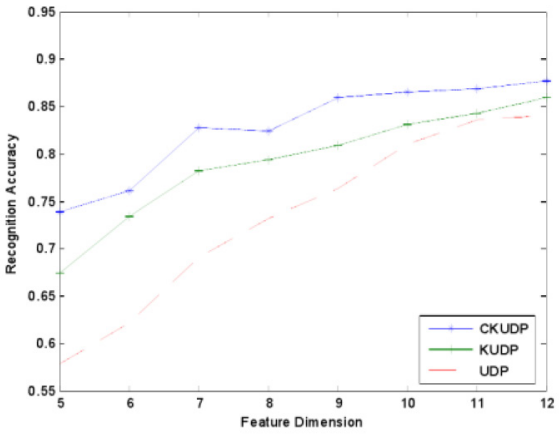


**Figure 2**. The rate of three typical algorithms (UDP, KUDP and CKUDP) on the Bridgeman database in the standard experiment database

Table 1 show the result on the mixed kernel function of Gaussian and Polynomial kernel function and Gaussian kernel on the Bridgeman database in the standard experiment database which can be seen from the following.

A great deal of research has shown that sparse representation based classification (SRC) is a powerful tool for face recognition. Sparse coding is an unsupervised learning algorithm that learns a concise high-level representation of the inputs, given only unlabeled data; representing each input as a sparse linear combination of a set of basic functions, whereas the importance of sparsity is greatly affirmed in SRC

**Table 1**. The result on the mixed kernel function of Gaussian and Polynomial kernel function and Gaussian kernel on the Bridgeman database in the standard experiment database

| | The mixed kernel function of Gaussian and Polynomial kernel function | | | | | Gaussian kernel | | | |
|---|---|---|---|---|---|---|---|---|---|
| $K$ | $\mu_K$ | $\alpha_K$ | $\theta_K$ | $\sigma_K$ | MSE | $\mu_K$ | $\sigma_K$ | $\theta_K$ | MSE |
| 1 | -0.0667 | 1.7524 | 1.9867 | 0.8439 | 0.038 | 0.095 | 1.4008 | 1.0494 | 0.0237 |
| 2 | -1.76E-04 | 0.0746 | 0.7134 | -0.0676 | 0.0332 | -4.7673 | 1.0517 | -0.2366 | 0.0201 |
| 3 | 0.8867 | 0.6558 | 0.0337 | 0.0022 | 0.0327 | 4.4735 | 0.6216 | -0.1999 | 0.0164 |
| 4 | -3.9484 | 0.669 | 0.5761 | 0.226 | 0.0282 | 7.451 | 0.9633 | 0.1676 | 0.0148 |
| 5 | -- | -- | -- | -- | -- | 0.1248 | 0.7153 | -0.0681 | 0.0144 |
| 6 | -- | -- | -- | -- | -- | -7.8283 | 0.6534 | -0.8148 | 0.014 |
| 7 | -- | -- | -- | -- | -- | 0.1888 | 0.1695 | -0.0013 | 0.0136 |
| 8 | -- | -- | -- | -- | -- | 1.1826 | -0.0164 | -0.0218 | 0.0131 |
| | Training error:0.0281 | | | | | Training error:0.0131 | | | |
| | Test error:0.0278 | | | | | Training error:0.0245 | | | |
| | Run time:3.326s | | | | | Training error:5.057s | | | |

and in abundant relevant research. Most researchers neglected the collaborative representation (CR) in SRC. In this chapter, a modified and efficient approach for face recognition is proposed, based on combining two of the most successful local face representations, collaborative representation based classification and regularized least square (CRCJ-ZLS) with bilateral filtering (BF). The combination of the two representations yields considerably better performance than either when elemental alone. Furthermore, experiments and their results show that the method proposed in this work outperforms several alternative methods.

**Conclusions**

In this paper, the author researched on the face recognition in color picture using the characteristic extraction based on the kernel algorithm. A variety of methods are proposed in the frame of the sparse representation and dictionary learning to improved algorithms, essentially, which is an extension for the sparse representation to study the problem of face recognition and under different conditions for imaging face.

The combination of the two representations yields considerably better performance than either when elemental alone. Furthermore, experiments and their results show that the method proposed in this work outperforms several alternative methods.

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