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Locality-Sensitive Hashing of Soft Biometrics for Efficient Face Image Database Search and Retrieval

Ameerah Abdullah Alshahrani * and Emad Sami Jaha

Department of Computer Science, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia
* Correspondence: asalemalshahrani@stu.kau.edu.sa

Abstract: As multimedia technology has advanced in recent years, the use of enormous image libraries has dramatically expanded. In applications for image processing, image retrieval has emerged as a crucial technique. Content-based face image retrieval is a well-established technology in many real-world applications, such as social media, where dependable retrieval capabilities are required to enable quick search among large numbers of images. Humans frequently use faces to recognize and identify individuals. Face recognition from official or personal photos is becoming increasingly popular as it can aid crime detectives in identifying victims and criminals. Furthermore, a large number of images requires a large amount of storage, and the process of image comparison and matching, consequently, takes longer. Hence, the query speed and low storage consumption of hash-based image retrieval techniques have garnered a considerable amount of interest. The main contribution of this work is to try to overcome the challenge of performance improvement in image retrieval by using locality-sensitive hashing (LSH) for retrieving top-matched face images from large-scale databases. We use face soft biometrics as a search input and propose an effective LSH-based method to replace standard face soft biometrics with their corresponding hash codes for searching a large-scale face database and retrieving the top-k of the matching face images with higher accuracy in less time. The experimental results, using the Labeled Faces in the Wild (LFW) database together with the corresponding database of attributes (LFW-attributes), show that our proposed method using LSH face soft biometrics (Soft BioHash) improves the performance of face image database search and retrieval and also outperforms the LSH hard face biometrics method (Hard BioHash).

Keywords: locality-sensitive hashing (LSH); face image retrieval; face recognition; face biometrics; face soft biometrics; searching similar images; database search; large-scale databases

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1. Introduction

The rapid growth of search engines and social sites has led to a tremendous amount of multimedia data being created on the internet every day, including text [1], photographs [2], and videos [3]. Hence, there has been a sharp increase in the use of enormous image databases over the past few years. The emergence of content-based image retrieval (CBIR) methods in the research community has been inspired by the prevalence of big multimedia data [4,5]. Image search and retrieval have recently attracted much attention because of the increasing necessity to extend their capabilities and efficacy to be better suited for handling large-scale databases, which may include billions of samples. Furthermore, large-scale searches necessitate very efficient and precise retrieval techniques. CBIR has a wide range of applications in several fields [6]. For a specific input photograph, the content-based retrieval process retrieves the appropriate images from the image database. Pair-wise label similarity is the fundamental technique for locating pertinent photos, and it uses one of two methods to measure the distance between features in the images: Manhattan distance or k nearest neighbor (kNN) [7]. The goal of face image retrieval is to determine the ranking result for a given query in a face image database. Due to the widespread use of photo sharing in social networking services, there is a considerable need for more efficient content-based face image retrieval in large-scale databases. When dealing with enormous datasets, it is critical for an image search algorithm to rank a large number of images accurately and quickly so that the most related ones appear first in the result. Moreover, finding a human face image in a vast database that may contain a huge number of people's face images is quite tricky [6]. Figure 1 shows the major steps in a face image retrieval system (FIRS).

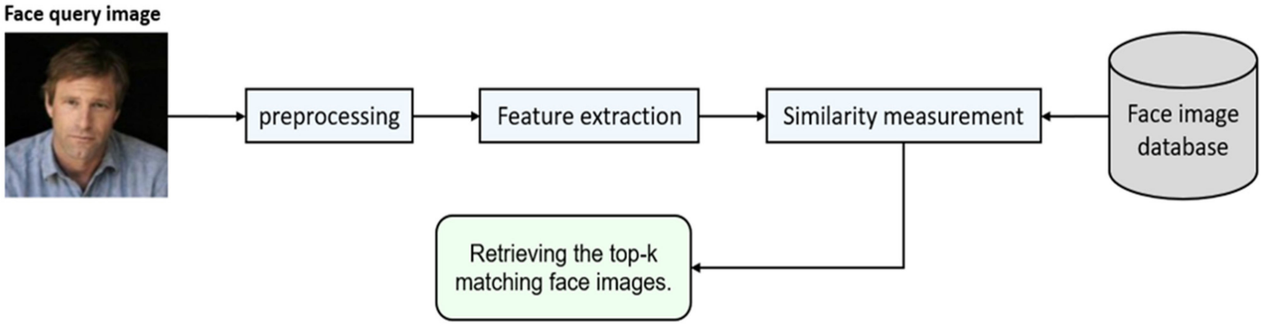

Figure 1. Generic face image retrieval system.

In some cases, due to a great degree of similarity between matching faces, such as twin faces, for example, the retrieved image may not be as accurate as required. In that instance, facial marks, as well as the shape of identical twins' faces, can further be used to distinguish them, and thus the system is able then to retrieve only the relevant photos that are requested [8]. Hence, feature extraction from image pixels plays a vital role in facial image retrieval. In general, the image content features can form a retrieval system based on multiple attributes. Such multiple attributes help to identify and differentiate similar images in the database and index/rank the results depending on their similarity. Many research efforts have concentrated on retrieval systems for multiple attributes of images, but the desired high performance is still a challenging task [9]. Moreover, the retrieval of encrypted image data is still difficult because it must be performed rapidly while protecting privacy [10]. As a quick solution to the problem of the time spent, as well as that of high storage cost during query and image retrieval, hash technology can be effective. The main goal of hashing is to set simplified representative codes for data with high dimensionality. The basic procedure for hashing involves assigning images of comparable content to similar binary codes, so that their semantic similarity can be maintained [11].

The motivations for this study were as follows: Hash functions have received considerable attention in image retrieval lately, and they have played a significant role in improving image retrieval performance. Identifying humans is deemed a fundamental requirement in many applications, but, due to the revolution of digitization around the world and the rapid increase in the number of people using social media in the last decade, there exists a huge amount of multimedia data, which needs to be more efficiently handled with improved retrieval performance and reduced processing time.

Although face image retrieval using a content-based method is a well-established technology used in many real-world applications, it requires enormous amounts of storage and is time-consuming, adversely affecting performance. This problem remains even when using biometric data with much lower dimensionality, such as face soft biometrics, to retrieve a similar face image, especially with large databases of unconstrained face images. As such, face-hard- and soft-biometric-based hash codes are being investigated, used, and compared for use in the retrieval of face images, with a view to improving retrieval performance along with reducing retrieval time. To the best of our knowledge, the current research literature has yet to investigate whether replacing the standard face soft biometrics with their corresponding hash codes using LSH (Soft BioHash) can speed up the search, shorten the time needed to find a matching face image, and improve retrieval performance. Thus, the key contribution of this research work is to show how retrieval performance and retrieval time can be improved by the proposed methods of Soft BioHash and also to investigate and illustrate the efficiency of the proposed methods in comparison with the traditional method that substitutes hard face biometrics with their corresponding hash codes based on LSH (Hard BioHash).

The rest of this article is organized as follows. Section 2 reviews related works. Section 3 explains the locality-sensitive hashing (LSH) technique. The proposed methodology is described in Section 4. In Section 5, the experimental evaluation and results of our proposed method are explained. Finally, Section 6 presents the conclusions of this research work.

2. Literature Review

This section discusses related work on different face image retrieval and recognition strategies. Related studies can be categorized with respect to our proposed approach into three categories: traditional face image retrieval, hash techniques for biometric recognition and retrieval, and face soft biometrics for face image retrieval.

2.1. Traditional Face Image Retrieval

In [12], the researchers observed that many documents currently employ a person's face photograph for identification purposes. As a result, employing a facial image to index and retrieve associated personal documentation papers has become a crucial application. They proposed an approach for retrieving documents based on face images via three phases: detecting the face image from the document for the query, feature extraction from detected face images, and retrieving all of the documents with a face image similar to that of the query document. Their used approach yielded 82.66% for Mean Average Precision (MAP).

In [13], the authors observed a need to solve the most significant shortcomings of the existing approaches, such as throughput, low precision, dependability, and the problem of excess segmentation requiring excessive processing. Therefore, they introduced a new approach for retrieving face images based on the content of the image using various similarity measurements. They concluded that different functional algorithms could be used at different steps in the overall process to make the system work better. On the other hand, [14] focused on the influence of the Spark computing engine on large-scale machine-learning-based facial picture retrieval. Their main processes were as follows: first, detecting the face using the Viola–Jones framework; second, performing feature code with the scale-invariant feature transform (SIFT) algorithm, dimension reduction with the principal component analysis (PCA) technique, and data storing with HBase; and, finally, matching with the KD-tree query algorithm. They highlighted their method's efficiency by demonstrating the outcomes of experiments applied to the CelebA dataset. In addition, they indicated that their research was still in its early phases and that in the future they would continue to look into further possibilities to investigate its potential applications.

2.2. Hash Techniques for Biometric Recognition and Retrieval

Several related research explorations have used different hash techniques for recognition, protection, and retrieval. In [15], the authors considered the problem of determining and authenticating an examinee's identity at random times throughout an exam to prevent cheating. Their main contribution was applying the pHash algorithm to implement the face recognition system. They were able to achieve a 98% recognition rate with their proposed features. However, the results were limited to showing only ten samples and twenty participants, and they did not experiment with their proposed method on a large dataset. In [16], a number of requirements were suggested for rapid face identification and retrieval. Their major proposed strategy for face identification and retrieval was deep-learning-based hashing, for which they employed the FaceNet model to extract deep facial features and then turned the face feature vector into binary hash codes for retrieval. Their conclusion was that a set of only 48 items retrieved with a hash code of length 64 could always retrieve the correct person for a particular query face image. Note, however, that their system needs to be more accurate in retrieving similar face images.

In [17], speeding up image retrieval and reducing storage space were the focus of their attention. To retrieve relevant pictures from the database, they presented a face-attribute-based approach employing a deep hashing network, where the method accepts face attributes as queries and returns a list of relevant photos. Their main finding was that their method outperformed some other face-picture retrieval algorithms that rely on hand-crafted features. However, their proposed method performance was observed to be notably affected by the distribution of the datasets. In [18], the authors tested various iterations of the LSH algorithm to reduce the time required to run the local feature hashing (LFH) process. They applied SIFT for feature extraction and PCA for dimensionality reduction and then used the LSH algorithm to reduce the time consumed in face recognition in large databases. According to their results, the LFH algorithm's response time was improved by some of these techniques. In their tests, they used more input photos than in earlier research studies. In addition, their system can deal with problems caused by facial accessories such as glasses. Note, however, that they applied their experiment only on a database containing a maximum of 2600 images.

In face recognition systems, it is deemed crucial to secure the extracted facial features (templates). Thus, in [19], they primarily considered the users' privacy in their face recognition system and the importance of securing the extracted facial features. They utilized BioHashing to safeguard face templates and focused on maintaining the same recognition accuracy in state-of-the-art face recognition models together with minimizing BioHashing length. As such, they generated protected templates using BioHashing of features extracted by state-of-the-art recognition deep neural network (DNN) models. In addition, by specifying two hypotheses, they showed how the performance of a system secured by BioHash might be impacted by the length of the BioHash. First, the ratio between the original dimension and the BioHash length determines how well BioHash-protected templates operate. Second, the effectiveness of BioHash-protected templates depends on the length of the BioHash. They explored two different facial recognition models on two datasets (LFW and MOBIO) to see which one worked best in real life. They found that the performance was only affected by the length of the BioHash.

2.3. Face Image Retrieval Using Face Soft Biometrics

In [20], the authors highlighted the benefits of using facial marks as complementary information for face recognition. They developed a novel approach to enhance the performance of existing face recognition systems by integrating them with data collected from facial markers. They first offered a method for automatically identifying facial markers, which were, subsequently, represented using histograms of oriented gradients (HoGs) and then matched taking into account their location within the face image. Their method presented good results without the need to categorize the identified face marks. As in [21], they focused on improving the accuracy of face image retrieval. This approach extracts essential features from the input face image using a deep convolutional neural network (CNN) approach [22–25]. In addition, an improved grey wolf optimization (GWO) approach was suggested to pick optimal features from the recovered features. Using this approach, they reported that it was possible to improve retrieval speed and accuracy while also addressing the drawbacks of current methods. On the other hand, in [26], the research interest was focused on examining the feasibility of improving face recognition capabilities by combining global face soft biometrics with conventional (hard) biometrics. To test the efficacy of these soft traits in enhancing a conventional face recognition method, a small set of six global soft biometrics were proposed and derived for each person in the FERET dataset and then fused with extracted facial Gabor features. To collect soft biometrics for every subject in the database, they utilized a crowdsourcing platform for face image data annotation. The findings of this study illustrated that the feature-level integration of classic

Gabor features and soft face traits can lead to improved face recognition performance, which was proven by both identification and verification metrics.

Y. Fang and Q. Yuan [27] proposed a model that merges the potency of attributes and hypergraphs into a single framework and uses it in various face image retrieval tasks. The model involves attribute-based hypergraph learning, attribute adaptation for metrics, and related feedback. The learned distance measure improves the accuracy of similarity retrieval and speeds up convergence in interactive face retrieval. The main conclusion is that the semantic difference between human and machine face perception is significantly reduced.

To bridge the semantic gap in face perception between humans and machines, in order to provide quick interactive face retrieval, Y. Fang et al. [28] suggested a prototype learning approach for facial attributes by creating the model's heuristic solution method and reformulating the theoretical justification for the interactive retrieval model. Each module of the prototype model was trained using a collection of facial characteristics associated with identity. The semantic representation was created from the prototype modules' outputs. They suggested a transfer selection approach based on the coherence measures in interactive face retrieval to adjust the prototype models across various databases. They found that the suggested attribute prototype representation can successfully help close the semantic gap even when cross-database transfer learning was used, according to their coherence analysis. Furthermore, the feature dimension in the retrieval process could be efficiently reduced using the prototype representation. However, users' subjectivity may have an impact on how well such interactive retrieval works.

3. Locality-Sensitive Hashing Technique

LSH is one of the methods most often used for locating approximative nearest neighbors in high-dimensional environments. The LSH was initially developed for the Hamming distance before being expanded to other different distances, including the well-known Euclidean distance. The original high-dimensional space is mapped to the projected low-dimensional space using random hash projections in LSH. There are two key benefits of LSH: its sub-linear query performance (in terms of the data quantity) and the theoretical assurances of query accuracy [29]. The LSH family H is a probability P distribution on a family H of hash functions h, where the similarity function S is established on the set of objects X and Y [30,31]. LSH can be formulated as follows:

$$P\, h \in\; H\, [h(X) = h(Y)] = S\ (X,\ Y) \tag{1}$$

The main idea of LSH can be summarized as the idea that the original image is represented by the LSH algorithm as a low-latitude binary hash code, instead of storing the high-latitude picture attributes directly. In addition, an index is created using the hash code that is generated to match and find the image's closest neighbors. To build an index, LSH will use the random projection method to create a set of hash tables. A hash table can have any number of buckets and feature vectors associated with it [32], where the number of buckets in the LSH concept is significantly less than the number of input items [31]. Figure 2 demonstrates the overall process of how LSH builds the indexes, enabling search and retrieval.

Hence, as shown in Figure 2, for achieving retrieval using a (query) input image (X_n), the image that is most similar is found by calculating the distance between hashes of the input image and each image in the database. Therefore, the possibility of similar samples being hashed into the same bucket has a higher chance than dissimilar samples. Thus, the green boxes become the most similar sample to the input image (X_n), where the distance between the hashes of the input image and the green box is smaller than the distance between the hashes of the input image and the yellow and red boxes. For example, in Figure 3, there are three pictures, and the two pictures on the right are remarkably similar. Since these two images of the same subject appear more similar from the semantic perspective, the distance between their hash codes h(man1) and h(man2) should then be closer than the distance between another subject's hash code h(woman) and any one of them, such as h(man1), as seen in Figure 3. As such, to identify similar photos that satisfy the query parameters when querying an image, acquire the bucket (subject) number, remove all the data from the relevant bucket (subject), do linear matching on that data, and then locate the matching images [32].

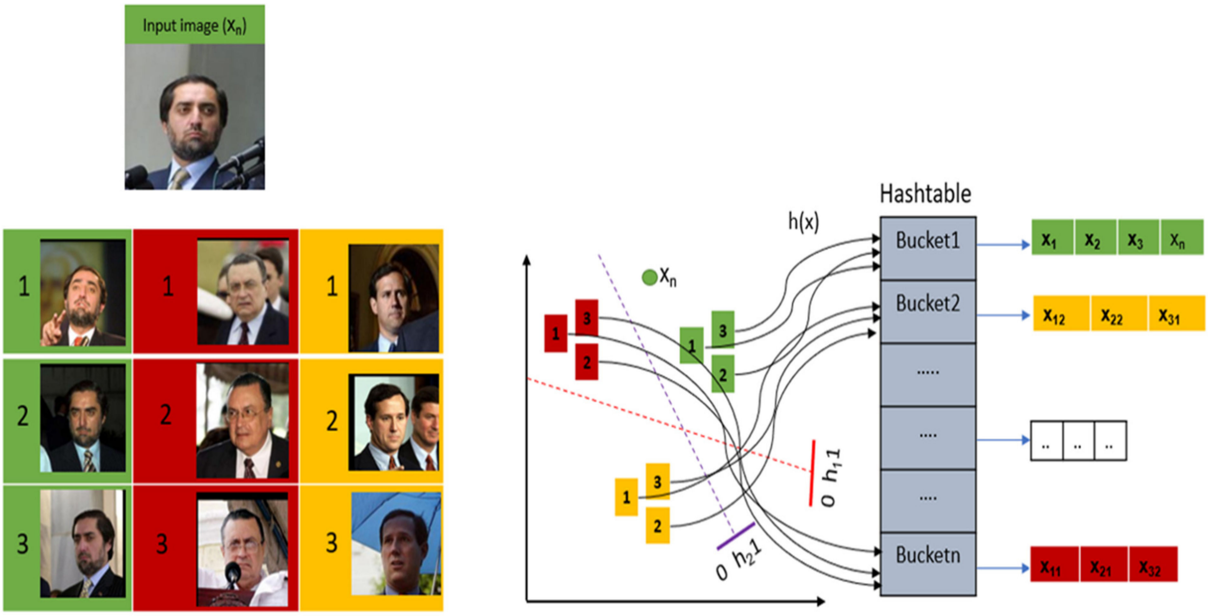

Figure 2. Creating an image data index using LSH; each bucket represents a subject in this context.

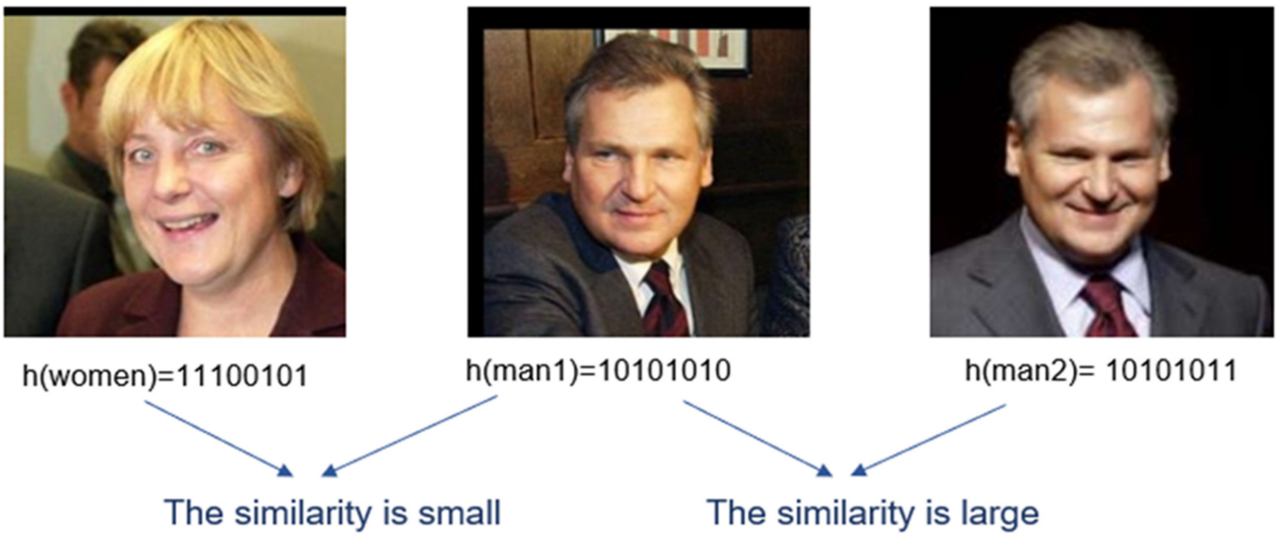

Figure 3. Hash and image similarities.

4. Methodology

This proposed research work aims to enhance face image retrieval in terms of improving the retrieval process and accuracy in a timely manner. Therefore, we investigated the ability of Soft BioHash to accurately retrieve face images and reduce retrieval time compared with the traditional Hard BioHash method by conducting the same experiment under the same circumstances in parallel for both methods, making the required changes, and then comparing the performance of these two methods. To accomplish our goal, we conducted experimental work in four main phases: In the data preprocessing phase, a face image was detected and normalized, and we mapped and formed it for the face soft biometrics. Feature extraction and hash generation for the face image (Hard BioHash) and hash generation for the face soft biometrics (Soft BioHash) were then performed. The distance metric was used to retrieve similar images. Finally, a performance evaluation was performed. Figure 4 illustrates an overview of the methodology adopted for the proposed research investigation.

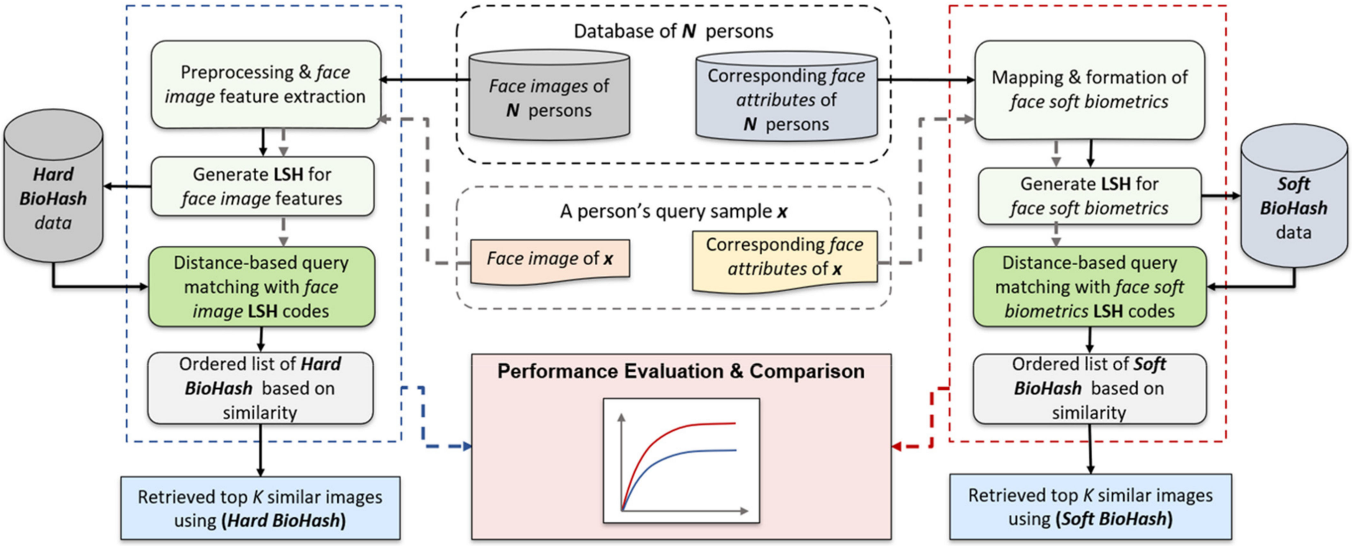

Figure 4. Overview of the proposed methodology.

4.1. Data Preprocessing

In this phase, we used only the face images in the Labeled Faces in the Wild (LFW) dataset [33] that has corresponding face attributes data in the LFW-attributes dataset [34], both of which will be described further in Section 5.1. For each image sample, the subject's face was detected as part of the preprocessing phase using a suitable face detection technique based on Haar cascade functions, as shown in Figure 5, the blue rectangle represents the area containing the face, where removed the background and eliminating any other elements apart from the face region. Next, for normalization, the detected face was cropped and then resized to 256 $\times$ 256 pixels and converted to grayscale. As for the ready-made LFW-attributes dataset of face attributes, we mapped and formed all of its face attributes data with the corresponding face image of the LFW dataset, then we dealt with the mapped and formed face attributes as a dataset of face soft biometrics. As such, in this context, there will be no need to describe the face attributes data annotation process, which can be found with more information in [34]; thus, we will move directly to describe the phase of hash generation of face soft biometrics.

Figure 5. Face detection process.

4.2. Feature Extraction and Hash Generation

After preprocessing, we extracted discriminative facial features from the normalized face images and minimized the resulting feature vector per image by using an assembly of discrete cosine transform (DCT) coefficients. DCT coefficients were calculated for an image of size $M \times N$, the image could be divided into overlapping blocks of size 32×32 pixels, and a 2D-DCT operation was performed on each block. It is important to note that each DCT block consisted of one DC coefficient and 1023 AC coefficients, and hence we obtained the frequency coefficient matrix of the same dimension. The following formula was used to compute the DCT coefficients:

$$F(u,v) = \frac{1}{\sqrt{MN}}\alpha(u)\alpha(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \times cos\left(\frac{(2x+1)u\pi}{2M}\right) \times cos\left(\frac{(2y+1)v\pi}{2N}\right) \\ where: \quad u = 0,1,\ldots,M \quad v = 0,1,\ldots,N \tag{2}$$

Note that face soft biometrics do not pass through the step of feature extraction. We then generated hashes for both the features extracted from the face images (Hard BioHash) and face soft biometrics (Soft BioHash). Eventually, for every sample in each database, we had both a Soft BioHash and a Hard BioHash.

4.3. Distance Metric to Retrieve Similar Images

This was the last step to get the top-k matching face images that were most similar for both the face image query and the face soft biometrics query. There are many usable distance methods to measure the similarity between hashes of the query image and database images, such as the Hamming distance, Manhattan distance, Euclidean distance, etc. In this research study, we adopted Euclidean distance in the retrieval process, which can be defined as follows:

$$D_{euc} = \sqrt{\sum_{i=1}^{p}(xi - yi)^2} \tag{3}$$

4.4. Performance Evaluation

To evaluate the proposed method, we determined which hash works best for retrieving face images. Therefore, we assessed and compared the performance of face image retrieval using Hard BioHash and face image retrieval using Soft BioHash. The performance of the retrieval techniques based on LSH can be estimated using the following metrics.

- Accuracy: The accuracy of a retrieval strategy is a statistical measure of how well it accurately recovers or eliminates a condition, such that it is the proportion of true results (including true positives (TP) and true negatives (TN)) out of the total number of tests run, where (FP) and (FN) denote false positive and false negative, respectively. The accuracy can be computed as follows:

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \tag{4}$$

- Precision: This is a metric for a retrieval technique's ability to positively search and retrieve the correct face image rather than the incorrect one and is defined as follows:

$$Precision = \frac{TP}{(TP + FP)} \tag{5}$$

- Recall: This is a metric that measures a retrieval technique's ability to positively retrieve the proper facial image all the time, and it is defined as follows:

$$Recall = \frac{TP}{(TP + FN)} \tag{6}$$

- F1-Score: When precision and recall are both equally weighted, the F1-Score is calculated as follows:

$$F1Score = 2 * \ Precision * \ Recall / \ Precision + Recall \tag{7}$$

- Execution time (retrieval time): This is a measurement of the average time required by a technique for retrieval. We measure the retrieval time according to the number of retrieved images.
- Cumulative match characteristic (CMC): The CMC curve is a statistic for evaluating the success of a biometric identification algorithm based on each rank's precision. Subsequently, identification performance is determined based on the relative ordering of match scores.

5. Experimental Results and Analysis

5.1. Face Image Database Description

The conducted experimental work in this paper used the Labeled Faces in the Wild (LFW) database, which is an unconstrained environment database, representing challenging data for the content-based face image retrieval domain and comprising a large number of face samples compared to other databases, along with a corresponding dataset of attributes (as soft biometrics). Some examples of LFW datasets can be found in Figure 6. It has two related datasets:

Figure 6. A few random samples from the LFW dataset.

LFW dataset: This is a well-known face dataset with over 13,233 images of 5749 people. Only 1680 of them have two or more pictures [33]. It was designed for conducting research on unrestricted face recognition. The dataset's images are completely unconstrained in terms of pose, illumination, expression, and occlusion.

LFW-attributes dataset: This is a dataset of attributes (as soft biometrics) acquired for LFW images consisting of 73 attributes for 13,143 images [34]. The presence of an attribute is indicated by a positive value, and its absence or negation is shown by a negative value.

5.2. Results

The conducted experiments offered promising results and illustrated the potential capability of the proposed method for face image retrieval, both in terms of reduced time consumption and in terms of significantly improved performance. In order to assess the proposed method's capabilities and the retrieval performance variation using datasets varying in content and size, we applied our method to two subsets comprising 1000 and 5743 samples of 823 unique people who have three or more images, where each subset constituted the same number of samples of the same persons from each of the LFW and LFW-attributes datasets. Then, we split each dataset into 75% for training and 25% for testing. We trained the adopted model by defining the hyperparameters, which were the hash size, the number of hash tables, and the dimensionality of the input vector. The experiments were divided into two types as follows:

Experiment 1 was concerned with the face image, as the DCT was utilized for the feature extraction process. Based on the features extracted by DCT, we calculated a hash function h(x) based on a locality-sensitive hashing dimension reduction method to build a hash of a 24-bit size for the input query, where the number of hash tables equals the number of samples (1000 and 5743), and the dimensionality of the input matrix is 32×32, where similar feature points are stored in the same bucket. Lastly, we retrieved the top 20 face images by using Euclidean distance to measure how similar the Hard BioHashes of the query face image were to all the stored Hard BioHashes in the database. In Figure 7, the yellow square shows the correct image that matches the input Hard BioHash query, which is the third image in the top 20 face images retrieved.

Figure 7. Example of top 20 retrieval results of a query image that correctly retrieved at rank 3.

Experiment 2 was concerned with face soft biometrics, and we directly generated the hash code for the mapped and formatted face attributes based on LSH, as they did not require feature extraction. The hyperparameters had the same values as in Experiment 1, except that the hash table was equal to the number of attributes (i.e., 73). According to the LSH method, similar feature points were stored in the same bucket. Finally, Euclidean distance was used to compare the similarity, as we were able to retrieve the top 20 face images that matched the input hash query.

Time complexity was measured for the retrieval approaches using computational time. For the hashing algorithm in the above experiments, the total time needed to find similar face images based on either Hard BioHash or Soft BioHash of all the images in the testing phase was first calculated, and then the average time in seconds was given for retrieving the top 20 similar images. Table 1 presents the average execution time and performance evaluation for obtaining the top 20 matching images for the input query. It shows that our proposed approach based on Soft BioHash was superior in terms of attaining data retrieval in much less time than the standard approach based on Hard BioHash for large image datasets. In addition, the table offers a comparison of the accuracy results obtained from the two experiments mentioned above, with varying numbers of samples.

Table 1. Comparison of the retrieval accuracy results and the average execution time in seconds consumed in the retrieval process.

Method	Number of Samples	Accuracy of Rank 20	Average Accuracy up to Rank 20	Average Accuracy up to Rank 60	Average Time (in Seconds)
Hard BioHash	1000	0.498	0.364	0.522	0.89
	5743	0.294	0.214	0.317	58.7
Soft BioHash	1000	**0.784**	**0.684**	**0.780**	**0.14**
	5743	**0.628**	**0.530**	**0.647**	**0.50**

From Table 1, it can be seen that our proposed method of Soft BioHash is feasible and effective, as the retrieval accuracy increased by 28.6% when applied to 1000 samples and further increased by 33.4% when applied to 5743 samples, with much shorter average retrieval times of 0.14 (seconds) and 0.50 (seconds), respectively, for retrieving the top 20 similar face images.

With a view to more fully evaluating and comparing the search and retrieval performance of our proposed method, Table 2 and Figure 8 present the performance results with four standard metrics that were adopted as performance measurements: accuracy, precision, recall, and F1-score, with varying numbers of data. Figure 8 shows a graphical performance representation; the horizontal axis of the graph shows the method type, and the vertical axis shows how well the face image retrieval was conducted based on the different evaluation metrics. As we can see from the results in Table 2, Soft BioHash obtained better results, by all metrics, on both of the datasets used and with different numbers of samples.

Table 2. Performance comparison of various evaluation metrics.

Evaluation Metrics	1000 Samples		5743 Samples	
	Hard BioHash	Soft BioHash	Hard BioHash	Soft BioHash
Accuracy	0.498	**0.784**	0.294	**0.628**
F1-score	0.453	**0.762**	0.275	**0.598**
Recall	0.498	**0.784**	0.294	**0.628**
Precision	0.504	**0.779**	0.307	**0.627**

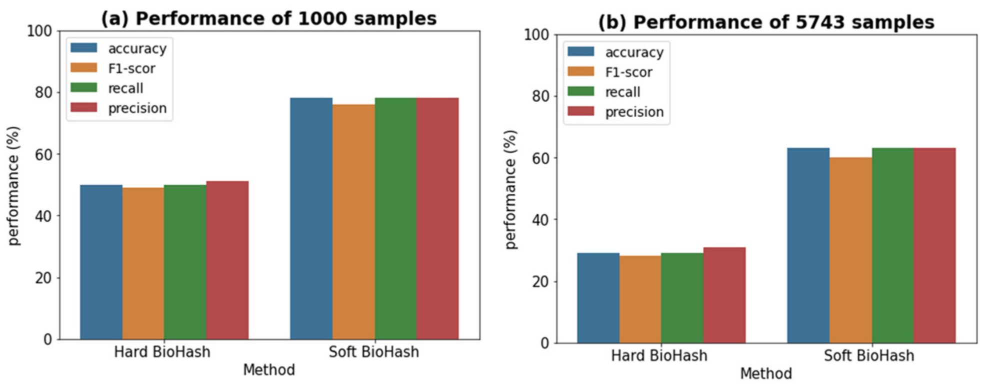

Figure 8. Performance comparison of Hard and Soft BioHash methods with various standard evaluation metrics. (**a**) Represents performance with 1000 samples; (**b**) represents the performance with 5743 samples.

The corresponding CMC curves (up to rank 60) were deduced to show the accuracy performance of the traditional method versus the Soft BioHash when tested for 1000 and 5743 samples, as illustrated in Figure 9. Figure 9a represents the accuracy performance of the Soft BioHash method compared with the traditional Hard BioHash method when tested for 1000 samples, while Figure 9b represents the accuracy performance of the Soft BioHash method compared with the traditional Hard BioHash method when tested for 5743 samples, where the Soft BioHash approach outperforms the traditional hash method (Hard BioHash) along the ranks from 1 to 60.

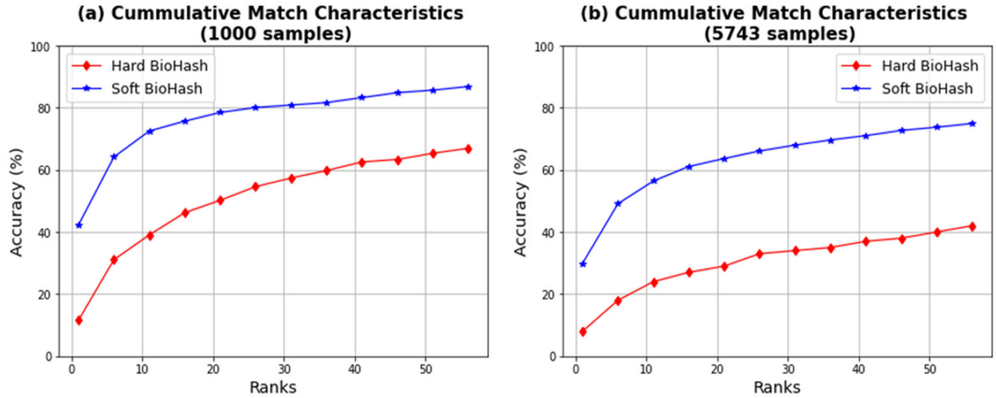

Figure 9. CMC curves of retrieval performance comparing the proposed method and traditional method when examined for different numbers of data samples.

5.3. Comparative Analyses

Table 3 provides a comparison of this study with other related earlier studies in the literature that used different locality-sensitive hashing techniques for face images in terms of the database used, the number of images used in each experiment domain, selected and used subsets of the dataset, the uncontrolled database environment, and, finally, the LSH-based method used. From Table 3, it can be seen that our study used hashes on an uncontrolled database representing a much more challenging scenario of content-based face image retrieval and face recognition domains. Moreover, Soft BioHash was uniquely applied, where it ran two separate experiments on the LFW and LFW-attributes datasets and tested the effects of the number of photos per person on the retrieval rate. Since we only chose people who had three or more images in the database, the total number of images per experiment became 5743 images. This all enhances the success of our proposed method that, as reported in Tables 1 and 2, had superior performance and improved speed of search versus the traditional method based on Hard BioHash.

Table 3. Comparative analysis of the current study and previous studies.

Study	Database	Number of Images	Selected and Used Subsets	Uncontrolled Environment	Hard BioHash	Soft BioHash
[18]	ORL, AR face, Stirling faces.	400, 2600, and 315, respectively.	All images of (ORL, AR face, and Stirling faces).	×	√	×
[35]	FERET, ORL, and AR.	14,126, 400, and over 4000, respectively.	The FERET dataset contains two unique image subsets (1980 and 4017), 100 images of ORL, and 98 images of AR.	×	√	×
[36]	Combination of CF1999 and TDF (CF), the database of faces (TDF), Caltech Faces 1999 (CF1999), Labeled Faces in the Wild (LFW)	Not mentioned, 400, 447, and 13,233, respectively.	500 to 12,000 images from different datasets.	√	√	×
Our work	LFW, LFW-attributes.	Over 13,233 and 13,143.	5743 of LFW and 5743 of LFW-attributes.	√	√	√

6. Conclusions

This research study aimed to improve face image retrieval in terms of retrieval speed and accuracy. Therefore, it investigated whether a Soft BioHash could more rapidly and accurately search and retrieve a similar target face picture than Hard BioHash. We designed two different types of experiments to test the effect of using LSH on the performance of retrieving face images: (1) face image retrieval using Hard BioHash; (2) face image retrieval using Soft BioHash. The experimental results clearly show that the proposed Soft BioHash offers a higher accuracy of 78% when applied to 1000 samples, and 63% when applied to 5743 samples, with average retrieval times of 0.14 s and 0.50 s, respectively. We determined from the results that using Soft BioHash improves retrieval performance and reduces the time spent in retrieving images similar to the input query. However, there is still a need to develop systems that automatically label datasets to collect soft biometrics. In the future, the proposed retrieval method can be extended to be applied to online face image databases.

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