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Robotic Facial Profile Identification using Neuro-Fuzzy System

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ABSTRACT

Facial recognition technology can verify or identify a person's identity. People can be recognized using facial recognition software in real-time or in images and videos. To identify the face, neural networks are trained to correctly classify the coefficients determined by the eigenface technique. The network is used to recognize the face photographs that are supplied to it after being trained on images from the face database. The basic difference between neural networks and fuzzy logic is that neural networks are mainly based on learning, help to perform predictions, and are difficult to extract knowledge from, while fuzzy logic isn't based on learning, helps to perform pattern recognition, and knowledge can easily be extracted. An artificial intelligence procedure called a neural network trains computers to examine evidence in a way similar to the human brain. Deep learning is a kind of machine learning method that uses networked nodes, or neurons, organized in a coated design to copy the associations of the human brain. A neuro-fuzzy system is an ambiguous system that applies data trials to govern its parameters (fuzzy rules and fuzzy sets) using a knowledge scheme inspired by or developed from neural artificial intelligence that merges fuzzy logic components with neural networks. One class of machine learning techniques used to model complicated patterns in data is neural networks. One kind of logic that permits approximate reasoning is fuzzy logic. Neuro-fuzzy systems are effective instruments for handling intricate, ambiguous, and ever-changing jobs. They combine the advantages of neural networks and fuzzy logic to attain exceptional outcomes.

Keywords: Deep Learning, Ensemble Models, Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs) and Feature Extraction.

INTRODUCTION

Face recognition is a powerful technology that has become increasingly important every day. It's fascinating how our brains are naturally wired to recognize faces and emotions effortlessly. This ability remains strong even with changes like aging, different conditions, or variations in appearance like beards or glasses. Advancements in automated face recognition have been ongoing since the 1960s. Still, it's now gaining more attention and significance, especially in addressing issues like identity falsification and intrusion into secure areas [1-2]. The need for reliable and user-friendly identification methods has led to the rise of biometrics as a promising alternative to traditional methods such as PIN codes or passwords. Biometrics, which focuses on verifying unique aspects of individuals, offers a more secure and efficient way of confirming identities. It's exciting to see how this technology is shaping the future of identification and security measures. Although there is still a long way to go before facial recognition technology can match human performance, considerable strides have been made in controlled settings [3-4].

However, computer-based face recognition algorithms are used in real-world scenarios where conditions are less controlled and individuals may not cooperate. It's fascinating to see the evolution of face recognition technology from 2D image-based approaches to the recent focus on 3D image-based face recognition [5]. The availability of affordable RGB-D cameras that provide depth information has opened up new possibilities for enhancing face recognition systems. By incorporating depth information along with RGB images, the algorithms can become more efficient and robust, especially in handling issues like non-uniform illumination and pose deviations that can hinder traditional 2D algorithms. Converting faces from 2D to 3D can indeed provide a normalized view of the faces in terms of pose and illumination, which can significantly enhance the recognition performance, especially in unconstrained scenarios. By utilizing the 3D model to generate normalized 2D images, you're effectively addressing the challenges posed by variations in position and brightness, hence improving the robustness and accuracy of the face recognition system. This method sounds like a promising way to daze the limitations of traditional 2D face acknowledgment systems and enhance performance in real-world applications [6-7]. It's impressive to see how advancements in technology are enabling innovative solutions to complex problems in face recognition.

Face Detection Using Biometrics

Face detection involves identifying all possible faces at diverse positions and masses within a given image. Finding any faces in the picture and, if so, providing their location and sizes is the main objective of face detection. Face detection in photos is essential for intelligent vision-based human-computer interaction (HCI) and surveillance systems [8]. The process typically involves distinguishing between images containing faces and those without faces. While humans find face detection to be a simple task, it poses significant challenges for computers due to distinctions in scale, position, alignment, pose, facemask expressions, illumination circumstances, and obstructions. Researchers have extensively studied face detection over the years, focusing on addressing challenges like scale, rotation, pose, and illumination variations [9].

Advancements in face detection techniques have shown considerable progress, with researchers continuously exploring and improving methods to enhance accuracy and efficiency. Its primary goal is to identify all potential faces in an image at different locations and sizes. The objective is to determine if faces are present in the image and provide their location and size. Researchers have extensively studied face detection over the years, focusing on addressing these challenges. Advancements in face detection techniques have shown significant progress, with researchers continuously exploring methods to improve accuracy and efficiency [10].

Biometrics

Face recognition with other biometric methods like fingerprinting, hand geometry, iris, retina, voice recognition, and signatures. Face recognition stands out due to its non-intrusive nature; users don't need to perform any specific actions like placing a hand or standing still. This makes it more user-friendly and convenient. Additionally, the equipment needed for face recognition is generally less sensitive to motion compared to other biometric technologies, making it easier to use in various settings [11]. The points I mentioned about the limitations of other biometric methods highlight the strengths of face recognition.

Feature Extraction

a) The DCT in One Dimension:

A 1-D sequence of length N with the most often used DCT definition is mathematically described as:

C(u) = alpha (u) * sum x = cos [(pi (2x + 1) * u) / (2N)] f(x) * 0 to N-1 f(x) = sum u = C(u) * 0 to N-1

alpha (u) * cos [(pi (2x + 1) * u) / (2N)] .... (1)

for x = 0, 1, 2, 3, 4, 5...., N-1

Where:

a (u) = sqrt (2/ N) for u = 0 for u $\neq$ 0; sqrt (1/ N)

b) The DCT in Two Dimensions:

N–AN-1 C (u, v) = a (u) α (v) ΣΣ f (x, y) cos π (2x+1) и 2 N COS π (2y+1) v 2N, is the formula for the 2-D DCT .... (2)

The 1-D case is directly expanded in this way. For (u, v) is 0, 1, 2...., N-1 and (u) and a (v), in the instance of 1D DCT.

The converse change is defined as N-AN-1 f (x, y) = Σ α (u) a (v) C (u, v) cos. π (2x+1) μ 2 N τος [π (2y+1) μ 2 N for every x, y 0, 1, 2, 3, 4, 5…...., N-1.

For u = 0 C (u = 0), it is evident from. The sample sequence's average value thus serves as the first transform coefficient. This figure is known as the DC Coefficient in writing. The term "AC Coefficients" refers to all other transform coefficients.

c) The Transform of Discrete Wavelets:

For DWT, the set of the mother wavelet's translation and dilation is defined as follows:

(t) = 2(2-k) Wjk(t)

In this case, j stands for the scaling factor, and k for the translation factor. It is easy to see the power of two natures in the dilation factor. Next, compute the forward and inverse transforms using the following:

equations: Cj. k= [w3. k(t)dt] f(t)

f(t) = C.kj. k(t)

An analytical wavelet set that closely fits the data's features should be selected for effective data decorrelation. This, along with the wavelet set's (b)orthogonality, will produce a set of sparse coefficients in the transform domain, which will lower the number of bits required for encoding.

Experiment Results Using DCT

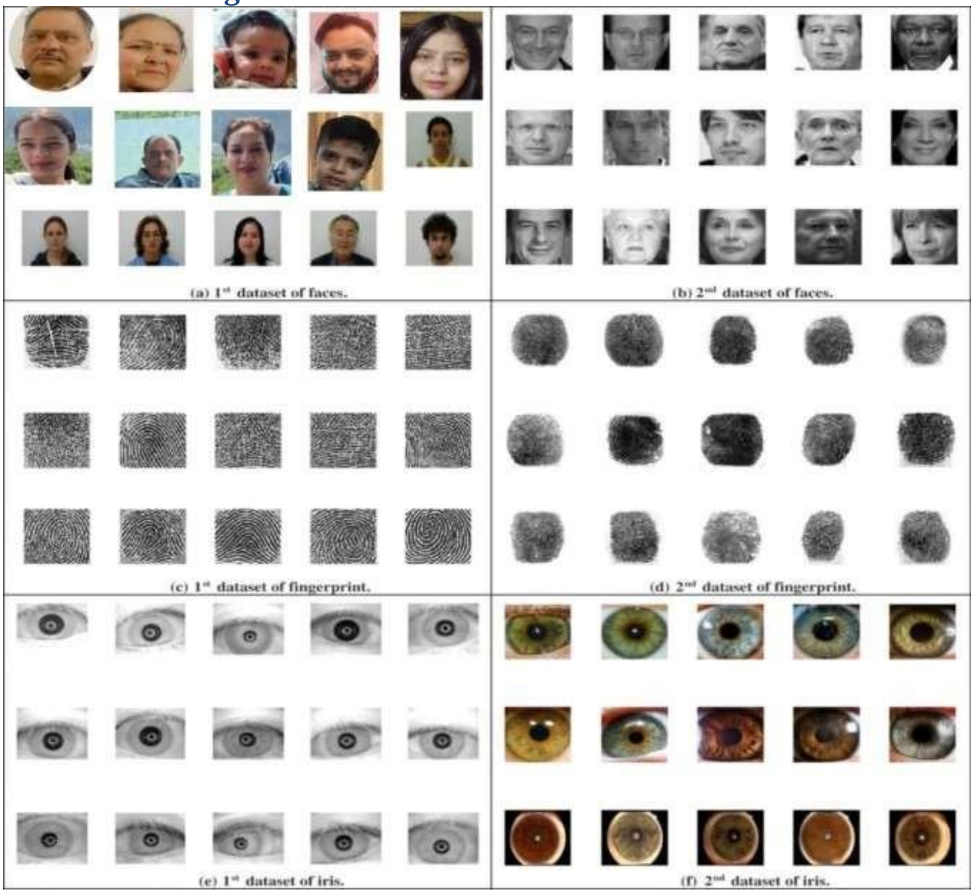


Figure 1. Feature Extraction and Experiment Results Using DCT

The utilization of 2D-DCT coefficients for feature abstraction in image processing. Dividing images into 8x8 blocks and extracting lower-frequency components using DCT is a common technique in image analysis. The implementation of 6 features per block and utilizing a Hidden Markov Model (HMM) with 6 states and 6 Gaussian Mixtures per state for recognition is a robust approach. The Viterbi recognizer is an efficient method for matching HMMs against test images to find the best match (Figure 1). Modeling images like fingerprints and faces using an ID HMM by assigning regions to states is a clever strategy [12]. Training HMMs without manually segmented data and allowing the models to cluster states autonomously is a noteworthy approach in unsupervised learning.

Image Recognized Using Compressed Domain

Face recognition technology, especially in the compressed domain. The idea of conducting face recognition directly in the compressed JPEG and JPEG 2000 domains without fully decompressing the images is quite innovative [6-7]. This approach could significantly enhance the speed and performance of face recognition systems. It's impressive how researchers like Delac et al. have explored this area to maintain recognition rates even in compressed image domains (Figure 2).

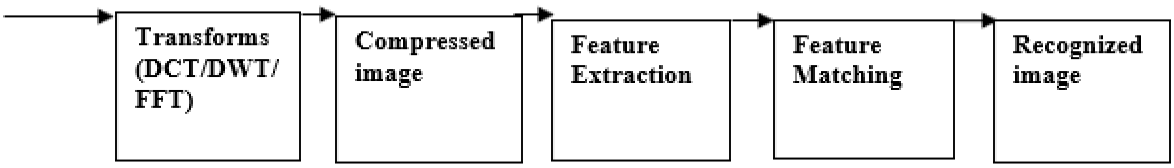


Figure 2. Face recognition technology in the compressed domain

Fast Fourier Transform (FFT)

formulated as, N-1 x (k) = x (n) W, 0 ≤ k ≤ N-1 0 -12万 WN = e

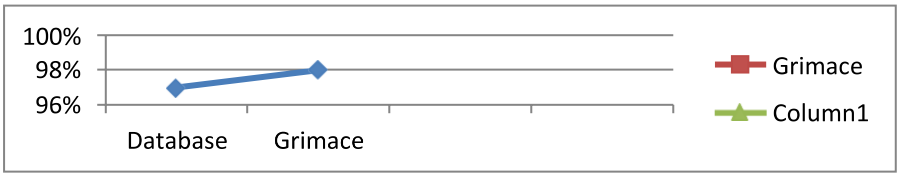
The frequency domain variable is called k, and the time domain variable is called n. For large datasets, the Fast Fourier Transform (FFT), provides a significant speedup in the calculation as compared to directly calculating the DFT. Particularly for datasets containing thousands or millions of points, the FFT technique dramatically reduces computational convolution from O (N^2) to O (N log N) operations. This speed enhancement has made DFT-based algorithms practical for various applications, ranging from digital signal processing to solving complex equations and multiplying large integers quickly [8-9]. FFT's effectiveness and adaptability make it essential in many different disciplines.

Comparing Recognition Rates Without Using Any Compression

The recognition rates for the two databases are compared, showcasing the effectiveness of the system. The comparison of recognition rates without compression is presented for the GRIMACE and created database. The recognition rates for both databases are shown, highlighting the differences in performance. Moreover, it shows the system's performance both with and without compression, showing a 2% rise in recognition rate when DWT compression is used [10]. Understanding the impact of compression and direct computation on recognition rates provides valuable insights into system efficiency and accuracy (Figure 3).

Grimace	**98%**
Created Database	97%

(a)



(b)

Figure 3. Comparing recognition rates without using any compression

Face Detection Using the Gaussian Membership Function, Adaptive Neuro-Fuzzy Interference System, And Fuzzy Interference System

It appears that the process involves two main parts: feature extraction using image processing and detection. In the image processing stage, the gray image is divided into blocks, and characteristics like edge presence, shade, and mixed range are identified within these blocks. Block connection with edges, shades, and mixed ranges can be determined by analyzing image metrics such as variance, average gradient, and the difference between maximum and minimum gradients. By partitioning the image and evaluating these parameters within blocks, the system can effectively extract features that aid in subsequent detection tasks [6].

Gaussian Membership

the Gaussian membership function to evaluate the membership values. The Gaussian membership function is a type of curve that is commonly used to represent vague, linguistic terms in the input space to have affiliation values between 0 and 1.

Now, the Gaussian membership function: -

mu Ai (x) = exp (sigma i ^ 2 * (c i - x) ^ 2 / 2)) n,

In this equation, the width of the i-th fuzzy set A_{i} is represented by sigma_{i}, and the center is represented by c_{i}. The system can efficiently model and assess the degree of membership for various inputs in the face identification process by employing the Gaussian membership function. In the method you mentioned, they use the Gaussian membership shape for training as input to the Adaptive Neuro-fuzzy Inference System (ANFIS).
Now, we have used the Sugeno fuzzy model formula:
z= f (x, y) for each x in A and each y in B,
where,
Fuzzy Sets in the Antecedent are A and B and
Crisp Function in the Consequent is z= f (x, y)
For the three variables, variance (ơ), Gdiff, and Gavg, membership functions are created. The membership function for the variance variable (o^2). Three MFs per fuzzy set correspond to three different departures from neutral. The selection of the MF shapes is based on the specific objectives. It's crucial in fuzzy modeling to choose an appropriate number of membership functions to preserve evocative verbal explanations.

Fuzzy Inference Systems (FIS)

Similar to neural networks, FIS maps inputs using input membership functions and the parameters that go along with them. The essential structure includes mapping input features to input involvement functions, which then prime to rules, output features, output affiliation functions, and finally to a single-valued output or result. In FIS, the input/output mapping is inferred through output affiliation functions and their constraints. A gradient vector, which indicates how well the FIS models the input/output data with a particular set of constraints, directs the adjustment of these constraints [5-6]. Constraints can be adjusted to minimize the error, which is calculated as the sum of squared discrepancies between the desired and real outputs, by employing the gradient vector. These rules help in decision-making within the FIS based on input conditions (Figure 3 and 4). The value following each fuzzy rule specifies its initial weight when it is executed; this value will be adjusted to the correct level at the end of training. The product operator can implement the intersection in a neuro-fuzzy system. Consequently, neuron I's output in Layer 3 is obtained as,

y i ^ (3) = x_{2i} ^ (3) ... x ki ^ (3) y R1 ^ (3) * x_{1i} ^ (3) * = mu B1* mu A1 = mu R1

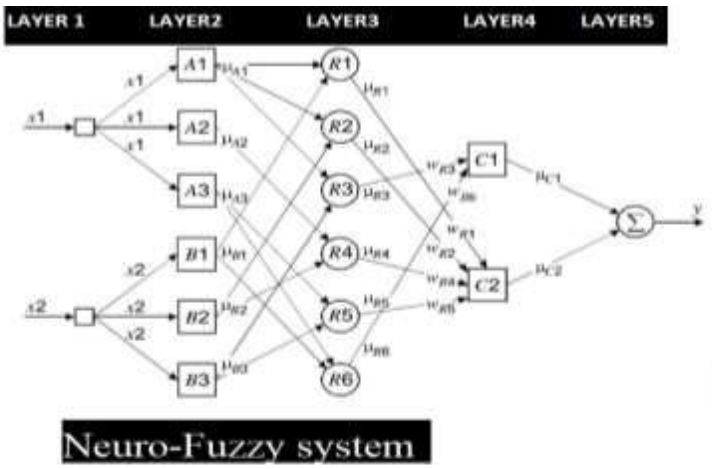


Figure 3. Neuro-Fuzzy system

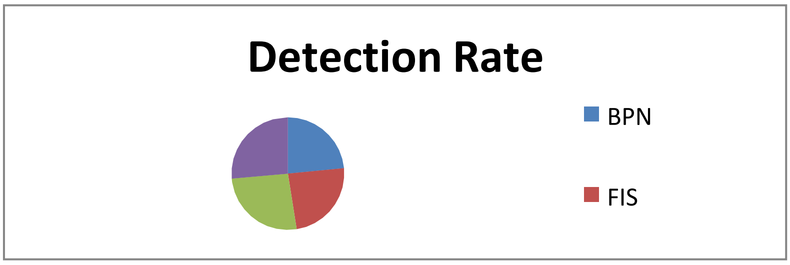


Figure 4. Detection Rate

Present and Future Work

the customized approach using the Edge Tracking Algorithm and BPN Network for face detection. MATLAB indeed provides robust mathematical and numerical support, making it a popular choice for implementing advanced algorithms in image processing and computer vision. The revealing rate of improvement achieved through these methods is significant and crucial in computer vision applications. Comparing the performance of different models like BPN Network, Neuro-Fuzzy, and ANFIS based on training set size for the Bio ID database is a valuable analysis to understand their effectiveness in face detection. The high detection rates observed, such as 98.5% for ANFIS with 150 training patterns, demonstrate the potential of these models to accurately detect faces. It's impressive to see the advancements in face detection techniques and the continuous efforts to enhance detection rates for better performance in various applications.

CONCLUSION

In my research work, the system's goal is to compress images using three different transforms: DWT, DCT, and FFT. By using this algorithm, we have achieved the best recognition rate of 96% using DWT. While the recognition rate might be slightly lower in the proposed system compared to a normal recognition system without compression, the benefits lie in reduced computational complexity, time consumption, and storage space requirements for the images in the database when utilizing compressed images for testing. This trade-off can be advantageous in scenarios where efficiency and resource optimization are crucial factors. face detection systems based on different approaches, such as BPN Network, FIS, Neuro-Fuzzy, and ANFIS. The system's significance lies in fuzzy membership, which helps in identifying crucial features in human faces and their relative distances, providing size and rotational invariance. ANFIS exhibits faster performance as it requires fewer iterations and generalizes well even with fewer training samples compared to BPN models. For instance, ANFIS achieves a 96% detection rate with 100 training samples, while the BPN Network needs 150 training samples to reach the same detection rate, indicating the efficiency of ANFIS in requiring fewer training patterns for similar performance.

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