Face Sketch to Photo Matching Through Dynamic Local Feature Extractions and Cascaded Static

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Abstract

By using a method of cascading static and dynamic local feature extraction, we attempt to deal with the identification of a photo from a face sketch effect of these effects in this process. To ensure that the feature vectors created are depending upon the appropriate patches. Along with that approach, we include the closest neighbours technique for matching sketches and photos, which concatenates the feature vectors obtained from local static extraction. Following the extraction of the image's characteristics, the most comparable images are narrowed down based on their closest neighbours. Eventually, feature vectors from the local dynamic extraction approach are used to rematch these images. The closest neighbours technique is used to match the feature vectors. The major goal of this technique is to increase the detection system's precision while simultaneously increasing recognition rates and feature stability.

1. Introduction

Less sleep, lengthy periods of nonstop driving, or any other physical problem, such as brain abnormalities, can all affect a driver's ability to pay attention. According to several studies on traffic accidents, driver weariness is a factor in about 30% of collisions. When a driver drives for a longer amount of time than is typical for a person, this causes excessive exhaustion and also leads in tiredness, which causes the driver to get sleepy or lose consciousness. Drowsiness is a complicated phenomenon that indicates a drop in the driver's alertness and consciousness levels. There are a few indirect approaches that may be utilised to detect tiredness even if there is no direct way to do so. In the first parts, various techniques for gauging driver tiredness are discussed. These techniques include vehicle-based assessments, physiological measures, and behavioural measures. These techniques can be used to create an intelligence system that warns the driver when they are sleepy and helps to avoid accidents. A description of the benefits and drawbacks of each system is provided. The best approach is selected and suggested in accordance with benefits and drawbacks.

The method for developing the full system is then described using a flow chart, which involves continually recording the image in real-time before framing it. The next step is to evaluate each frame to determine face first. The next step is to find the eyes if a face is found. Following a positive eye detection result, the quantity of eye closure is calculated and compared to standards for eyes in a sleepy condition. If drowsiness is discovered, the driver is alerted; otherwise, the cycle of looking for faces and recognising drowsiness is repeated. Later parts provide a full explanation of object detection, face detection, eye detection, and eye detection. A few experiments on object detection are conducted since faces are a sort of object. Different methods are suggested and discussed for both face detection and eye detection. Principal Component Analysis and the Eigen face method, which form the theoretical foundation for system design, are described. We are aware that the face has a complex, multifaceted structure. To recognise a face, one requires excellent calculation methods and methodologies. A face will be treated as a two-dimensional structure in this technique, and as such, it should be identified. Face recognition in this instance uses Principal Component Analysis (PCA). The projection of facial pictures into that specific face area is the aim here. The variation or disparity between the required known faces is then encoded. The face space is decided and defined by the Eigen face. These faces are represented by eigen vectors. Each set of faces is included in these vectors. There are instances where the nose, eyes, lips, and other facial characteristics resemble one another.

The Raspberry Pi serves as the system's primary piece of hardware. The algorithm for determining the condition of the eyes was created using all four of the aforementioned approaches. The recommended approach was then implemented using the correct code, the appropriate preparation for implementation In order to document how the system responded and operated, many individuals were taken. The form of a circle denoted the opening of the

eyes. If a motorist is found to be sleepy, the circle that would normally indicate an eye closure will not display. Results were displayed using a number of images that showed both closed and opened eyes. The system's shortcomings were then discussed, and it was highlighted that more work would need to be done in the future to address them and create a reliable intelligent driver aid system. System functionality as a whole that has been planned and executed is included in the concluding section. The term "drowsiness" refers to a lower level of awareness that is characterized by fatigue and trouble staying awake but that is quickly awoken by uncomplicated stimuli. Lack of sleep, medicine, drug usage, or a mental illness might be the cause. Fatigue, which can be both mental and physical, is the main cause. Muscle fatigue, sometimes referred to as physical tiredness, is the temporary breakdown in a muscle's capacity to perform at its optimum. Mental fatigue is the temporary incapacity to maintain peak psychological functioning.

The slow onset of mental fatigue can result from any intellectual effort and can vary depending on an individual's psychological capacity as well as other elements like lack of sleep and general health. Mental fatigue has been linked to decreased physical performance. It may show itself as sluggishness, lethargy, or a lack of mental coherence. Based on the data currently available, driver drowsiness has progressively risen to the top of the list of factors contributing to traffic accidents that culminate in fatalities, serious physical injuries, and monetary losses. Drivers who fall asleep behind the wheel face the danger of losing control and hitting another car or immovable objects.

Computer vision is an effective and practical solution to this issue that takes advantage of these visual properties. This study introduces a technique for detecting driver weariness by assessing the condition of the eyes and yawning. This project's goal is to create a simulation and algorithm for tiredness detection. The emphasis will be on developing an algorithm and simulation that will properly track the driver's blinking and yawning and notify (through textual warning in the simulation example) the driver if weariness is detected.

2. Literature Survey

As reported by the National Highway Traffic Safety Administration, driver sleepiness is directly responsible for 100,000 accidents each year that are reported by the police. According to the NHTSA, driver sleepiness caused 1,550 fatalities, 71,000 injuries, and \$12.5 billion in costs. The National Sleep Foundation reports that 51% of adult drivers have acknowledged to dozing off behind the wheel or being tired behind the wheel. One of the biggest factors in road accidents is driver weariness. Up to 45% of American adults in 2012 possessed a smartphone. Smartphones' growing computing capabilities make it possible for computer vision algorithms to function pretty quickly. Compared to many other tiredness detection systems, which employ in-vehicle cameras or EEG sensors, a smartphone-based fatigue detection solution being more transportable and more reasonably priced. The feature stability was improved as a result of the extraction of features from the different phases. However, because of the categorization, the process's accuracy is poor [1].

The "SMART CAP" gadget measures brainwaves to prevent inebriated drivers from creating accidents. The smart cap has five integrated electrodes that are shaped like a forehead band and are used to collect the EEG signal. Preprocessing is done on the obtained EEG signal before it is sent over Bluetooth to the intelligence unit, which is a microprocessor. The EEG signal is divided into alpha, beta, gamma, and delta waves using this procedure. It is based on the observation that alcohol consumption causes a decrease in theta activity and an uptick in alpha activity. The brain's electrical impulses are captured via electroencephalography (EEG). To prevent accidents, the brain waves are brainwaves that have been boosted and saved (neural oscillations). These brain waves show the activity as it is happening in different parts of the brain. According to a study of auto accidents, drivers' lack of preparation accounts for 20% of incident causes. As a result, the engine won't start if the decomposed EEG data contains any significant irregularities. The state of the driver and their driving style are utilised to identify fatigued drivers. The status of the driver is a clear sign of their level of weariness. To the contrary hand, sensors that are integrated inside a vehicle may be used to assess driving behavior [2].

One of the most frequent reasons for fatal traffic accidents worldwide is driver fatigue. According to an NHTSA examination of National Highway Traffic Administration (NHTSA) statistics, driving while fatigued increases the likelihood of a crash by 4–6 times compared to attentive driving inattention. Due to its regular occurrence, driver weariness has grown to be a significant socioeconomic issue. Much attention has been paid to a system created to identify driver sleepiness and issue a warning when a potential threat is present. According to the World

Health Organization (WHO), India has the world's worst roads. According to research, one of the primary causes of the rising number of accidents is driver exhaustion and sleepiness. Motorist weariness has a crucial irony in that the driver may be too exhausted to recognise his own degree of sleepiness. To prevent traffic accidents, supporting systems that assess a driver's degree of alertness must be used [3].

Driver weariness impacts driving abilities in three ways: (1) coordination is compromised, (2) response times are slowed down, and (3) judgement is compromised. According to a poll, more than 50% of annual traffic accidents are the consequence of driver weariness. The problem of using technology to identify driver weariness or sleepiness is intriguing. The literature has previously documented a variety of methodologies for the detection of driver sleepiness. One of the most popular methods for spotting tiredness among car drivers is Driver Alert. Others include the Mercedes-Benz Attention Assist, the Volkswagen Fatigue Detection System, the Ford Driver Alert, and the Volvo Driver Alert Control. By using a camera and breaking up the visual signal into frames, video may be acquired. The frame grabber's delivered frames are taken one at a time by the face detection programme. The eyes detection feature looks for the driver's eyes in the car. The sleepiness detection feature determines whether or not the driver is sleepy. Utilizing a set of pre-defined samples allows for this [4].

The importance of complexity measure, nonlinearity, disorder, and unpredictability may be attributed to the nonlinear interaction between functional and anatomical subsystems that developed in the brain under both healthy conditions and different illnesses. It is suggested to use Multiscale Permutation Entropy to calculate the degree of complexity of long-range temporal correlation time series EEG data from Alcoholic and Control participants those were acquired from the machine learning repository at the University of California. The most well-known complexity measure for brain dynamics, the Lempel and Ziv complexity measure C(n), can be used as an alternative to EEG analysis. The spectrum entropy, approximation entropy, and median frequency are further often used complexity metrics. The human brain has millions of neurons, each of which produces an electric voltage field for a certain type of mental activity. When recorded and quantified using electrodes positioned on the scalp, the EEG signal in a typical adult brain varies from 1 to 100 microvolts. Numerous researchers examine EEG signals obtained when subjects were experiencing various mental illnesses, including dementia, Alzheimer's disease, epilepsy, alcoholism, and drowsiness [5].

3. Proposed Ststem

In order to extract facial characteristics from the sketch picture, this approach for face recognition system combines two layers of features, such as Static Local Feature Extraction and Dynamic Local Feature Extraction. The test features are then created by concatenating those characteristics. The photo images that match test characteristics are matched using the features. We don't use low pass filtering, as is done in the Gaussian pyramid, to blur the pictures in order to shorten the calculation time. Image resolution is simply decimated after every second sample to minimise computation.



Fig 1: Block Diagram

Then, instead of analysing every pixel in an input picture, segmentation is initiated from the top of the pyramid. The top layer of a four-layer pyramid has a side that is eight times smaller than the input image's side. As a result, the computation time is decreased by a factor of 64 on average along with the amount of pixels. A binary map is made for each tier of the pyramid. The binary map is first made up entirely of zeros. The values associated with the coordinates of pixels that are designated as skin tones are all one. The resultant binary map is double-sided interpolated to the lower layer below. The following are a few benefits of the suggested approach:

- Cascade feature extraction increases the stability of the feature.
- Because of the efficient classification approach, the recognition rate has increased.
- To sketch faces, this method is reliable.



Fig 2: System Architecture

Various phases that are involved while implementing proposed approach are being explained under following section:

1. Input image

Adding an image to the workspace requires the imread command. Imread reads one of the sample images included with toolbox, an image, and stores it in an array called I, determining from the file that the graphics file format is Tagged Image File Format. (TIFF). Use the imshow function to display the picture. The Image Viewer software also lets you see images. The imtool function launches the Image Viewer programme, a unified environment for viewing pictures and carrying out certain typical image processing operations. In addition to offering all of imshow's picture display features, the Image Viewer app also gives users access to a number of other tools for examining and browsing photos, including scroll bars, the Pixel Region tool, Image Information tool, and the Contrast Adjustment tool.

2. Face Alignment

Difference of Gaussians, a feature-enhancement technique used in imaging science, subtracts one version of an original picture that has blur from another that has less blur. The blurred pictures are created in the straightforward case of grayscale photographs by applying different standard deviation Gaussian kernels to the initial grayscale photos. When an image is blurred with a Gaussian kernel, primarily high-frequency spatial information is inhibited. The spatial information between the ranges of frequencies saved in the two blurred pictures can be kept by subtracting one image from the other. As a result, the band-pass filter used by Gaussians to distinguish between them eliminates all but a small number of the spatial frequencies contained in the original grayscale image.

3. Feature Extraction

Convolutional neural networks are a kind of deep neural networks most often employed to analyse visual vision in deep learning. Multilayer perceptrons are modified into CNNs. Typically, when we talk about multilayer perceptrons, we're talking about fully linked networks, where all of the neurons in one layer are interconnected with all of the neurons in the layer above. As a result of their "complete connectivity," these networks are susceptible to overfitting data. One common technique for regularisation is to increase the magnitude of weights and add it to the loss function. However, CNNs employ the hierarchical structure of the data to piece together more complex patterns from smaller, simpler ones, which is a distinct method to regularisation. In terms of connection and complexity, CNNs are at the bottom end of the scale.

4. Cascaded Feature Extraction

The two feature values are merged to generate a bigger test feature since cascading is analogous to concatenating. Vertical concatenation and Horizontal concatenation are both permitted in MATLAB. When two matrices are concatenated by using commas to separate them, they are simply added horizontally. Horizontal concatenation is the term for it. As an alternative, two matrices are added vertically if you concatenate them by separating them with semicolons. Concatenation vertical is the term for it.

5. Similarity Measure

A non-parametric method for pattern recognition's classification and regression is the k-nearest neighbour algorithm. In both cases, the input consists of the k nearest training examples in the feature space. The outcome of k-NN classification is a class membership, regardless of whether it is used for classification or regression. The neighbours of an item choose the class to which it is assigned based on the majority vote of its k closest neighbours (k is a positive integer, typically small). If k = 1, the item is simply added to the class of its one closest neighbour.

4. Results

The major goal of this procedure is to increase the detecting system's precision. Furthermore to raise the feature stability and recognition rate. By using a technique of cascading static and dynamic local feature extraction, we try to address the effect of these factors on the ability to recognize a picture from a face sketch. To ensure that the feature vectors created are depending upon the appropriate patches. In this procedure, we introduced a brand-new technique for extracting local features that combines cascading static and dynamic local feature extraction. The following screenshorts' findings show that the suggested cascaded static and dynamic local feature extraction method achieves higher levels of accuracy when comparing face drawings with exaggerated form to photographs. This is because the form exaggeration effect is taken care of for the n number of possibilities via static local feature extraction matching by employing dynamic local feature extraction.



Fig 3: Input Image



Fig 4: Feature Extraction



Fig 5: Performance Table



Fig 6: Performance Analysis

5. Conclusion

Under this procedure, a brand-new local feature extraction technique has been introduced built on a cascading mix of static and dynamic local feature extraction. The findings show that the suggested cascaded static and dynamic local feature extraction demonstrates greater accuracy when matching face drawings with exaggerated form to photographs. This is due to the fact that the form exaggeration effect is handled by using extraction of dynamic local features for the n candidates that have been chosen for further consideration after static local feature extraction matching.

6. Future Enhancement

Laplacian filters are derivative filters that are used to identify edges in photos where there is a quick change. The picture is typically smoothed (for example, using a Gaussian filter) before the Laplacian is applied since derivative filters are particularly sensitive to noise. The Laplacian of Gaussian (LoG) operation is a two-step method.

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