

An Adaptive Weighted Face Recognition Method Fusing Block-based LBP and Global Pixel Intensity Features

Shangsong Chen¹, Jianqiang Gao^{1*}, Li Li^{1*}, Xiu Liu²

¹*School of Medical Information Engineering, Jining Medical University, Rizhao 276800, Shandong, China*

²*Department of Ultrasound Medicine, Yantai Affiliated Hospital of Shandong Medical and Pharmaceutical University, Yantai 264100, Shandong, China*

ABSTRACT: To address the limitation that pure block-based LBP features ignore global intensity distribution in face recognition, this paper proposes an adaptively weighted fusion method that combines block-based LBP texture features with global pixel intensity features. First, the face image is divided into multiple sub-blocks to extract LBP texture histograms, while the image is simultaneously downsampled to a low-resolution global feature of 30×30 pixels to capture the overall intensity distribution. A tunable fusion weight α is introduced to attenuate the global feature, and α is automatically determined as a hyperparameter through cross-validation. Experimental results on three public face databases—ORL, Yale, and Extended Yale B—demonstrate that the proposed method achieves or exceeds the pure LBP baseline under all block partition schemes. Under extreme illumination conditions on Yale B with 2×2 partitioning, the fusion method significantly improves accuracy from 53.18% to 93.92%, an enhancement of over 40 percentage points. The optimal fusion weight α consistently falls within the minimal range of 0.005-0.05, validating the core hypothesis that global intensity features should serve an auxiliary role in the fusion process. This work provides new insights and experimental evidence for the complementary fusion of local texture and global intensity information.

KEYWORDS - Face recognition, Local Binary Pattern, Block-based LBP, Global pixel feature, Feature fusion, Adaptive weight

I. INTRODUCTION

Local Binary Pattern (LBP) [1] is a classical texture descriptor that encodes local texture via pixel-wise grey-level comparisons. Ahonen et al. [2] demonstrated the effectiveness of block-wise LBP histogram concatenation. However, LBP relies solely on ordinal intensity relations; under extreme lighting, its comparative logic is severely corrupted and discriminative power diminishes. Although deep learning-based methods such as FaceNet [6] and DeepFace [7] have achieved superior accuracy on large-scale datasets, their heavy dependence on massive training data and high computational resources limits their deployment in small-sample or edge-computing scenarios. Feature fusion is a

common strategy to combine complementary information sources. Previous fusion methods often require complex feature extraction steps, and manual or equal-weight fusion lacks data-driven adaptability.

In this paper, we propose a concise method using the down sampled original image as global pixel intensity features, complementary to block LBP features. The extraction is highly efficient (only scaling and normalization). An adaptive weight selection mechanism automatically determines the optimal fusion ratio via cross-validation, avoiding subjective preset weights.

II. INTRODUCTION TO EXISTING METHODS

2.1 LBP Operator

For a center pixel I_{center} and P neighboring pixels I_n , the LBP code is given by:

$$\text{LBP}(I_{\text{center}}) = \sum_{n=0}^{P-1} s(I_n - I_{\text{center}}) \cdot 2^n \quad (1)$$

Where $s(x) = 1$ if $x \geq 0$, otherwise 0 . By counting the frequency distribution of LBP codes in sub-blocks, texture histograms are obtained. Uniform patterns and rotation invariance are often used to reduce dimensionality and enhance

2.2 Principal Component Analysis (PCA)

PCA is a linear dimensionality reduction method [3] that projects high-dimensional data onto a lower-dimensional subspace while retaining maximal variance. In this paper, PCA is applied to remove redundancy in the fused feature vectors, retaining 95 % cumulative variance contribution.

2.3 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised classification algorithm [8] that finds an optimal hyperplane that maximizes the margin between classes. We adopt the RBF kernel, with kernel parameters C and γ automatically optimized via grid search and 5-fold cross-validation on the training set.

III. IMPROVING METHODS

3.1 Block LBP feature extraction

The face image is uniformly divided into $m \times n$ non-overlapping sub-blocks. For each sub-block, a 256-dimensional LBP histogram is extracted. All histograms are L1-normalized and concatenated sequentially to form a global texture feature vector with dimension $d_{\text{lbp}} = m \times n \times 256$. Four block schemes ($2 \times 2, 3 \times 3, 4 \times 4, 5 \times 5$) are tested to analyze the impact of granularity.

3.2 Global pixel feature extraction

To capture the global intensity distribution, the original grayscale image is downsampled to $30 \times$

30 pixels via bilinear interpolation. This operation filters out high-frequency textures and retains low-frequency light/dark contours. The 30×30 matrix is vectorized into a 900-dimensional vector and normalized to $[0,1]$. Pre-experiments indicated that 30×30 achieves the best balance between accuracy and dimension (ORL accuracy 98.5 %, dim 900) compared to 20×20 (97.2 %) and 40×40 (98.3%, dim 1600).

3.3 Adaptive weighted fusion strategy

The two sets of features are fused at the feature level. Let F_{lbp} be the block LBP feature, and F_{global} be the global pixel feature. The fused feature F_{fused} is defined as:

$$\alpha^* = \operatorname{argmax}_{\alpha \in \mathcal{A}} \left[\frac{1}{K} \sum_{k=1}^K \text{Acc}(F_{\text{val}}^{(k)}(\alpha), T_{\text{val}}^{(k)}) \right] \quad (1)$$

$$F_{\text{fused}} = [F_{\text{LBP}}, \alpha^* F_{\text{global}}] \quad (2)$$

$F_{\text{val}}^{(k)}$: Using the current candidate weight α , the fused feature vector is constructed on the KTH fold validation set. $T_{\text{val}}^{(k)}$: The true label of the KTH fold validation set. Where $\alpha \in [0,1]$ is the fusion weight. When $\alpha = 0$, it degenerates to pure LBP; when $\alpha = 1$, direct concatenation (equal weights). The optimal α is automatically selected from candidate set $\{0, 0.001, 0.005, 0.01, 0.05, 0.1, 0.15, 0.2, 0.3, 0.5, 0.7, 1\}$ via cross-validation, ensuring the global feature plays an auxiliary rather than dominant role.

3.4 Overall process of the system

(1) Preprocess images to uniform 112×92 pixels. (2) Extract two-channel complementary features: block-wise LBP histograms and downsampled global pixel vector. (3) Apply adaptive weighted fusion to obtain F_{fused} . (4) Reduce dimension via PCA (95% variance) and classify using RBF-SVM. The framework is illustrated in Figure 1.

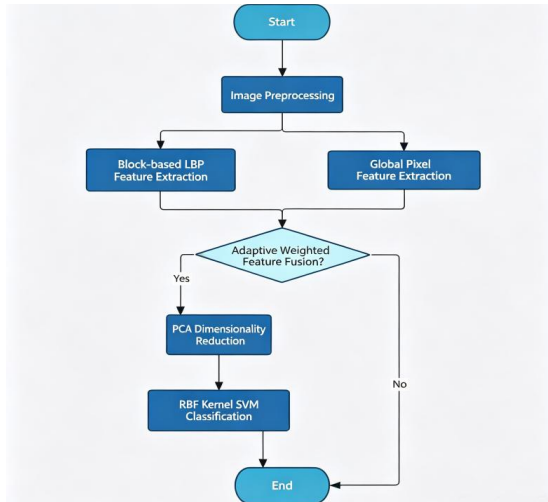


Figure 1. Flowchart.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Experimental Setup

Datasets: (1) ORL:40 subjects, 10 images each (400 total), 92×112 pixels. Variations in expression and pose. (2) Yale: 15 subjects, 11 images each (165 total), 100×100 pixels. Focus on expression variation. (3) Extended Yale B: 38 subjects, ~64 images each (2414 total), 192×168 pixels. Acquired under 64 illumination conditions, ideal for evaluating robustness against severe illumination changes.

Evaluation: Stratified 10-fold cross-validation is performed. The final metric is average accuracy and standard deviation. A nested validation framework is used: outer 10-fold for performance evaluation, inner 5-fold for hyperparameter tuning. Grid search is used for SVM parameters $C \in \{0.1, 1, 10, 100\}$, $\gamma \in \{0.001, 0.01, 0.1, 1\}$. The optimal α is determined on the training set.

4.2 Selection and analysis of fusion weights

Figure 2 shows the α -accuracy curve on the YaleB dataset under 2×2 blocks. This condition is chosen because the pure LBP baseline is only 53.18%, leaving sufficient room for improvement from global features. The curve exhibits four stages:

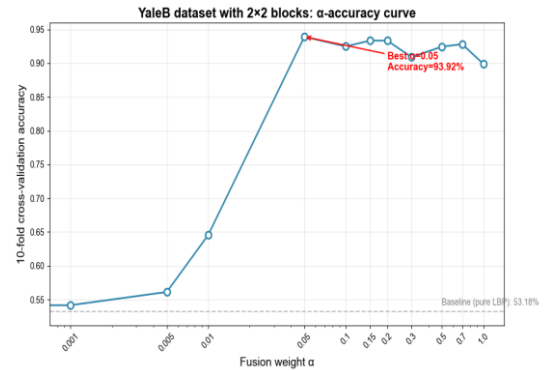


Figure 2. α -accuracy curve under 2×2 blocks of YaleB dataset

(1) Low weight stage ($\alpha = 0.001 \sim 0.01$): Minimal improvement (accuracy rises to 64.6% at $\alpha = 0.01$).

(2) Fast jump stage ($\alpha = 0.01 \sim 0.05$): Accuracy sharply climbs to 93.92%. The global features start to complement the degraded LBP features at sufficient intensity.

(3) High-bit stable stage ($\alpha = 0.05 \sim 0.7$): Accuracy stays above 91.0%, indicating robustness to parameter choice.

(4) Slight decline stage ($\alpha = 0.7 \sim 1.0$): Accuracy drops to 89.9% at $\alpha = 1$, but still far exceeds the pure LBP baseline. This confirms that global features should participate in an auxiliary role ($\alpha = 0.05$ is optimal).

4.3 Joint optimization of blocking strategy and weights

Figure 3 illustrates the accuracy improvements of the fusion method over pure LBP baseline on the three datasets.

(1) Significant improvement on YaleB under 2×2 : Accuracy jumps from 53.18% to 93.92% (+40.74%). Coarse-grained LBP nearly fails under extreme illumination, and global features reconstruct crucial inter-class boundaries.

(2) Decreasing gain with finer blocks: On Yale, the improvement drops from 3.57 points (2×2) to 0 (3×3). On YaleB, improvement drops from 40.74

to 1.18 points (3×3). With finer blocks, LBP becomes self-sufficient, making global features redundant.

(3) Small but stable gain on ORL: All block schemes yield 0.2% – 0.5% improvements. Under 3×3 , ORL achieves a perfect 100% accuracy, demonstrating that global features are at least harmless and can provide marginal benefits even when the baseline is high.

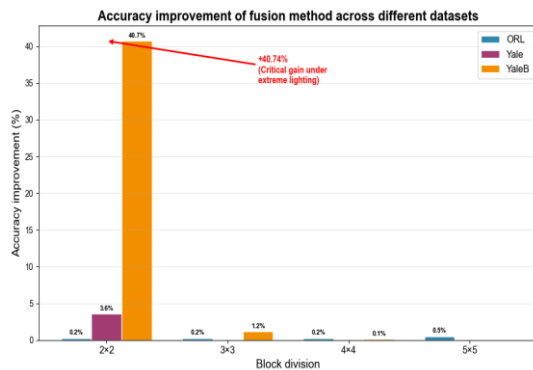


Figure 3. Accuracy improvement on three datasets under different block schemes.

Figure 4 shows the optimal α values:

- (1) Optimal α is always minimal: In all non-zero cases, α ranges between 0.005 and 0.10.
- (2) High stability on YaleB: For $2 \times 2, 3 \times 3, 4 \times 4$, optimal $\alpha = 0.05$ consistently, showing robustness to block
- (3) Increasing α with finer blocks on ORL: α increases from 0.005 ($2 \times 2, 3 \times 3$) to 0.05 (4×4) and 0.10 (5×5). This is because fine-grained LBP loses spatial structural relations; slightly increasing α compensates for this gap.
- (4) $\alpha = 0$ cases: On Yale ($\geq 3 \times 3$) and YaleB (5×5), pure LBP is already sufficient. The cross-validation conservatively selects $\alpha = 0$ when no clear benefit exists.

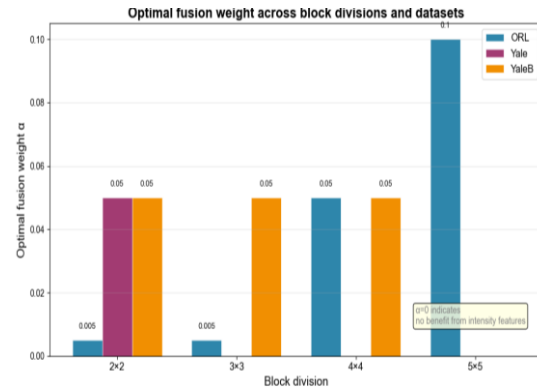


Figure 4. Optimal fusion weights of different datasets under various blocking modes.

Table 1 quantitatively presents the ORL data set results. It reveals two key insights. First, while finer blocks like ($5, 5$) significantly increase the LBP feature dimension to 6400, the best performance is achieved by the ($3, 3$) partition, which reaches a perfect 100% accuracy with only 2304 dimensions. Second, the optimal α increases as the partition becomes finer, rising from 0.005 to 0.1. This suggests that fine-grained LBP features require a slightly stronger contribution from global intensity features to compensate for the loss of spatial structure information. The minimal accuracy improvements (+0.0025 to +0.0050) confirm that on the ORL dataset, the global features play a marginal but consistently positive auxiliary role.

Table 1. Detailed quantitative results of the fusion method on the ORL data set.

Block	LBP dimension	Baseline ($\alpha=0$)	Best α	Fused Acc	Boost
(2,2)	1024	0.9950	0.005	0.9975	+0.0025
(3,3)	2304	0.9975	0.005	1.0000	+0.0025
(4,4)	4096	0.9950	0.05	0.9975	+0.0025

Bloc k	LB P di m	Baseli ne ($\alpha=0$)	Best α	Fuse d Acc	Boost
(5,5)	640 0	0.9850	0.1	0.99 00	+0.00 50

4.4 Confusion matrix analysis

Figure 5 compares cumulative confusion matrices on YaleB under 2×2 blocks.

(1) Pure LBP (left): Diagonal elements are faint, off-diagonal areas are dense. The accuracy is only 53.18%, indicating severe misclassification.

(2) Fusion method (right): Diagonal elements are intensely dark, off-diagonal regions are clean. Accuracy reaches 93.92%. The comparison visually confirms the method effectively restores classification capability under extreme illumination.

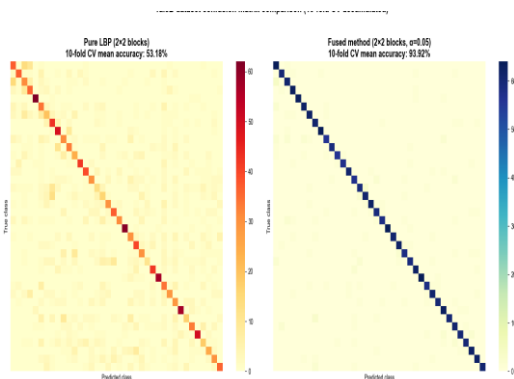


Figure 5. Comparison of cumulative confusion matrices for YaleB dataset.

4.5. Cross-Dataset Analysis

(1) Auxiliary role of global features: Optimal α consistently stays within 0.005-0.10. The four-stage α -accuracy curve on YaleB proves global features must serve a supporting, not dominant, role.

(2) Inverse relationship between LBP discriminability and feature value: The higher the pure LBP baseline, the less improvement global

features provide (from 40+ points on YaleB 2×2 down to 0 on Yale 3×3).

(3) Impact of block granularity: Coarse-grained blocks (2×2) have weaker LBP features, leaving larger complementary space for global features ($\alpha=0.05$). Fine-grained blocks (5×5) make LBP self-sufficient, pushing α toward 0. ORL shows an exception: under mild lighting, finer blocks require slightly higher α to compensate for lost spatial structure.

4.6. Summary

Extensive experiments on ORL, Yale, and Extended Yale B show the proposed method achieves or exceeds pure LBP accuracy under all partition schemes. Under YaleB extreme illumination, accuracy improved from 53.18% to 93.92%. ORL achieved 100% accuracy under 3×3 blocks. The optimal α consistently lies in the minimal range 0.005 – 0.10. The confusion matrix comparison confirms the method's advantage in suppressing cross-class confusion caused by illumination.

V. SUMMARY AND PROSPECT

5.1 Summary of Work

This paper proposes a lightweight adaptive weighted face recognition method combining block-based LBP and global pixel intensity features. We design a simple two-channel scheme (texture and intensity) and introduce a data-driven adaptive fusion weight α to balance them. Extensive experiments on ORL, Yale, and YaleB verify that optimal α is always in the minimal range (0.005-0.10), confirming global features serve only an auxiliary role. The inverse correlation between LBP discriminative power and fusion improvement reveals the dynamic relationship among block granularity, fusion weight, and performance.

5.2 Future Perspectives

Future work will explore (1) multi-scale global features to enrich intensity information, (2) dynamic weights adjusted based on lighting quality assessment, and (3) non-uniform blocking strategies to allocate finer blocks to key facial regions (eyes,

nose, mouth). Additionally, validation on larger datasets with occlusions (e.g., AR dataset) and integration of this interpretable mechanism with deep learning frameworks will be investigated.

VI. Acknowledgements

This work is partly supported by the Education Project of Industry University Cooperation of the Ministry of Education under Grant No. 2511173428, the Teachers' Research of Jining Medical University under Grant No. JYFC2019KJ014, and the Doctoral Research Foundation of Jining Medical University under Grant No. 2018JYQD03, China. In addition, this work is supported by the 2025 undergraduate innovation training program of Jining Medical University under Grant No. cx2025121, China.

REFERENCES

- [1] T. Ojala, M. Pietikainen and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, July 2002, doi: 10.1109/TPAMI.2002.1017623.
- [2] T. Ahonen, A. Hadid and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 12, pp. 2037-2041, Dec. 2006, doi: 10.1109/TPAMI.2006.244.
- [3] Matthew Turk and Alex Pentland. 1991. Eigenfaces for recognition. *J. Cognitive Neuroscience* 3, 1 (Winter 1991), 71 - 86. <https://doi.org/10.1162/jocn.1991.3.1.71>
- [4] P. N. Belhumeur, J. P. Hespanha and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, July 1997, doi: 10.1109/34.598228.
- [5] A. S. Georgiades, P. N. Belhumeur and D. J. Kriegman, "From few to many: illumination cone models for face recognition under variable lighting and pose," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 23, no. 6, pp. 643-660, June 2001, doi: 10.1109/34.927464.
- [6] F. Schroff, D. Kalenichenko and J. Philbin, "FaceNet: A unified embedding for face recognition and clustering," 2015 *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA, 2015, pp. 815-823, doi: 10.1109/CVPR.2015.7298682.
- [7] Y. Taigman, M. Yang, M. Ranzato and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," 2014 *IEEE Conference on Computer Vision and Pattern Recognition*, Columbus, OH, USA, 2014, pp. 1701-1708, doi: 10.1109/CVPR.2014.220.
- [8] V. N. Vapnik, "Statistical Learning Theory," John Wiley & Sons, 1998.
- [9] N. Zhou, R. Liang and W. Shi, "A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection," in *IEEE Access*, vol. 9, pp. 5573-5584, 2021, doi: 10.1109/ACCESS.2020.3046715.