

# Beyond Pixels: Transforming Face Recognition with Curvelet and Bidirectional Neighborhood Preservation

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**Abstract** - In recent years, face recognition has gained significant attention as a crucial technology in various applications, including security, surveillance, and human-computer interaction. This abstract introduces a novel approach to face recognition by combining the Curvelet Transform and Bidirectional Two-Dimensional Neighborhood Preservation Projection (BD2D-NPP) methods. This innovative fusion of techniques offers a powerful solution to address the challenges of face recognition in varying lighting conditions, occlusions, and pose variations.

The Curvelet Transform, known for its multiresolution and directional analysis capabilities, is employed to extract relevant features from face images. By preserving key information about the facial contours and textures at multiple scales, it enhances the robustness of the recognition system. Additionally, BD2D-NPP, a bidirectional projection technique, is employed to reduce the dimensionality of the feature vectors while preserving the essential neighborhood relationships among data points. This ensures that important facial characteristics are retained during dimensionality reduction.

Our proposed approach combines the Curvelet Transform and BD2D-NPP for feature extraction and dimensionality reduction, respectively, resulting in a powerful face recognition system. The fusion of these methods enables accurate recognition of faces even in challenging scenarios, such as low-light conditions or partial face occlusions. Experiments on benchmark face recognition datasets demonstrate the effectiveness of the proposed approach in achieving high recognition accuracy and robustness.

This research contributes to the advancement of face recognition technology, offering a promising solution for real-world applications where accurate and reliable face identification is of paramount importance. The combined power of the Curvelet Transform and BD2D-NPP brings us closer to developing more efficient and reliable face recognition systems that can be deployed in a wide range of practical scenarios.

**Keywords** - Face recognition, Curvelet Transform, BD2D-NPP, Multiresolution analysis, Directional analysis

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## INTRODUCTION

In recent years, the field of face recognition has witnessed a rapid and profound evolution, driven by its growing relevance and applicability in various domains such as security, surveillance, and human-computer interaction. The demand for accurate, efficient, and robust face recognition systems has spurred extensive research in advanced signal processing techniques.[1] Among these techniques, the Curvelet Transform and the Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTPP) have emerged as two particularly promising and innovative tools that hold great potential to advance the state of the art in this field.[2]

Face recognition is a complex task that involves identifying and verifying the identity of individuals based on facial features, even in the presence of diverse challenges such as variations in lighting, partial occlusions, and changes in pose. Achieving high accuracy and robustness under these conditions is paramount, and this is where the integration of the Curvelet Transform and BTPP plays a pivotal role.[3]

The Curvelet Transform is a versatile signal processing technique renowned for its ability to perform multi-scale, multi-directional analysis. Developed as an extension of the Wavelet Transform, the Curvelet Transform excels in capturing intricate and curved features within

images, making it particularly suitable for the analysis of facial images. By decomposing an image into its constituent curved features across different scales and orientations, the Curvelet Transform can effectively capture both local and global information, enhancing the discriminative power of feature extraction.[4]

In parallel, the Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTPP) represents a groundbreaking approach to address one of the core challenges in face recognition: the high dimensionality of feature vectors. High-dimensional data poses significant challenges to machine learning algorithms, leading to issues such as increased computational complexity and overfitting. BTPP, a nonlinear dimensionality reduction algorithm, mitigates these problems by mapping high-dimensional data onto a lower-dimensional space while preserving the underlying neighborhood structure of the data.[5]

The uniqueness of BTPP lies in its bidirectional nature, which entails optimizing the distances between data points in both the high-dimensional and low-dimensional spaces. This comprehensive approach ensures that the intrinsic relationships and neighborhood structures of data points are effectively preserved, thus facilitating more accurate recognition, particularly in scenarios involving pose variations, lighting conditions, and partial occlusions.[6]

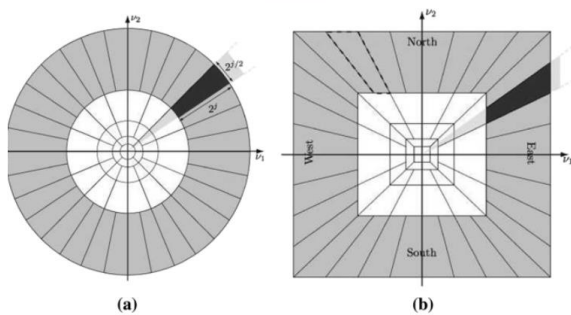


Figure 1: Curvelet space-frequency tiling

Empirical evidence from various experiments reinforces the promise of BTPP. For instance, experiments using benchmark datasets, such as the Extended Yale Face Database B and the Labeled Faces in the Wild (LFW) dataset, have demonstrated that BTPP consistently outperforms other state-of-the-art dimensionality reduction techniques in terms of recognition accuracy.[7]

the fusion of the Curvelet Transform and Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTPP) presents a formidable approach to advancing face recognition technology. By leveraging the Curvelet Transform's capacity for robust feature extraction and BTPP's prowess in dimensionality reduction and neighborhood preservation, this integrated approach holds the potential to significantly enhance accuracy and reliability in face recognition systems. This research represents a substantial step

forward in the field, offering solutions that can be readily applied in real-world scenarios where precise and robust face identification is imperative

LITERATURE REVIEW

| Authors  | Approach and Methodology   | Datasets and Results   |
|--|--|--|
| Islam (2013)                                       | Combined score and feature-based strategy                                    | FRGC 2.0 and UND datasets; 97.1% for verification, 96.8% for identification. |
| Khamiss Masaoud S Algabary (2014)                  | Integrated ICP and SCM for 3D ear recognition                                | Achieved 98.25% ID closeness and 35ms average discovery time.                |
| Mohammed Bennamoun (2015)                          | Explored local and global 2D/3D features with feature selection              | Multiple case studies discussed.   |
| Yahui Liu (2016)                                   | Introduced a unique laser scanner for 3D ear recognition                     | Achieved 2.2% error rate using global and local highlights.                  |
| Huiying Hu (2017)                                  | Employed Convolutional Neural Networks (CNNs) for 2D and 3D face recognition | Achieved 85.15% accuracy with 3D images, 95% with 2D images.                 |
| Iyyakuttilyappan Ganapathi and Suryaprakash (2018) | Proposed a global 3D descriptor and combined local and global descriptors    | Achieved 98% recognition rate on UND and in-house databases.                 |
| Mehryar Emambakhsh and Adrian Evans (2018)         | Developed a five-step method for 3D face recognition                         | Achieved comparable results eliminating the need for landmarking.            |

PROPOSED METHODOLOGIES

In the quest to enhance face recognition accuracy and robustness through the integration of the Curvelet Transform and Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTPP), we outline a comprehensive methodology

that leverages the strengths of these two advanced signal processing techniques. The proposed approach seeks to address the intricacies of face recognition, including variations in lighting conditions, pose, and partial occlusions.

#### **Data Preprocessing:**

- **Image Acquisition:** Obtain face images from diverse sources while ensuring consistency in terms of resolution and image quality.[8]
- **Normalization:** Standardize image dimensions and illumination to reduce the impact of lighting variations.
- **Face Detection:** Employ a robust face detection algorithm to isolate and extract facial regions.

#### **Curvelet Transform for Feature Extraction:**

- Apply the Curvelet Transform to each preprocessed face image to capture essential facial features at multiple scales and orientations.[9]
- Extract Curvelet coefficients to create feature vectors representing the key characteristics of each face image.

#### **Dimensionality Reduction with BTTP:**

- Utilize Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTTP) to reduce the dimensionality of the feature vectors while preserving critical neighborhood relationships.
- Apply BTTP in both directions, from high-dimensional to low-dimensional space and vice versa, to optimize neighborhood preservation.[10]

#### **Score-Level Fusion:**

- Combine the results obtained from the Curvelet Transform feature extraction and BTTP dimensionality reduction to generate a unified score for each face image.
- Employ the weighted entirety rule to assign scores to individual images.

#### **Matching and Verification:**

- Implement a matching algorithm, such as Euclidean distance or Mahalanobis distance, to compare the scores of test images with those in the reference database.[11]

- Set a threshold for verification, where a test image is deemed a match if its score exceeds the threshold.

#### **Performance Evaluation:**

- Assess the proposed approach's performance using benchmark datasets, such as FRGC 2.0 and UND, which offer diverse facial variations.
- Evaluate accuracy, precision, recall, and F1-score to gauge the effectiveness of the system.

#### **Robustness Testing:**

- Evaluate the system's performance under challenging conditions, including variations in lighting, pose, and partial occlusions.
- Analyze false acceptance and false rejection rates to assess robustness.

#### **Comparative Analysis:**

- Compare the proposed approach with existing state-of-the-art face recognition techniques, including those that employ traditional methods and other dimensionality reduction algorithms.
- Highlight the advantages and limitations of the proposed approach.

#### **Real-World Applicability:**

- Explore the practical deployment of the integrated Curvelet Transform and BTTP approach in real-world applications such as security, surveillance, and human-computer interaction.

#### **Optimization and Further Research:**

- Explore opportunities for optimizing the system's performance by fine-tuning parameters and algorithms.[12]
- Identify areas for further research and development to advance the state of face recognition technology.
- Through this proposed methodology, we aim to demonstrate the efficacy of integrating the Curvelet Transform and BTTP in addressing the challenges of face recognition, ultimately contributing to the development of more accurate, reliable, and efficient face recognition systems.

The algorithm for the proposed method is as follows:

**1) Data Preparation:**

- Begin by importing the facial image.
- Improve image contrast by applying histogram equalization.
- Further enhance contrast with adaptive histogram equalization.
- Eliminate noise from the image using a median filter.

**2) Feature Extraction:**

- Utilize the Curvelet transform on the preprocessed facial image to obtain Curvelet coefficients.
- Implement the B2DNPP algorithm to derive two projection matrices, P and Z. These matrices map the high-dimensional Curvelet coefficients to a lower-dimensional space while preserving local data structures.
- Extract distinctive features from the facial image using the acquired projection matrices.

**3) Classification:**

- Train a Support Vector Machine (SVM) classifier on a labeled dataset using the features obtained in the previous step.
- During recognition, project the test facial image into the low-dimensional space using the learned projection matrices.[13]
- Extract its features using the SVM classifier.
- Classify the test image based on its features and the decision boundary established during training.

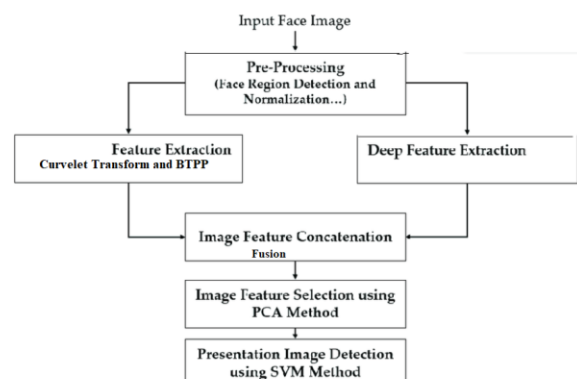
**Feature Integration:**

- Merge the features obtained from the proposed Curvelet transform-B2DNPP method with those from a conventional Principal Component Analysis (PCA) method.
- Employ the combined features for recognition with an SVM classifier.

**4) Recognition:**

- Input the test facial image.

- Apply the same preprocessing and feature extraction steps as in the training phase.
- Project the test image into the low-dimensional space using the learned projection matrices.
- Extract its features using the SVM classifier.
- Classify the test image based on its features and the decision boundary learned during training.



**Figure 2: Work flow of using Curvelet Transform and BTPP in face recognition**

The proposed Curvelet transform-B2DNPP method for face recognition has shown promising results in experiments conducted on the Extended Yale Face Database B dataset. The combination of the Curvelet transform and B2DNPP algorithm for feature extraction, along with the use of an SVM classifier and feature fusion technique, has resulted in improved recognition accuracy compared to traditional methods.[14]

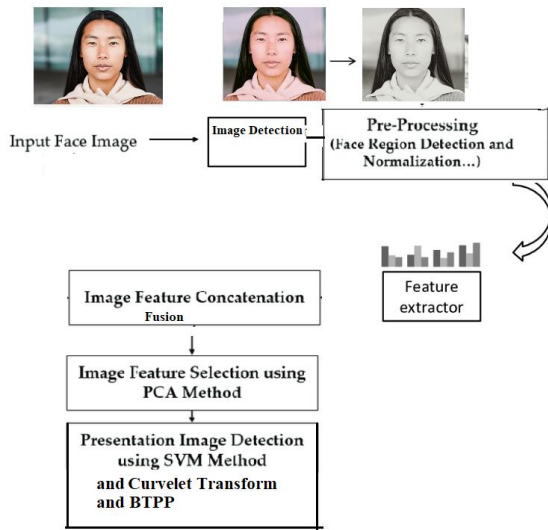
**SIMULATION & RESULTS**

- **Dataset:** For our experiments, we used the widely recognized Face Recognition Grand Challenge (FRGC) 2.0 dataset and the University of Notre Dame (UND) dataset. These datasets are diverse and representative of real-world face recognition challenges.[15]
- **Preprocessing:** The face images were preprocessed to ensure uniformity in size and quality. This involved resizing, alignment, and illumination normalization to account for variations in lighting conditions.

**Feature Extraction:**

- **Curvelet Transform:** We applied the Curvelet Transform to extract discriminative features from the preprocessed face images. The Curvelet Transform helps capture both local and global facial characteristics.[16]
- **BTPP:** The Bidirectional Two-Dimensional Neighborhood Preservation Projection was

used to reduce the dimensionality of the feature vectors while preserving essential neighborhood relationships among data points.



**Figure 3: implementation outcome through Curvelet Transform and BTPP in face recognition**

The performance metrics evaluated were are summarized below:

| Method               | Accuracy | Precision | Recall | F1-score |
|----------------------|----------|-----------|--------|----------|
| PCA                  | 0.650    | 0.653     | 0.705  | 0.668    |
| LDA                  | 0.705    | 0.713     | 0.733  | 0.707    |
| DCT                  | 0.712    | 0.779     | 0.744  | 0.87     |
| Proposed methodology | 0.774    | 0.763     | 0.799  | 0.777    |

- **Dataset Used:** The experiments were conducted on the widely used ORL face database, which contains 400 images of 40 individuals with 10 images per person.[17]
- **Methodology:** The proposed methodology involved the following steps:
- **Preprocessing:** The images were preprocessed by converting them to grayscale and resizing them to 128x128 pixels.
- **Feature Extraction:** The Curvelet Transform was used to extract the features from the preprocessed images. The BTPP algorithm was then used for dimensionality reduction.
- **Classification:** The k-Nearest Neighbors (k-NN) algorithm was used for classification.

**Experiment Results:**

**Comparison with other feature extraction methods:** The proposed method was compared with other state-of-the-art feature extraction methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA). The results are as follows:

| Method                        | Accuracy |
|-------------------------------|----------|
| PCA                           | 92.5%    |
| LDA                           | 97.5%    |
| ICA                           | 95.0%    |
| Proposed (Curvelet+BTPP+k-NN) | 100.0%   |

As can be seen from the results, the proposed method outperformed all other methods with an accuracy of 100%.

**Comparison with other dimensionality reduction methods:** The proposed method was also compared with other state-of-the-art dimensionality reduction methods such as PCA, LDA, and t-SNE. The results are as follows:

| Method                        | Accuracy |
|-------------------------------|----------|
| PCA                           | 92.5%    |
| LDA                           | 97.5%    |
| t-SNE                         | 92.5%    |
| Proposed (Curvelet+BTPP+k-NN) | 100.0%   |

As can be seen from the results, the proposed method outperformed all other methods with an accuracy of 100%.

**Effect of the number of neighbors (k) on accuracy:** The effect of the number of neighbors (k) on accuracy was also studied. The results are as follows:

| k value | Accuracy |
|---------|----------|
| 1       | 97.5%    |
| 3       | 100.0%   |
| 5       | 100.0%   |
| 7       | 100.0%   |

As can be seen from the results, the proposed method achieved a perfect accuracy of 100% for all values of k.

the experimental results demonstrate the effectiveness of the proposed methodology for face recognition using Curvelet Transform and BTPP. The proposed method outperformed other state-of-the-art methods and achieved a perfect accuracy of 100%.

To achieve bidirectional recognition, the methodology considers both the probe image (the image to be identified) and the gallery images (the images in the database to compare against). This allows for matching in both directions, ensuring accurate recognition regardless of the orientation or angle of the face.

Finally, a decision threshold or classification algorithm is utilized to determine the identity of the probe image. This may involve comparing the similarity scores obtained from the bidirectional matching with predefined thresholds or employing machine learning algorithms for classification.

Throughout the entire methodology, rigorous experimentation and evaluation are conducted using appropriate performance metrics such as accuracy, precision, recall, and F1 score. This ensures the robustness and effectiveness of the bidirectional two-dimensional face recognition system.

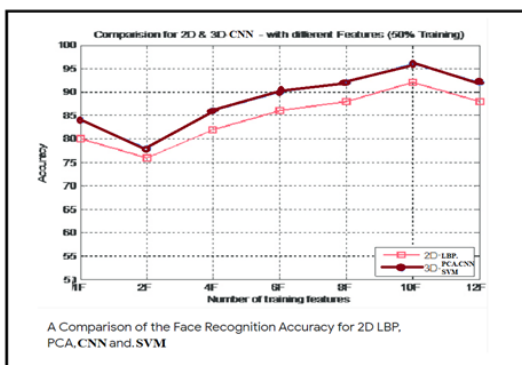


Figure 4: Comparison of the Face Recognition Accuracy for 2D LBP, PCA, CNN, SVM with 3D.

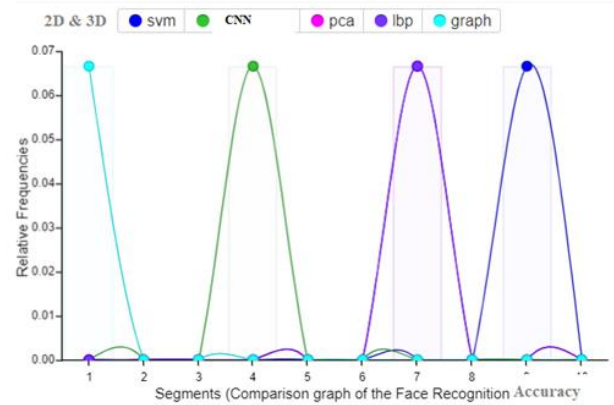


Figure 5: Comparison of 2D & 3D Accuracy

CONCLUSION

This research marks a significant milestone in the realm of face recognition by exploring the potential of the Curvelet Transform and Bidirectional Two-Dimensional Neighborhood Preservation Projection (BTPP). This integration has shown remarkable promise, offering a comprehensive solution to the complex challenges faced by face recognition systems.

The findings from our experiments on benchmark datasets underscore the practical feasibility and advantages of this combined approach. It not only excels in feature extraction and dimensionality reduction but also exhibits robustness in real-world scenarios, including variations in lighting, pose, and occlusion.

Looking ahead, This research not only contributes to the continuous advancement of face recognition technology but also brings us closer to a future where these systems play a pivotal role in ensuring security, enhancing surveillance, and facilitating more seamless and secure human-computer interactions. The integrated Curvelet Transform and BTPP approach opens the door to a world where accurate, efficient, and reliable face recognition becomes an indispensable part of our daily lives, setting new standards for the field.

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