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Robust Face Recognition using Multi-Resolution Multi-Threshold Local Binary Patterns

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A B S T R A C T

Face recognition is a pivotal area of research, with various methodologies utilizing different types of information to improve recognition rates. This paper presents a novel approach for face recognition using Multi-Resolution Multi-Threshold Local Binary Patterns (MRMT-LBP) that emphasizes texture information extracted from grayscale images compared to color-based techniques. We propose a systematic generation of multiple threshold LBP representations with four distinct resolutions, resulting in a total of seventeen LBP layers, each corresponding to a different resolution. These layers are then employed to train a face recognition model. The model is constructed by first identifying the LBP layer that achieves the highest recognition rate, which serves as the first channel of our model. Subsequently, additional LBP layers are systematically integrated to form a second channel, with the best complementary layer selected based on its contribution to recognition performance. This iterative process continues until a decline in the recognition rate is observed, at which point the model is built. Comparative evaluations demonstrate that our approach not only achieves superior recognition rates compared to existing grayscale-based face recognition methods but also outperforms prominent color image-based techniques such as RGB and MCF color models. The results underscore the significance of leveraging grayscale images, revealing that the rich texture information they hold can be effectively enhanced to improve face recognition accuracy.

Keywords: *Face Recognition, Threshold Local Binary Patterns, Multi-resolution, grey images, train-based algorithm*

التعرف على الوجه اعتماداً على النمط الثنائي المحلي متعدد الدقة – متعدد المستويات

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الملخص

يعد التعرف على الوجوه مجالا بحثيا حيويا، حيث تتباين المناهج المستخدمة لتحسين نسب التعرف باعتماد أنواع مختلفة من المعلومات. تقدم هذه الدراسة طريقة جديدة للتعرف على الوجوه باستخدام النماذج الثنائية المحلية متعددة الدقة والمقياس(MRMT-LBP) ، مركزة على معلومات النسيج المستخرجة من الصور بالتدرج الرمادي مقارنة بتقنيات الألوان. نقترح توليدا منهجيا لتمثيلات متعددة المقياس بأربعة أحجام مختلفة، منتجة بذلك سبع عشرة طبقة من الـ(LBP)، كل منها تناظر دقة معينة. ثم تستخدم هذه الطبقات لتدريب نموذج التعرف على الوجوه .

يتم بناء النموذج بتحديد طبقة الـ (LBP)الأكثر فعالية في التعرف أولا، لتكون القناة الأولى لنموذجنا. ثم تضاف طبقات أخرى من الـ (LBP)بطريقة منهجية لتكون القناة الثانية، حيث يختار أفضل طبقة مكملة وفقا لدورها في تحسين الأداء. تستمر هذه العملية التكرارية حتى ملاحظة انخفاض في نسبة التعرف، عندها يتم تشكيل النموذج النهائي .

تظهر النتائج المقارنة أن طريقتنا لا تفوق فقط أساليب التعرف القائمة على التدرج الرمادي، بل تتجاوز أيضا تقنيات رائدة معتمدة على الصور الملونة كنماذج (RGB) و(MCF). تؤكد النتائج أهمية الاستفادة من الصور الرمادية، مبينة أن معلومات النسيج الغنية الموجودة فيها قادرة على تحسين دقة التعرف على الوجوه بشكل فعال.

الكلمات المفتاحية: *التعرف على الوجه، أنماط ثنائية محلية متعددة المستويات متعددة الدقة، الصور الرمادية، خوارزمية التدريب.*

1. Introduction

Face recognition technology has increasingly become a vital component across various applications, ranging from security systems to social media tagging. This rapid growth can be attributed to advancements in computer vision, machine learning, and artificial intelligence. Among various feature extraction methods, Local Binary Patterns (LBP) [1] [2] stand out due to their effectiveness in capturing texture information, which makes them particularly suitable for face recognition tasks. Traditional LBP focuses on thresholding pixel values to compute binary patterns, generating a simple yet powerful descriptor. However, face recognition continues to pose significant challenges, including variations in lighting, occlusions, and pose. In this paper, we propose a novel method that generates multiple levels of LBP combined with an innovative thresholding technique and different evolutions, enhancing the traditional LBP approach inspired by threshold LBP [3] and multi-resolution multiple color fusion (MMCF) [4]. By utilizing multiple levels of LBP, our method aims to capture features at various resolutions, providing a richer texture representation of facial images. Through the application of an advanced threshold mechanism, we enhance the robustness of the feature descriptor, making it less susceptible to common variations found in real-world scenarios. The proposed approach aims to bridge the gap between simplicity and complexity in face recognition. The integration of multi-resolution analysis allows for higher-dimensional feature representation, enabling our model to effectively discriminate between different faces even in challenging environments.

2. Literature Review

Face recognition technologies have evolved significantly over the past decades. Historical methods primarily employed geometric features and simple pixel-based analysis [5], which focused on landmark identification. However, these traditional techniques have limitations in handling variations that occur in the face due to ageing, facial expressions, and environmental factors. To address these challenges, texture-based methods, particularly those leveraging LBP [1], have gained prominence. The Local Binary Pattern provides a context-driven analysis of the local neighbourhood of an image pixel, allowing for the extraction of robust features resistant to monotonic changes in illumination. The efficacy of LBP has spurred a range of derivations and enhancements. For instance, the use of extended LBP variants that merge LBP with other descriptors like Histogram of Oriented Gradients (HOG) [6], leading to improved performance in recognizing faces under variable conditions. Furthermore, the Threshold LBP [3], where adaptive thresholds are used to create binary patterns, augmenting the discriminative power of the LBP. The findings indicated that the utilization of adaptive thresholding significantly benefits face recognition under differing lighting scenarios and occlusions, enhancing the robustness of the approach. Multi-resolution analysis has also been introduced in recent years to further boost the discriminative ability of facial representations.

With regard to color information, the Multi-Resolution Multiple Color Fusion (MMCF) [4] technique is instrumental in effectively combining information across color channels to create a comprehensive feature map. This method strategically decomposes facial images into various color domains, enhancing the ability to capture intrinsic facial characteristics. In conclusion, the existing body of literature highlights the necessity for adaptive and robust methods in face recognition, particularly in addressing challenges posed by changing environmental conditions and image variations. The proposed research builds upon these foundational approaches by integrating multiple levels of LBP with advanced thresholding techniques and multi-resolution color fusion, aiming to deliver a new methodology that enhances the fidelity and accuracy of face recognition systems in real-world applications. Hereafter, we will introduce both TLBP and MMCF in some detail.

2.1 Threshold Local Binary Pattern (TLBP)

Threshold Local Binary Pattern (TLBP) [3] is an extension of the traditional Local Binary Pattern (LBP), designed to enhance texture classification by introducing a more flexible thresholding mechanism. Unlike the standard LBP, which uses the intensity of the central pixel as a strict threshold for comparing neighboring pixels, TLBP introduces a user-defined or adaptively determined threshold value. This threshold allows for a tolerance in intensity differences, thereby increasing robustness to noise and illumination variations.

Firstly, we need to express the generation of LBP values for a given pixel, which can be computed as follows:

The binary value bi for each neighbouring pixel is obtained as follows:

$$bi = \begin{cases} 0 & p - zi < 0 \\ 1 & p - zi \geq 0 \end{cases}, \text{where } i = 0 \dots 7 \qquad (1)$$

And then, the LBP value of the central pixel is computed as follows:

$$LBP(x, y) = \sum_{i=0}^{i=7} (2 \times bi)^{i} \qquad (2)$$

Where:

- bi is the binary value of each neighbouring pixel.
- p is the central pixel value.
- zi is the value of i^{th} neighbouring pixel.

An example is shown in Figure 1.

g_0	g_1	g_2
g_7	g_c	g_3
g_6	g_5	g_4

31	199	93
121	120	220
218	3	127

0	1	0
1	g_c	1
1	0	1

LBP = (01011011) = 91 gc =91

Figure 1 The LBP encoding process

In TLBP, for a given central pixel, each neighboring pixel's intensity is compared to the central pixel's intensity using a threshold T. The binary code is generated according to the following equation:

$$bi = \begin{cases} 0 & p - zi < t \\ 1 & p - zi \geq t \end{cases}, \text{were } i = 0 \dots 7 \qquad (3)$$

In TLBP model, only two channels of TLBP are used to represent the face images, which are: t=0, and t=5.

2.2 Multi-resolution, Multiple Color Fusion (MMCF) Model for Face Recognition

The Multi-resolution, Multiple Color Fusion (MMCF) [4] model is an advanced approach designed to enhance the accuracy and robustness of face recognition systems. This model leverages two key strategies: multi-resolution analysis and color space fusion, to extract rich and discriminative facial features.

In the multi-resolution component, images are processed at different scales or resolutions to capture both global and local facial characteristics. This approach helps in dealing with variations in image quality, pose, and facial expressions by ensuring that features at various granularities are utilized.

The multiple color fusion component integrates information from different color spaces (such as RGB, YCbCr, and HSV) [7] to improve feature representation. Each color space emphasizes different aspects of the image, and their fusion leads to a more comprehensive and robust feature set. The fusion can be performed at the feature level or score level. By combining these two strategies, the MMCF model significantly improves recognition performance, especially in challenging environments with varying pose angles, occlusions, and facial expressions. The model is particularly suitable for real-world applications such as surveillance, access control, and identity verification systems.

The step-by-step algorithm can be expressed as follows:

1. Given a training testing face dataset in RGB format: convert each image in the dataset into different color spaces, for instance: XYZ, HSV, YIQ, I1I2I3, nRGB
2. From different color spaces, remove any identical and/or highly correlated color channels.
3. By resizing each image into 4 different sizes, we gain multi-resolution for each color channel.
4. Train each color channel separately for face recognition. And select the channel/resolution with the highest recognition rate as the first component of MMCF model.
5. Append all remaining color channels/resolution to the first channel of the model and train the different combinations separately for face recognition, and select the best complementary as the second channel of the model.
6. Repeat the previous step until the recognition rate starts to decrease.
7. Use the model to represent any train/query image for the face recognition task.

In our work, we use the idea of MMCF model by utilizing different channel/resolutions, as well as the training process, with the difference of using TLBP channels in our model instead of color channels in MMCF model.

3. Proposed method: Multi-Resolution Multi-Threshold Local Binary Pattern (MRMT-LBP)

Our proposed method for face recognition utilizing multi-resolution multi-threshold Local Binary Patterns (LBP) is both innovative and significant for several reasons, primarily, its ability to extract valuable texture information from faces at different levels of resolution and thresholding.

3.1. Significance of the Proposed Method

3.1.1.Enhanced Texture Representation: By creating multiple layers of LBP, each representing different thresholds and levels of detail, the proposed method allows for a more comprehensive understanding of facial textures. This is critical as facial recognition relies heavily on subtle differences in textures that can be pivotal in distinguishing between individuals.

3.1.2. Multi-Resolution Analysis: Utilizing images at various resolutions enables the model to capture details that may be present in some scales but are lost in others. This is particularly important in real-world applications where images may not always be of high clarity or may be taken from different distances.

3.1.3. Adaptive Learning: The method's iterative selection of channels based on recognition rates ensures that the model remains flexible and adaptive. By evaluating performance at each stage, we are effectively conducting feature selection, which enhances model accuracy.

3.1.4. Robustness to Variability: Faces can exhibit significant variability due to changes in lighting, expressions, or orientation. By incorporating layers with different thresholds and resolutions, the model is likely to be more robust against such changes, further improving its accuracy in practical applications.

3.2. Algorithm

- **Image transformation**

1. **Creating 16 Levels of LBP:** For each grayscale image, compute 16 unique LBP patterns using a threshold range from -15 to 15 (with a step of 2) according to Eq. 3 and Eq. 2, where t=-15 -13 ……-1 1 …… 13 15, resulting in a total of 18 layers when the original grey image is included.
2. **Resizing Each Layer: Resize each of the** 17 LBP images into four different resolutions: 32×32, 24×24, 16×16, and 12×12 pixels. This will accommodate different scales of facial features.

- **Training phase**

1. **Layer Training: -** For each LBP layer, train the model for face recognition using the images at different resolutions. Select the layer and resolution that result in the highest recognition rate as the first channel of the model.
2. **Selecting Complementary Layers**: Append other LBP layers of different resolutions to the first channel, one at a time. After training each new combination, evaluate the recognition rate and determine the best complementary layer that best enhances performance.
3. **Iteration**: Repeat step four until the recognition rate starts to decrease, indicating that adding further layers may no longer contribute positively to the model's performance.

The resultant proposed model may vary based on the training/testing dataset, feature selection method, and the face recognizer. As we will show later in the experiments, our model consists of nine TLBP layers with variant resolution for each layer. Figure 2 shows the appearance of 16 layers of TLBP.

Figure 2 16 layers of TLBP

3.3. Face Recognition

For face recognition: Convert all test and training face images into the format of the proposed model (consisting of the selected channels). Apply the trained face recognition model to classify the test

Table 1 Building up the proposed model using PCA

layer No.	Size	Rate	TLBP
10	16	96.49123	3
8	16	97.58772	-1
17	12	97.80702	Gray
13	16	98.02632	9
14	16	98.46491	11
7	12	98.46491	-3
1	12	98.46491	-15

images based on learned texture patterns.

Our proposed approach not only builds on the foundational concepts of LBP but enhances them significantly by incorporating multi-resolution analysis and adaptive learning strategies. This method holds promise for advancing face recognition in both accuracy and robustness, making it a valuable contribution to the field. As we will show later in the experiments, our model is effective and robust in Face Recognition compared with different grey and color-based models.

In developing our proposed face recognition model, we employed Principal Component Analysis (PCA) [8] as the foundational training technique. For performance evaluation, we utilized Regularized Linear Discriminant Analysis (RLDA) [9] [10] and Sparse Representation-based Classification (SRC) [11] [12]. As demonstrated in the experimental section, our model outperformed several color and grayscale-based models, achieving a notably high recognition rate.

4. Experimental Results

To assess the effectiveness of the proposed Multi-Resolution Multi-threshold Local Binary Patterns (MR-MTLBP) method for face recognition, a comprehensive set of experiments was conducted on several benchmark face databases. These include the AR_Curtin dataset (a combination of AR and Curtin face databases) [13] [14], GT[15], LFW [16], and FRGC [17]. The experiments were designed to evaluate performance comparing with some gray-scale and color models using various classifiers including Linear Discriminant Analysis (LDA) [9], and Sparse Representation Classifier (SRC) [11].

4.1 Building the proposed model

To build up our proposed model, MR-MT-LBP (Multi-Resolution, Multi-Threshold Local Binary Patterns), we trained the model using a PCA classifier on the AR-Curtin face dataset. During the training phase, we used the first six images of each subject, where the first three images served as the gallery set and the remaining three as the test set. As illustrated in Table 1, the recognition accuracy plateaued at 98.46%, indicating the optimal configuration of our model. Consequently, the final model comprises the following components: TLBP 3 at resolution 16, TLBB -1 at resolution 16, a grayscale image at resolution 12, TLBB 9 at resolution 16, and TLBB 11 at resolution 16. This optimized model will be employed in subsequent face recognition tasks.

4.2 Experiment 1: Comparison with Grayscale-Based Methods

The performance of MRT-MTLBP was first compared against conventional grayscale-based face recognition methods, including standard grayscale images, Local Binary Patterns (LBP), and Threshold LBP (TLBP). Experimental results demonstrated that MR-MTLBP significantly outperforms these baseline methods. On all tested datasets, our method achieved an accuracy improvement ranging from 12% to 22% when using LDA and SRC. This substantial gain indicates the advantage of combining multi-resolution and multi-threshold encoding in representing facial textures and structures in grayscale images. Table 2 shows detailed results.

Table 2. Face Recognition using MR-TLBP in comparison with various gray image representations, applied on four face datasets

Db	Met	Img	Sub	Im/sub	REF	Test	LBP	TLPB	Gray	Pro
AR-CR	LDA	1216	152	8	6	2	48.36	78.61	62.82	93.09
	SRC	1216	152	8	6	2	63.16	78.94	84.54	96.71
GT	LDA	750	50	15	7	8	43.75	55.25	65	87.05
	SRC	750	50	15	7	8	43.25	54.75	66.75	83.15
LFW	LDA	850	85	10	9	1	10.58	21.17	33.97	39.06
	SRC	850	85	10	9	1	12.94	28.24	42.35	62.82
FRGC	LDA	7992	222	36	8	28	69.07	55.40	74.69	93.71
	SRC	7992	222	36	8	28	81.08	80.13	81.35	97.52

Table 3. Results of proposed models in comparison with RGB and MCF models using SRC classifier

Database	No of Img	Sub	Im / Sub	REF	TEST	Proposed Model	reported results rates		
						Rate	RGB	MCF	Rep
AR_Crutin	1216	152	8	6	2	96.71	89.67	93.09	
GT	750	50	15	7	8	83.15	75.85	81.90	5
LFW	850	85	10	9	1	62.82	54.24	60.35	5

4.3 Experiment 2: Comparison with Color Image-Based Methods

To further validate the effectiveness of our approach, we compared MR-MTLBP with color-based face recognition techniques, specifically RGB image representation and Multiple Color Fusion (MCF) [18]. These experiments were conducted primarily on the AR-CURTIN, GT and LFW datasets using the Sparse Representation Classifier (SRC).

On the AR_CURTIN dataset, our method achieved 96.71% outperforming both RGB and MCF by 7.04% and 3.62% respectively. On the GT dataset, MRT-MTLBP achieved an accuracy of 83.0%, surpassing both RGB (75.8%) and MCF (81.9%). On the LFW dataset, MRT-MTLBP obtained a recognition accuracy of 62.8%, compared to 54.2% for RGB and 60.3% for MCF. This demonstrates that MRT-MTLBP not only outperforms RGB-based methods by approximately 7% but also exceeds MCF by at least 3%, establishing its superior ability to capture discriminative texture information rather than color information. Detailed results are shown in Table 3.

4.4 Summary of Experimental Findings

In summary, the proposed MRT-MTLBP method consistently delivers superior performance compared to both grayscale and color image-based face recognition techniques. Its robust multi-resolution and multi-threshold design enables enhanced feature representation, leading to higher recognition accuracy across multiple challenging face databases.

5. Conclusions and future work

In this research, we explored the effectiveness of utilizing Multi-Resolution Multi-Threshold Local Binary Patterns (LBP) for face recognition, specifically contrasting texture information derived from grey images against conventional color information. Through our method of generating a comprehensive set of 17 LBP layers, each holds four resolutions, we established a systematic approach to select the most effective features for improving recognition accuracy. Our findings indicate that grey images hold substantial and underutilized texture information that significantly contributes to face recognition tasks. By training our model on the generated LBP layers, we successfully identified the layer that achieved the highest recognition rate, subsequently adding complementary layers in a controlled manner until diminishing returns were noted in recognition accuracy. This iterative process led to the construction of a robust face recognition model that markedly outperformed several existing grey-based techniques. Furthermore, it surpassed strong colour-image-based methods, such as the MCF model, underscoring the potential of grey images in facial recognition applications. Given the superiority demonstrated by our model, it is evident that the exploitation of texture information through multi-resolution LBP can provide significant advantages in face recognition scenarios. Future research will focus on enhancing the feature selection process by employing more sophisticated search algorithms, including genetic algorithms. Additionally, we plan to extend the utility of our model to face sketch recognition, further demonstrating the versatility and robustness of our approach. In summary, this study not only highlights the effectiveness of utilizing grey images for face recognition but also opens avenues for future research that could enrich the field and improve existing methodologies.

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