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Original Article

A Hybrid Lbp (Local Binary Pattern) - Gwt (Gabor Wavelet Transform) Face Extraction Technique for Age Invariant Face Recognition System

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ABSTRACT

Face recognition across ages is an important problem in face recognition system and has many applications, such as passport photo verification, image retrieval, surveillance. The major challenge of most face recognition systems degrade severely under nuisance factor like age, occlusion, motion blur, facial expression, pose and illumination variations which make their implementations fail in practice. Currently emerging solutions and implementations couldn't handle the major challenges, especially age variations wholly in an accurate and computationally- efficient manner. To the best of our knowledge, Gabor Wavelet Transform (GWT) and Local Binary Pattern (LPB) have been recognized as the two most successful local feature extraction methods for local- based face representation. This work therefore proposed a hybrid LBP-GWT face extraction technique for age invariant face recognition system and compared its efficiency with the existing algorithms using some specific evaluation techniques. LBP-GWT feature extraction technique was developed using feature level fusion. Feature level fusion involves consolidating the feature sets obtained from multiple Feature Extraction Techniques (LBP and GWT) into a single feature. Particle Swarm Optimization (PSO) was used to reduce the features dimensions. Finally, Support Vector Machine (SVM) was used for classification and recognition. The hybrid LBP-GWT accuracy was tested on FG-NET aging database. The result showed hybrid LBP-GWT exhibit the lowest computational time followed by LBP and GWT respectively. In terms of recognition accuracy, the hybrid approach shows 100% accuracy while the recognition accuracy for LBP and GWT are 89.14% and 81.23% respectively. Finally, we evaluate our results with other recent work on age invariant recognition which shows hybrid LPB- GWT performs better. The Hybrid LBT-GWT feature extraction technique shows remarkable improvement over other existing algorithms in terms of computational time complexity and recognition accuracy when implemented in aging invariant face recognition system.

Keywords: Face recognition, Age invariant, Gabor Wavelet Transform (GWT), Local Binary Pattern (LBP), Hybrid

INTRODUCTION

Identifying a subject by their face using only their facial features is known as face recognition. A facial recognition system is a technology that can compare a human face from a digital photo or video frame to a database of faces. Such a system, which locates and measures face features from an image, is commonly used to authenticate individuals through ID verification services [1]. Face recognition has garnered much attention in the last three decades since it is seen to be a more straightforward use of image analysis and pattern recognition [2]. For automated face recognition, a variety of techniques from several research fields, including vision, image processing, pattern recognition, and machine learning, are required [3]. Face recognition systems usually use a one-to-one or one-to-many technique to match the attest subject's (probe image) face image to the gallery data after enrolling face photos of several subjects as gallery data [4]. A facial recognition system's ability to perform mass identification without the test subject's cooperation is one of its main advantages; however, when compared to other biometric techniques, face recognition may not be the most reliable and efficient. Quality measures are crucial in facial recognition systems because face images can vary greatly, and factors like illumination, expression, pose, and noise during face capture can affect the

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system's performance [5]. Facial recognition has the highest rates of false acceptance and rejection of any biometric system, so there have been concerns raised about the software's effectiveness or bias in cases involving law enforcement, housing and employment, and railway and airport security. As people age, their faces change significantly. Facial recognition across age groups is a significant issue with a wide range of applications, including image retrieval, surveillance, and passport photo verification [6]. Because human faces can change significantly over time in a variety of ways, such as texture, form, hairstyle, the existence of spectacles, etc., this is a difficult undertaking [7]. The primary indicator of facial aging in younger age groups is facial growth; in later age groups over 18, it is represented by relatively major texture changes and small shape changes brought on by changes in weight, wrinkles, or skin stiffness. As a result, both kinds of aging processes must be compensated for by an age correction plan [7]. More often than not, most existing age-invariant face recognition systems are computationally very expensive, which makes them difficult to implement in practice. This is because such implementations are based on holistic feature extraction techniques, which are highly sensitive to illumination and aging conditions [8, 9]. This research aims to build a hybrid LBP-GWT feature extraction method for face recognition systems that are age-invariant. The goals of this review are to (i) Provide an age-invariant, computationally effective LBP-GWT feature extraction method. (ii) As performance evaluation measures, computing time, false acceptance rate (FAR), and false reject rate (FRR) are to be used to compare the effectiveness of the suggested LBP-GWT feature extraction technique to LBP and GWT. (iii) Comparison of the proposed method with other age-invariant face recognition methods on the FG-NET database.

Local Binary Pattern (Lbp) In Face Recognition

To conduct face recognition, there are several ways to extract the most valuable features from (preprocessed) face photos [10]. The Local Binary Pattern (LBP) approach is one of these feature extraction techniques. A digital image's texture and shape can be described using LBP [11]. To accomplish this, an image is divided into multiple small sections, from which the characteristics are taken. These characteristics are made up of binary patterns that characterize the areas around the pixels in the regions [12]. An image representation is created by concatenating the features that were extracted from the regions into a single feature histogram. The similarity (distance) between the histograms of the images can then be used to compare them [13]. Numerous studies have shown that face recognition with the LBP approach performs exceptionally well in terms of speed and discrimination. The approach appears to be rather resilient against face photographs with varying facial expressions, lighting circumstances, image rotation, and aging of individuals due to the way the texture and shape of images are described [14]. In various tasks involving face detection, face recognition, facial expression analysis, demographic (gender, race, age, etc.) classification, and other related applications, LBP has been used for facial representation [15].

Gabor Wavelet Transform (Gwt) In Face Recognition

The Gabor wavelet was introduced by David Gabor in 1946. In a sinusoidal plane wave, the Gabor wavelet is modulated with a particular orientation and frequency using the Gaussian envelope [16]. It is suitable for changing the contents of the pattern of orientation-dependent frequency since it can show the structure of spatial frequency while maintaining information about spatial relations [17].

Local Approaches for Age-Invariant Face Recognition

Duan *et al.* [18] introduced an advanced algorithm for face recognition against age invariants using multi-feature discriminant analysis (MFDA), which combines scale-invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) to encode the local features. Kulbacki *et al.* [19] introduced a method using coordinate patches and GMMs to estimate facial ages. In their method, the face image of an individual is encoded as an ensemble of overlapped spatially flexible patches. (SFPs), each of which integrates coordinates information together with the local features that are extracted by 2D discrete cosine transform (DCT). These extracted SFPs are modeled with GMMs to estimate the age of a person in the input facial image, by comprising the sum of likelihoods from total SPFs of the hypothetic age. Akinyemi, [20] also proposed a manifold learning technique in which a low-dimensional manifold is learned from a set of age-separated face images. Linear and quadratic regression functions were applied to the low dimensional feature vectors from the respective manifolds in face age estimation. Bourlard and Popescu-Belis, [21] presented an approach to perform face verification across age progression by using a Q-stack classifier.

METHODOLOGY

In this research, two (2) local Face Extraction Techniques (FETs) i.e., Local Binary Pattern (LBP) and Gabor Wavelet Transform (GWT) combined in a feature-level fashion using sum rule fusion strategy to realize an improved feature extraction method referred to as LBP-GWT FET for the age-invariant FRS.

Research Framework

Generally, there are four basic stages involved in FRS development [22]:

i. Face Detection
ii. Face Pre-processing
iii. Feature Extraction
iv. Recognition via classification

This research work is composed of four (4) development phases:

i. Acquisition of probe and gallery images (still/frontal images) from the FG-NET aging dataset.
ii. Development of an LBP-GWT FET which incorporates both two (2) local feature extraction approaches.
iii. Evaluation of the proposed LBP-GWT age invariant FET against LBP and GWT using False Acceptance Rate (FAR), False Rejection Rate (FRR), and computation time as performance evaluation metrics.

Development of an FRS incorporating the proposed age–invariant FET at the feature extraction stage of the FRS.

Conceptual Design of the Developed LBP-GWT FET

The conceptual design and control flow of the developed feature extraction technique using the feature-level configuration are depicted below:

Feature Extraction Performance Evaluation Metrics

1. The False Accept Rate (FAR): This is the percentage of probes a system falsely accepts even though their claimed identities are incorrect [23].

$$\text{FAR} = \frac{\textit{number of false accepts}}{\textit{number of impostor scores}}$$

2. The False Reject Rate (FRR): This is the percentage of probes a system falsely rejects even though their claimed identities are correct. A false acceptance occurs when the recognition system decides a true claim is false [23].

$$\text{FRR} = \frac{\textbf{number of false rejects}}{\textbf{Number of genuine scores}}$$

Receiver Operating Characteristic (ROC) Curve: The Receiver Operating Characteristic (ROC) curve plots the FRR against the FAR, termed the equal error rate (EER), and is often used to summarize verification performance. A verification algorithm achieves perfect performance if it reaches a 0.0% FRR at a 0.0% FAR. Processing time: This represents the time required to process and recognize all faces in a frame. This parameter depends on the platform where the recognition is implemented and will dictate if real-time functionality is available or not.

RESEARCH TOOLS/INSTRUMENTS

The research instruments used to achieve the aim of this research work are presented. These include the FG-NET aging dataset and the simulation tool.

The FG-NET Aging Dataset

To benchmark an algorithm, it is important to use a standard test database. Therefore, in this research work, the FG-NET aging dataset composed of 1,002 face images from 82 different subjects was used to evaluate the performance of the developed age-invariant FET. This dataset is challenging as the images vary in terms of age [6].

The Simulation Tool

The simulation tool that was used in this work is MATLAB. This is because MATLAB is a very powerful computing system for handling calculations involved in scientific and engineering problems. The name MATLAB stands for MATrix LABoratory. With MATLAB, computational functions and graphical tools to solve relatively complex science and engineering problems can be developed and implemented [24]. The image processing, vision, neural network, math, wavelet, and some user-defined toolboxes were specifically adopted.

RESULT AND DISCUSSION

The result of the feature extraction algorithms considered is summarized below;

Table 4.1: Summary of the result of the performance of each algorithm

Algorithm	Average Processing time(sec)	FAR (%)	FRR (%)	Recognition Accuracy (%)
LBP	7.5264	10	8	91.14
GWT	8.8796	12	15	86.34
LBP-GWT	7.3412	0	0	100

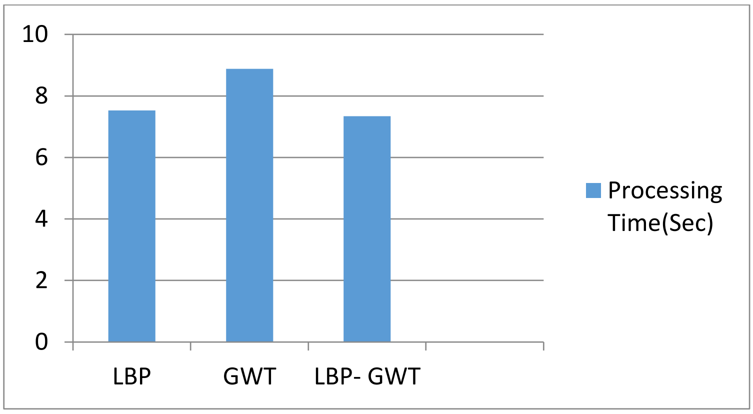

Figure 4.1a: A chart showing the performance of each algorithm according to their computational time (Processing time)

It shows that Hybrid LBP-GWT exhibits the lowest computational time overhead, followed by LBP and GWT respectively.

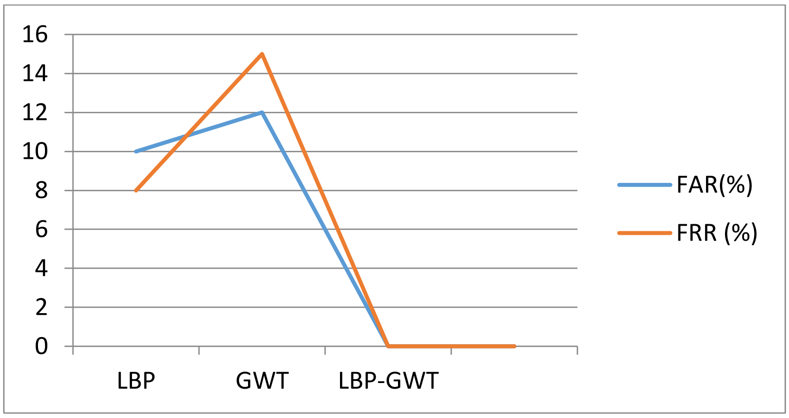

Figure 4.1b: A graph showing the performance of each algorithm according to its False Acceptance Rate (FAR) and False Rejection Rate (FRR). The figure above shows that Hybrid LBP- GWT has no (0) False acceptance and no False Rejection which gives it the best performance.

Based on these results, it shows that hybrid LBP-GWT exhibits the lowest computational time. However, LBP also exhibits lower computational time overhead and is better off than the GWT. This result confirms the report by Basar *et al*. [25] of LBP exhibiting low computational complexity which makes it widely acceptable. Using the FAR and FRR performance evaluation metric, the result returns nil for both false acceptance and rejection acceptance when tested on hybrid LBP-GWT which gave us 100% recognition accuracy. Therefore, the combined LBP-GWT feature extraction technique shows remarkable improvement over LBP and GWT in terms of computational complexity and recognition accuracy when implemented in an aging invariant face recognition system. Finally, this work was evaluated with other work on age invariant recognition which shows hybrid LBP-GWT performs better. The table below shows the comparison of the result with the existing age-invariant recognition system.

Table 4.2: Comparison of age-invariant face recognition methods on FG-NET database

Approach	Number of subjects, images in probe, and gallery	Identification Rate	References
Learn Aging patterns on concatenated PCA coefficients of shape and texture from full face across a series of ages.	FG-NET (10,10)	38.1%	[26]
Learn aging patterns based on PCA coefficients in separated 3D shapes.	FG-NET (82,1002)	37.4%	[27]
HOG features descriptor. PCA and LDA (for dimension reduction).	FG-NET (10,10)	69%	[28]
Use latent Identity. They design a Latent Identity Analysis (LIA) method to learn weight and bias parameters for the LF-CNN.	FG – NET (82, 1002)	88.1%	[29]
K-nearest neighbor (KNN) and SVM classifier (for age group greater than 40)	FG – NET (1000)	98.25%	[30]
Hybrid LBP-GWT +PSO+SVM.	FG – NET (82,1002)	**100%**	Achieved Method

CONCLUSION

This research work has resulted in overall success, being able to perform significantly better compared to existing algorithms. The hybrid LBP- GWT exhibited the lowest computational time when compared with LBP and GWT respectively. In terms of recognition accuracy, the hybrid approach shows 100% accuracy while the recognition accuracy for LBP and GWT are 89.14% and 81.23% respectively. The result shows combining LBP and GWT increases recognition accuracy in age–invariant systems in a computationally – efficient manner.

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