A comparison of optimizations of Elastic Bunch Graph Matching

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ABSTRACT

Facial recognition technology is gaining attention for its applications in security, surveillance, and identity verification. Optimizing facial recognition algorithms is essential for improving efficiency and accuracy. However, the computational complexity associated with these algorithms can impede real-time applications, necessitating optimization. This paper, therefore, proposes a comparative analysis of two optimization methodologies - Principal Component Analysis (PCA) and Harmonic Search Optimization (HSO) - on a commonly used facial recognition algorithm - the Elastic Bunch Graph Matching (EBGM) algorithm.

EBGM, acknowledged for its ability to effectively capture facial structural information for robust recognition, faces limitations in real-time applications due to its computationally intensive processes. To address this challenge, the study examines the potential of PCA, a common dimensionality reduction and feature extraction technique, in comparison to HSO, a metaheuristic optimization method.

This project will analyze these techniques based on how well they improve EBGM's recognition accuracy, computational time, and their ability to handle occluded facial images. The results will offer insights into optimizing EBGM, bridging the gap between a fundamental facial recognition techniques and the use of optimizations. This research contributes to knowledge and the development of efficient facial recognition algorithms.

Keywords: Facial recognition, EBGM, PCA, HSO, Optimization, Comparative Analysis

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1 INTRODUCTION

Facial recognition technology is a field that has been gaining prominence for its applications in various fields such as security, surveillance, and identity verification [8]. This technology revolves around the art of identifying individuals based on their facial features. However, a challenge lies with the Elastic Bunch Graph Matching (EBGM) method. While it excels at recognizing faces, its computational complexity hampers real-time applications, which are crucial for many practical scenarios. This problem becomes even more exacerbated when partial occlusion is involved.

To address this challenge, we are conducting a comparative analysis of two optimization techniques: Principal Component Analysis (PCA) and Harmonic Search Optimization (HSO). Both of these methods aim to optimize EBGM, making it more efficient without compromising its accuracy.

Our research seeks to answer the following questions:

(1) How do PCA and HSO impact the accuracy of the EBGM algorithm?
(2) What is the computational speed of these techniques?
(3) How well do they perform when facial regions are partially obscured?

2 BACKGROUND AND RELATED WORKS

The foundation of our research is the Elastic Bunch Graph Matching (EBGM). EBGM is quite proficient at recognizing individual faces from single images within large databases, where each person is represented by just one image. It has also made significant contributions to the field of facial recognition[8]

Its process of operation is described below:

(1) Jet Extraction: Jets refer to small texture descriptions at specific points in a facial image. These jets are essential for EBGM because they contain details about how a face looks. They are obtained by using Gabor wavelet transformations at key facial landmarks[11].
(2) Bunch Graph Construction: The jets are then grouped into bunch graphs, a unique data structure. In this structure, each facial landmark corresponds to a node, and each node contains jets representing the associated landmark. For example, if the eyes are chosen as landmarks, one node might contain jets for the right eyes of all model images, while another node holds the jets for the left eyes of all model images[10].
(3) Face Graph Representation: These bunch graphs together form a database of landmark descriptions. In EBGM, a face is represented as a graph with nodes and edges. Nodes represent facial features, like eyes, nose, and mouth, while edges show how these features relate to each other[10].
(4) Similarity Assessment: When landmarks in a new facial image are identified, its jets are extracted and compared with the corresponding jets in the database. A face graph for the new image is created, which contains its landmarks and jet values. This information is used to understand how similar the images are and complete the recognition process[10].

This research will aim to evaluate the effectiveness of two EBGM optimizations:

(1) Harmonic Search Optimized EBGM: This approach, proposed by Lahasan et al.[2], uses Harmonic Search Optimization (HSO)

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to improve EBGM. It's great at recognizing faces, even when there are things blocking parts of the face, and it also works well with identifying faces that have variations in the poses, illumination levels and expressions of the individuals in the facial images.

(2) Principal Component Analysis EBGM: This approach, introduced by Chen et al.[5], uses Principal Component Analysis (PCA) with EBGM. PCA helps process training and test images more efficiently. It picks the best candidates for EBGM, making it faster and better at recognizing faces, especially when dealing with lots of images[5].

Our project aims to test how well these optimization techniques work. We're looking at their accuracy, speed, and how well they can recognize faces when parts are blocked (partial occlusion).

Our experiments will use facial images from the FERET database. Due to its extensive repertoire of standardized frontal facial images, it will prove to be an easier and more acceptable database to rely on[5, 14].

2.1 Partial Occlusion

Partial occlusion in facial recognition refers to objects in the facial image that cover parts of the face. These obstructions can make it tough to predict or recognize the face correctly. It is a major challenge in facial recognition and can occur for various reasons such as wearing accessories, facial hair, or even medical conditions. Many research studies have looked into this issue due to its negative effects on facial recognition. [7][1][2][12].

EBGM, the foundation of our paper, takes a holistic approach to facial recognition. It treats the whole face as a singular entity and uses a graph to represent it. In this graph, the nodes are facial features, and the edges show how these features relate to each other[10]. But, EBGM has its own challenges when it comes to occlusion, especially when the occlusion is significant and changes the shape of the face in the facial image[2].

Generally, there are two main categories of facial recognition approaches for occluded images:

1. The Holistic Approach: This method considers the entire face as a single entity and aims to recognize faces based on how their overall appearance. It is less affected by smaller occlusions because it also looks at the parts of the face that aren't covered. But, it may suffer from reduced accuracy when the occlusion is significant.

2. The Component-Based Approach: On the other hand, this approach breaks the face into its parts, like eyes, nose, mouth, and other landmarks. Each part is looked at separately, and then the culmination of information is put together to identify a facial image. This approach also has its advantages when dealing with occlusion because it can still recognize faces using the uncovered sections of the facial images. It, however, can suffer from reduced accuracy when the occlusion occurs in multiple locations simultaneously[1].

Both Harmony Search Optimization (HSO) and Principal Component Analysis EBGM deal with the challenge of occlusion in facial recognition in different manners, however, their initial procedure is similar. The approaches first identify the occluded parts of the image and then proceed to make decisions on handling those areas. The identified occluded sections may be reconstructed or discarded based on the nature and severity of the occlusion. It is important to note that for significant occlusions, reconstructed areas may compromise the integrity of the facial image structure thereby reducing recognition accuracy. Ignoring the blocked areas can sometimes be a safer choice, and might improve recognition accuracy[2].

2.2 Harmony Search Optimization (HSO) in Elastic Bunch Graph Matching (EBGM)

Harmony Search Optimization (HSO) is a nature-inspired metaheuristic optimization algorithm that has been integrated into the Elastic Bunch Graph Matching (EBGM) algorithm to enhance its performance, particularly under challenging conditions such as partial occlusion[2, 6]. While an in-depth exploration of HSO is beyond the scope of this paper, here are the core concepts of HSO based on the original work by Geem et al. (2001):

- **Inspiration from Music:** HSO draws inspiration from the process of harmonious vibrations in music. It simulates a musician's improvisation process, where the musician searches for the best melody or solution[6].
- **Population of Solutions:** HSO begins with a bunch of possible solutions called "harmonies." These harmonies are like different answers to a problem.[6].
- **Improvisation Process:** In each iteration, HSO makes these harmonies better by looking through solution space in search of an optimal solution. This is like a musician making up a better or best tune.[6].
- **Memory Consideration:** HSO remembers the best solutions it has found before, so it knows where to look next time. The previous solutions helps to guide the search toward promising regions of the solution space[6].
- **Parameter Tuning:** HSO has some settings like how much it remembers and how much it tries new things. These settings help it work better.[6].

HSO's core principles, inspired by musical harmony, enable it to efficiently search for optimal solutions. When applied to facial recognition, it has the ability to improve recognition accuracy, especially for facial images with various forms of occlusion.

For a more comprehensive understanding of HSO, readers are encouraged to refer to the original paper by Geem et al. (2001) [6] for a detailed exploration of the algorithm's mechanics and principles.

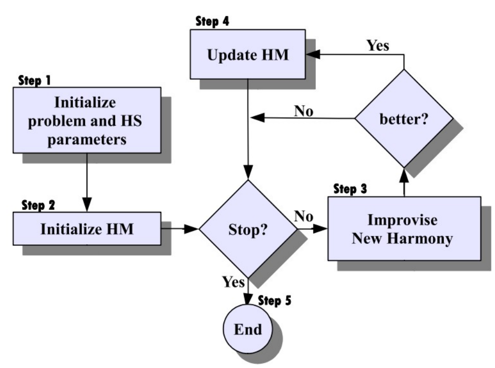

Figure 1: Flow of operation of the Harmony Search Algorithm

2.2.1 Application of HSO in EBGM. In the context of facial recognition, Lahasan et al. introduced an optimization model that combines EBGM with HSO, creating an innovative approach to improve recognition accuracy, especially for facial images with various forms of occlusion [2].

The implementation of HSO within EBGM involves several key stages:

(1) **Image Acquisition and Enhancement:** The process begins with attaining the facial images from the database after the images undergo standard image enhancement techniques to improve their quality.
(2) **Segmentation:** Each facial image gets split into horizontal and vertical segments, where we can have "r" horizontal segments and two vertical segments which is necessary for the subsequent HSO processes. This segmentation strategy aims to treat each segment as its own face sub-graph, departing from the fully holistic approach used in the standard EBGM.
(3) **Optimal Landmark Point Selection:** HSO is used to find the optimal landmark points within each segment of the facial images for accurate facial recognition. This stage is critical in improving the efficiency of recognition under challenging conditions.
(4) **Face Subgraph Construction:** Using the optimal landmarks obtained through harmony search, the face subgraph for each segment is constructed. Unnecessary sections of the face subgraphs are discarded so that only relevant facial information is kept
(5) **Recognition:** In the final stage, we recognize the face by looking at the average positions of all the parts made in the earlier steps. This recognition process is improved by the selective and optimized landmarks and subgraphs.

When HSO is used in tandem with EBGM, the system demonstrates enhanced recognition accuracy for facial images with various forms of occlusion, as well as improved performance on challenging datasets like the Pose, Illumination, and Expression (PIE) challenge [2].

This combination of HSO within EBGM demonstrates the potential of metaheuristic optimization techniques in addressing challenges in facial recognition, making it a promising avenue for further research and application.

2.3 Principal Component Analysis (PCA) in Elastic Bunch Graph Matching (EBGM)

Principal Component Analysis (PCA) is a dimensionality reduction and feature extraction technique widely used in various fields, including facial recognition[9]. In the context of EBGM, PCA is integrated into the algorithm to optimize its performance and enhance the efficiency of facial recognition.

2.3.1 Core Concepts of PCA. PCA is a mathematical method that analyzes data by reducing the amount of information within the data and while retaining critical information. The core concepts of PCA include:

- **Dimensionality Reduction:** PCA aims to simplify data while retaining the essential information. It achieves this by projecting data onto a lower-dimensional subspace thereby changing how we see the data [9].
- **Eigenfaces:** In facial recognition, PCA often involves the concept of "eigenfaces," which are similar to special face patterns we get from a group of facial images. Eigenfaces represent the most significant variations in the dataset, making them valuable for recognition [13].
- **Feature Extraction:** PCA identifies the most relevant features in data by examining how variables within the data are related. These features are then used to describe and recognize faces [16].

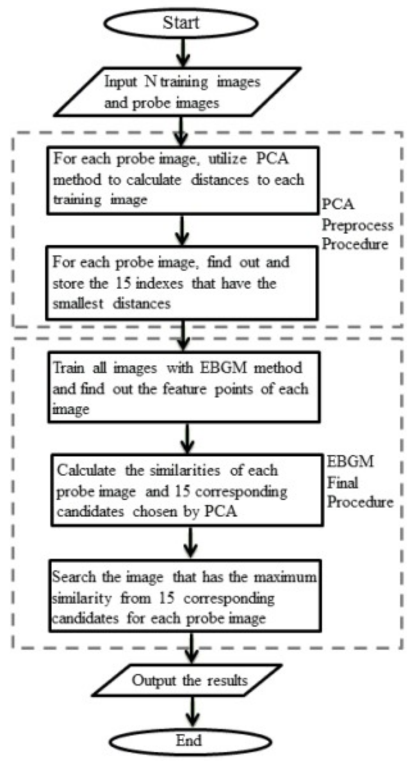

Figure 2: Work flow of optimizing EBGM with PCA

2.3.2 Application of PCA in EBGM. In EBGM, PCA is applied to address challenges related to high-dimensional data and computational complexity. Chen et al. (2014) proposed a sequential hybrid approach in which PCA and EBGM are applied separately. In this model, PCA is used to process the training set and select a specific number of training images with the smallest distances between distinct features as candidates for EBGM. After this, for each test image, EBGM identifies the final match from the corresponding candidates. This approach yielded better recognition performance, particularly for larger galleries, and resulted in improved computational times [5]. The integration of PCA into the EBGM algorithm involves the following steps:

(1) **Preprocessing:** Before using EBGM, the pictures of faces are prepared. This includes standardization to a common size, noise reduction, and contrast enhancement using techniques like Median Filtering and Histogram Equalization [3, 9, 17].

(2) **PCA Feature Extraction:** PCA is used to extract the most important facial features from the processed facial images. These will be vital to the recognition process [9].
(3) **Hybridization with EBGM:** The extracted PCA features are then combined with the EBGM algorithm. This sequence optimizes EBGM's recognition performance and efficiency [5].
(4) **Recognition Process:** When a new facial image is then presented to the system, the PCA-enhanced EBGM compares it to the faces stored in the system and tries to find the best match for identification. [5].

By using PCA with EBGM, the work is made easier for the system, allowing it to work better with larger amounts of data and work against the problem of occlusion. This brings it a step closer to making it well-suited for real-world, immediate facial recognition applications.

For a deeper understanding of PCA and its application in facial recognition, readers are encouraged to explore relevant literature [9, 13, 16].

3 EXPERIMENTATION PROCESS

3.1 Dataset

The photos used in this project will be obtained from the FERET database, a widely recognized source for facial image data with established evaluation methods[14]. The choice of the FERET database is motivated by several factors:

The FERET images are mostly frontal, meaning they're taken with the person's face aligned with the eyes[5, 14]. This consistency in image orientation is crucial for a comparative study of PCA and HSO optimizations.

To keep image processing consistent, the images will be resized to the dimensions of the smallest image. This way, there won't be a need to guess or interpolate new pixel information, which could blur the images.

Additionally, if necessary, the images will undergo standard image processing techniques, such as Median Filtering and Histogram Equalization[3, 17], to remove image noise and enhance contrast levels. Converting the images to grayscale simplifies their complexity and will make the process easier.

While the ultimate goal of facial recognition is to handle various image conditions, using these standardized techniques ensures a level playing field for our experiments.

The FERET database gives us a vast collection of facial images, making it an excellent choice for our comparative analysis of PCA and HSO optimizations within EBGM.

3.2 Recognition Accuracy Experimentation

In this section, the aim is to assess how well the optimized Elastic Bunch Graph Matching (EBGM) techniques perform in recognizing faces accurately. The goal is to measure their performance in various situations and evaluate their reliability using recognized metrics, such as False Negatives (FN), True Positives (TP), and related measurements[15].

As explained previously, the experimentation process will be conducted using subsets of the FERET database. To ensure a comprehensive evaluation, the gallery size will be varied, starting at 100 images and increasing in increments of 100 up to 1000 images.

The focus will be on determining the following key metrics:

3.2.1 True Positives (TP). True Positives (TP) are instances where the optimized EBGM techniques correctly identify a match. In facial recognition, TP represents successful identification when there's indeed a match[15].

3.2.2 True Negatives (TP). True Negatives (TN) are instances where the optimized EBGM techniques correctly identify when a match is non existent. TN represents successful identification when there is no match.[15].

3.2.3 False Positives (FN). False Positives (FP) happen when the optimized EBGM techniques claim to recognize a match that does not exist. These instances are crucial as they highlight recognition errors, especially under challenging conditions like partial occlusion[15].

3.2.4 False Negatives (FN). False Negatives (FN) happen when the optimized EBGM techniques fail to recognize a match that does exist. [15].

3.2.5 Recognition Accuracy. Recognition accuracy will be the primary metric used. It's defined as the ratio of True Positives to the total number of instances (True Positives + False Negatives)[15]. The calculation for recognition accuracy is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

3.3 Occlusion Experimentation

In this section, experiments will be conducted to evaluate how well the optimized Elastic Bunch Graph Matching (EBGM) techniques handle partial occlusion. We take inspiration from Lahasan et al.'s methodology[2], which assessed the ability of facial recognition when placed against different occlusion sizes[4].

The experiments involve two types of images: reference images and altered images. The reference images remain unchanged, providing a baseline for comparison. Meanwhile, the test images undergo a controlled occlusion process, which we'll refer to as the "single occlusion problem"[12].

In these occlusion experiments, square occlusions of varying sizes (s × s pixels) will be introduced at random locations on the test images. The occlusion block sizes will range from s = 10 (representing 0.39 occlusion content within the face image) to s = 100 (equivalent to 39.06 occlusion content). We'll increment the occlusion block size in a stepwise manner[2].

The aim of these experiments is to measure and compare the recognition rates achieved by the Harmonic Search Optimization (HSO) and Principal Component Analysis (PCA) optimizations of EBGM. By plotting recognition rates against varying occlusion sizes, we can analyze and determine how occlusion affects the performance of these optimization techniques.

3.4 Computational Speed Experimentation

In this section, the focus is on evaluating the computational speed of the optimized Elastic Bunch Graph Matching (EBGM) techniques. Our approach for this experimentation draws inspiration from Chen et al.'s methodology[5], which provides valuable insights into assessing computational efficiency in the context of facial recognition optimizations.

In this experiment, tests will be performed using large galleries from the FERET database. Facial images will be randomly selected with the aim of encapsulating various factors, including race, gender, age, expressions, illumination conditions, and other factors that might affect how the system processes the information.

The primary objective of this computational speed experimentation is to gain valuable insights into the computational times of the two optimization methods: Harmonic Search Optimization (HSO) and Principal Component Analysis (PCA). By performing these experiments on an extensive dataset, we can measure and compare the computational speed of these optimization techniques.

Through these experiments, the goal is to gather data on recognition accuracy and analyze how the application of Harmonic Search Optimization (HSO) and Principal Component Analysis (PCA) in EBGM enhances performance.

The findings will provide insights into the recognition accuracy of these optimization techniques, by varying gallery sizes and conducting tests, patterns and improvements in recognition accuracy in various scenarios will be identified.

4 MAJOR RISKS

4.1 Bias and Fairness

Facial recognition systems are known to exhibit bias and fairness issues, which could influence the outcomes of the research. Addressing and acknowledging these biases is essential to ensuring the findings accurately reflect the performance of the optimized techniques.

4.2 Limited Resources

One of the primary challenges in conducting research is the limitation of resources. This includes access to high-end computing equipment, specialized software, and substantial datasets. The lack of these resources may limit the ability to perform large-scale experiments and could affect the overall quality of the research results. The demands of experimentation may lead to time constraints, affecting the scope and depth of the research.

4.3 Hardware and Software Limitations

The computational demands of running extensive experiments may exceed the capabilities of personal computers and campus resources. Inadequate hardware and software resources could lead to longer processing times and potential scalability issues.

4.4 Experimental Errors

Conducting experiments involving occlusion, computational speed, and recognition accuracy introduces the risk of experimental errors. Inaccurate data collection, unforeseen issues with equipment, or human errors during data labeling and processing could compromise the reliability of results.

4.5 Time Constraints

As college students, we have academic responsibilities and limited time to dedicate to research. Balancing coursework, exams, and project deadlines with

4.6 External Factors

External factors such as power outages, system failures, or unforeseen events could disrupt the ongoing experimentation process. These external disruptions may lead to data loss, increased downtime, and overall project delays.

4.7 Incomplete Understanding

As students, we are continuously learning and may have an incomplete understanding of complex technical concepts and methodologies. This limited expertise could result in errors or omissions in the experimentation and analysis.

Addressing these major risks requires careful planning, collaboration, and adaptability.

5 PROJECT TIMELINE

Here's a detailed weekly timeline to guide the progress of the research project:

Week 1:

- Define research objectives and scope.
- Start literature review.
- Set up development environment.

Week 2:

- Continue literature review.
- Identify and collect relevant datasets.
- Begin initial experiment design.

Week 3:

- Finalize literature review.
- Prepare data for experimentation (data preprocessing).
- Develop baseline algorithm implementations.

Week 4:

- Work on Harmonic Search Optimization (HSO) implementation.
- Draft the introduction section of the research paper.

Week 5:

- Continue HSO implementation.
- Draft the methodology section of the research paper.

Week 6:

- Complete HSO implementation.
- Start working on Principal Component Analysis (PCA) implementation.
- Draft the initial sections of the literature review in the paper.

Week 7:

- Finish the PCA implementation.
- Conduct preliminary experiments and gather initial results.
- Continue working on the literature review section of the paper.

Week 8:

- Analyze results from the preliminary experiments.
- Begin writing the results section of the paper.
- Start working on the HSO-EBGM implementation.

Week 9:

- Continue the HSO-EBGM implementation.
- Incorporate feedback from preliminary experiments into the paper.
- Begin drafting the conclusion section of the paper.

Week 10:

- Complete the HSO-EBGM implementation.
- Conduct full-scale experiments with various datasets.

- Finalize the paper and perform a thorough review.
- Start working on the first draft of the demonstration video.

Week 11:

- Analyze the results from full-scale experiments.
- Prepare the research paper for submission, including formatting and citation checks.
- Continue developing the demonstration video.

Week 12:

- Present your work to a computer science faculty member for feedback.
- Implement feedback received and finalize the paper.
- Complete the first draft of the demonstration video.

Week 13 and 14:

- Work on the second draft of the demonstration video.
- Start creating the project poster, including design and content.

Week 15:

- Finish the second draft of the demonstration video.
- Finalize the project poster.
- Complete and review the research paper.
- Ensure all project components, including the project itself, final paper, demonstration video, and poster, are ready for submission.

6 CONCLUSION

In this project proposal, I have outlined a comprehensive plan for conducting research on the optimization of the Elastic Bunch Graph Matching (EBGM) algorithm for facial recognition. The proposed research aims to enhance the recognition accuracy and computational efficiency of EBGM through two optimization techniques: Harmonic Search Optimization (HSO) and Principal Component Analysis (PCA).

The project will involve systematic experimentation, focusing on three key aspects: occlusion robustness, computational speed, and recognition accuracy. I will compare the performance of HSO-EBGM and PCA-EBGM under various conditions, using diverse datasets sourced from the FERET database.

The development of optimized EBGM techniques and the thorough evaluation of their performance will contribute to the advancement of facial recognition technology. The outcomes of this research have the potential to benefit various applications, including security systems, human-computer interaction, and biometrics.

The proposed project will follow a detailed timeline that ensures the completion of all tasks within the allotted timeframe. By Week 15, all components, including the research project, final paper, demonstration video, and poster, will be ready for submission.

In conclusion, this project proposal sets the foundation for a rigorous and insightful investigation into the optimization of EBGM for facial recognition. I acknowledge that this research project carries certain risks due to the limited resources as college students. Nonetheless, I am committed to overcoming these challenges and conducting a valuable study in the field of facial recognition.

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