Force Field Feature Extraction Using Fast Algorithm for Face Recognition Performance

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Abstract. Face recognition is method of recognizing individuals by facial expressions. It has become essential for security and surveillance applications, including banks, organisations, workplaces, and social areas, and is needed everywhere. In face recognition, there are a variety of difficulties faced, including face shape, age, sex, lighting, and other variable factors. Another problem is that the scale of the servers for these apps is relatively limited. Education and acknowledgment, thus, are increasingly complicated. In recent years, many unchanged features have been proposed in the literature, in this paper approach the use of the fast algorithm as local descriptors, and as we shall see, it is not only fixed-size features, but also offers the advantage of being highly efficient. The proposed approach allows distinguishing the destination after converting the image to the HSV system, after which the force field features will be extracted using the fast algorithm and then classification by using the distance for three methods (Manhattan, Euclidean, and Cosine) through which a comparison is made to choose the best resolution, as it was found that the resulting accuracy of the two dataset (ORL and UFI) is 99.9%.

1. Introduction

Due to the availability of feasible technologies after thorough study in this area and vulnerabilities in other identity schemes, the biometrics area has gained utmost interest and made its position as the most secure option for recognition in the recent past. Nevertheless, efforts to build a more user-friendly solution that satisfies security framework specifications are already in force, delivering more detailed outcomes, securing our information and safeguarding our privacy. In conventional identification approaches, ambiguities occur as they authenticate individuals and give them access to virtual and physical realms that investigate the actions and conduct of a person [1]. Physiological features and traits in sequence. Over the last ten years or so, face recognition has become a common field in computer vision science and one of the most promising image processing and understanding applications. Because of the existence of the issue, it is not only of concern to computer science researchers, but also to neuroscientists and psychologists. It is the common assumption that advancement in computer vision technology can give neuroscientists and psychologists valuable insights into how the human brain functions, and vice versa. Studies [2]. A general statement of the issue of face recognition (in computer vision) can be formulated as follows: Recognise or check one or more individuals in the scene using a recorded facial database, provided still or video images of a scene. [3].
Facial expression is a nonverbal communication technique, since it uses gestures to communicate messages. For the facial recognition devices, though, voice variance induces vagueness. Several facial recognition technologies have been developed that function well in a regulated framework for the videos. Different facial expressions display different moods, people's emotions, and change the faces' structure, and it becomes difficult for the machine to identify the face if there is slight variance in the picture. Researchers have experimented with facial expression in mind for face recognition. There are numerous approaches to this issue, such as model-base approaches, muscle-base approaches, motion-based approaches, etc. [4].

2. Literature Review
In this paragraph, some previous researchers will be reviewed that have used fast algorithms to depict face recognition.

Gupta, S [5] The feature-based technique for 2D face images was implemented. For function extraction, accelerated robust features (SURF) and scale-invariant feature transformation (SIFT) are used. For experimental analysis, five public databases, namely Yale2B, Face 94, M2VTS, ORL, and FERET, are used. In this thesis, different combinations of SIFT and SURF features have been evaluated with two classification techniques, namely decision tree and random forest. Writers with a mixture of SIFT (64-components) and SURF (32-components) have recorded a maximum recognition accuracy of 99.7 percent.

Yong LI [6] Present CNN with Concentration System (ACNN) in the case of occlusions for facial expression recognition. In ACNN, the Gate Unit helps the model to transfer focus from the occluded patches to other unhindered and distinctive facial areas. We developed a patch-based pACNN that implements region decomposition to locate traditional facial sections that are linked to expression, given that facial expression is distinct in some facial regions. In the presence of occlusions, we have established an effective gACNN to complement global facial knowledge for FER. Intra- and cross-dataset measurement protocol studies have shown that ACNNs outperform other state-of-the-art approaches. Analyses of ablation suggest that ACNNs are able to transfer focus from occluded patches to other associated ones. For future work, as ACNNs rely on robust face recognition and facial landmark localization modules, we will research how to produce attention components in faces without landmarks.

Lucy Nwosu et.al [7] It suggests using facial parts to build a Facial Expression Recognition (FER) device based on a deep convolution neural network. A basic facial expression recognition approach that uses a combination of face detection, feature extraction and classification algorithms is explored. A two-channel convolution neural network is used in the proposed process, in which Facial Sections (FPs) are used as input to the first convolution layer, the extracted eyes are used as input to the first channel, while the input to the second channel is the jaw. In a completely connected layer that is used to acquire global information from these local features, information from both channels converges and is then used for classification. The Japanese Female Facial Expression (JAFFE) and the Expanded Cohn-Kanada (CK+) datasets are being checked to assess the accuracy of identification for the proposed FER system. The findings obtained suggest that the method offers enhanced classification accuracy when compared to other methods.

Gupta, S. et al.[8], suggested feature-based technique for 2D face images was implemented. For function extraction, accelerated robust features (SURF) and scale-invariant feature transformation (SIFT) are used. For experimental analysis, five public databases, namely Yale2B, Face 94, M2VTS, ORL, and FERET, are used. In this thesis, different combinations of SIFT and SURF features have been evaluated with two classification techniques, namely decision tree and random forest. Writers with a mixture of SIFT (64-components) and SURF (32-components) have recorded a maximum recognition accuracy of 99.7%.

Saini, Tajinder Kumar et al. [9] Presented attempts have been made to explain the technical phenomena in which the solution to facial recognition based on the decision tree is suggested using SVM and SURF. Pre-processing, which requires both the input image and all the images processed in the archive, comes first in this technique. Secondly, to remove facial attributes, image processing
operations are used. For the purpose of preparation and checking, the last decision tree with SVM and SURF foundation methodology is used. With regard to the error rate, matching time and overall accuracy graph, the suggested method shows better performance. More specific and better results are provided by the use of the decision tree.

3. The Proposed Method
The proposed method consists of three main stages namely: pre-processing image using HSV system, feature extraction using fast algorithm and classification using three method (Manhattan, Euclidean, and Cosine) as shown in Figure (1).

![Figure (1): The proposed method of face recognition](image)

3.1 Dataset
There are two categories of face dataset used in this paper:
1- **UFI (Unconstrained Facial Images)**: Contains images extracted from original images. Two different sections are found: the cropped image data set and the large image dataset. The first contains the cropped faces that were automatically extracted from the images using the Viola-Jones algorithm. Hence, the size of the face is approximately uniform and the images contain only a small portion of the background. This set contains 401 individual photos with 7 images for each person in the training set and one in the test set. Images were cropped at 128 x 128 pixels. Figure 2 shown Samples of UFI dataset.

![Figure (2): Samples of UFI dataset](image)

2- **ORL (Olivetti Research Laboratory)**: Faces dataset: 400 photos (10 different images for 40 different subjects). images were taken in various stages, assessing lighting and facial expressions. The size of each image is 92 x 112 pixels, with 256 levels of gray per pixel. 9 images of each person in the training group and one in the test group. Figure 2 shown Samples of ORL dataset.
3.2 Preprocessing stage

The proposed technique of the pre-processing is used the HSV space for the purpose of showing the image detail well. Color vision can be processed with RGB or HSV color space. RGB color space describes colors in terms of the amount of red, green, and blue. HSV color space describes colors in terms of hue, saturation, and value. The HSV color model is favored over the RGB model in cases where color definition plays a primary role. Similar to how the human eye appears to view colour, the HSV paradigm explains colours. In terms of a combination of primary colors, RGB describes color; HSV uses popular references such as colour, vibrancy, and brightness to characterize colour.

3.3 Feature Extraction

The proposed method consists of extracting facial features of the image using fast algorithm.

3.3 Fast Algorithm

Feature from an accelerated segment test (FAST) uses a Bresenham’s circle drawing algorithm with a diameter of 3.4 pixels for a reference mask. Compared to the nucleus value, measure 16 pixels for a full accelerated segment using the threshold. To block this wide trial, the corner criteria should be more relaxed. The criterion for a pixel must be an accelerated segment test (AST)-based corner that must have at least S pixels that have a clearer circle relation or darker than a threshold. Even 16-pixel values are disregarded. It is thus possible to use the value of S to calculate the observed corner at the highest angle.

Steps of FAST algorithm

Step 1. Choose a pixel $p''$ from an image. IPs reflect the strength of pixels. It is possible to define this pixel as a point of interest or not.

Step 2. Get a threshold representing the threshold strength value.

Step 3. Assume periphery a pixel $p$ represents the center of circle which has 16 pixels. (Brenham circle of radius 3.) $\text{comp}(\text{pix}, \text{pix}0) = \{ 1, |\text{img}(\text{pix}) - \text{img}(\text{pix}0)| < \text{thr}; 0, \text{otherwise} \}.$

Step 4. If the pixel wishes to find out as a point of interest, it needs "N" exposure contiguous pixels from the 16 pixels, either below or above IP by thr value.

Step 5. In order to make an algorithm quick, first match 1, 5, 9 and 13 of the strength of circle pixels with IP. At least three of these four pixels should accept the threshold level for this subsisting interest point. If at least three values of I1, I5, I9 and I13 are not below or above IP+thr, P is not a point of concern (corner). As a possible point of concern, a pixel p may be disqualified for this. Otherwise, if at least three pixels are up or down Ip + thr, look and scan the entire 16 pixels if 12 adjacent pixels fall into the norm.

Step 6. A same procedure can iterate for whole image's pixels.

3.4 Classification of face

There are two phases in decision tree classification, first is to generate the decision tree from the given training data and the second is the actual classification where decision rules of the formed decision tree are applied to the transaction having an unknown class label to classify it in one of the classes.

$$V = \sum_{i=1}^{M} \sum_{j=1}^{N} (f_{(i,j)} - \overline{f}_{(i,j)})^2$$
Where f is the feature extraction and f is the average value of the pixels in a face image. The algorithm for this classification is given below:

**Step1.** For each transaction to be classified, read one by one the decision rule from the Decision table.

**Step2.** Match the fields from the transaction with each decision rule.

**Step3.** First, try to find out perfect match and fill the Class field of the transaction with the class of matched rule.

**Step4.** If a perfect match is not found then among matched rules, the rule having the highest level is chosen and the class field of the transaction is filled with that class of matched rule.

### 4. Experimental Results

In this work, the performance of the fast algorithm applied to two datasets (ORL) and (UFI) is compared. Figure (4) shows the feature vector for fast algorithm. Table (1) shown force field feature extraction for fast algorithm.

![Figure (4): The feature vector for fast algorithm.](image)

| Original Image | HSV Image | Fast Algorithm |
|----------------|-----------|----------------|
| ![Image 1](image) | ![Image 2](image) | ![Image 3](image) |
| ![Image 4](image) | ![Image 5](image) | ![Image 6](image) |
| ![Image 7](image) | ![Image 8](image) | ![Image 9](image) |
| ![Image 10](image) | ![Image 11](image) | ![Image 12](image) |

**Table (1)** Force Field Feature Extraction for Fast Algorithm.
Three important metrics are used to measure performance evaluation, namely: false rejection rate (FRR), false acceptance rate (FAR), and accuracy rate (ACC) as shown in the equation. (1) equivalent (2) and equivalent (3).

\[
\text{ACC} = \left(1 - \frac{\text{FAR} + \text{FRR}}{2}\right) \times 100\% \quad (1)
\]

\[
\text{FRR} = \frac{\text{NO of Rejection genuine}}{\text{Total NO of genuine assessed}} \times 100\% \quad (2)
\]

\[
\text{FAR} = \frac{\text{NO of accepted imposter}}{\text{Total NO of imposter assessed}} \times 100\% \quad (3)
\]

Table (2) Displays the FAR and FRR test performance and accuracy rate of a face recognition system using ORL and UFI for three distance methods (Manhattan, Euclidean and Cosine distance).

**Table (2)**

Fast algorithm Comparison Between 40 Person from ORL Dataset and 401 Persons from UFI Dataset.

| Dataset   | Distance measures | FAR% | FRR% | ACC% |
|-----------|-------------------|------|------|------|
| ORL (40 subject) | Manhattan | 2.6  | 0    | 99.9 |
|           | Cosine            | 3    | 2.5  | 98   |
|           | Euclidean         | 2    | 4    | 98   |
| UFI (401 subject) | Manhattan | 19   | 26   | 99.9 |
|           | Cosine            | 20   | 25   | 97   |
|           | Euclidean         | 24   | 29   | 98   |

5. Conclusion

In this paper, the force field of the feature will be extracted using the velocity algorithm after converting the image to the HSV system, and then the force field features will be extracted using the fast algorithm and then classified using the distance for three methods (Manhattan, Euclidean, and cosine) distance through which a procedure was performed. The comparison is by calculating (ACC, FAR and FRR ) test performance the two data sets (ORL and UFI), and it is evident in Table (2) that the accuracy of the performance of the face is 99.9% in Manhattan Distance.
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