Facial recognition technology (FRT) is widely used in law enforcement, security, healthcare, and identity verification. Still, they struggle with accurate identification when individuals experience changes in their facial appearance, such as chemical burns, scars, weight loss, growth/removal of facial hair, cosmetic changes, or temporary skin alterations (e.g., swelling). These changes can result in misidentification, leading to problems in security systems, finding criminals, unlocking phones, workplace attendance, and missing person cases. This project aims to improve the accuracy of facial recognition systems by addressing misidentifications caused by such facial changes. The goal is to design a facial recognition system that focuses on skin texture rather than traditional facial landmarks, making it more adaptable to changes in facial appearance, by utilizing the Histogram of Oriented Gradients (HOG) algorithm. HOG provides an innovative approach to facial recognition by leveraging detailed skin texture patterns. This method focuses on capturing stable features such as pores and wrinkles to create unique texture maps for individuals. My approach aims to enhance recognition accuracy, even in the presence of facial alterations, providing a robust alternative to traditional methods reliant on landmarks or overall facial geometry.

The issue with using landmarks as a base for skin texture analysis is that the face is not always in the same position. Other factors play a role in the accuracy of the system, this gap can lead to inaccurate conclusions. There have been many cases in the U.S. where facial recognition software failed to recognize a person due to facial alterations as small as glasses and hair growth/loss, or as big as cosmetic changes and skin deformities that change facial traits (Raposo, V. L. 2023). These cases cause uncertainty in facial recognition software, slowly making it unreliable. Skin texture analysis is a critical aspect of face recognition technology, with several studies exploring its role in enhancing identification accuracy and addressing diverse challenges.

CURRENT STUDIES

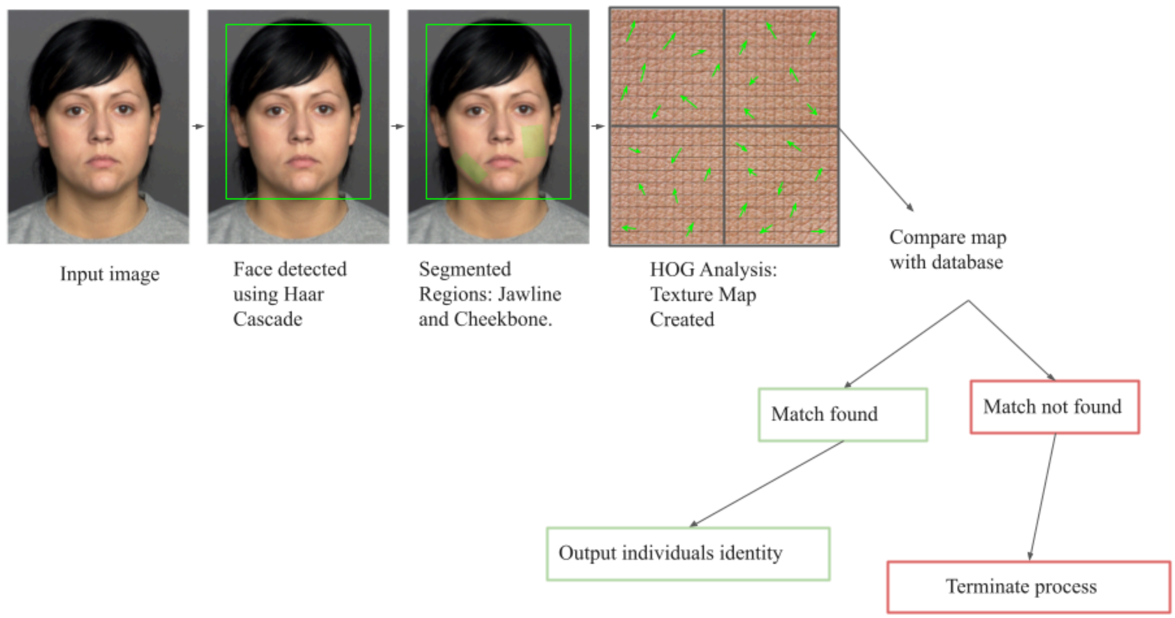
Guo & Liao (2023) developed the FaceSkin dataset; to balance privacy concerns with robust classification capabilities. This dataset focuses on facial skin patches to extract multi-attribute information, demonstrating the potential for accurate and scalable analysis without compromising personal identity. Such a dataset is particularly significant in advancing privacy-preserving techniques in biometric systems. Similarly, (Xie, Zhang, You, Zhang, and Qu 2012) conducted a detailed study on hand-back skin texture patterns to evaluate their utility for personal identification and gender classification. Using a texton learning approach under light representation, they showed how texture-based biometrics could achieve high accuracy across varied classification tasks. This research provides clear insights into the adaptability of skin texture recognition beyond the face, emphasizing its potential in broader biometric applications. These works illustrate a growing trend toward refining biometric systems to leverage texture-based attributes while addressing key concerns such as privacy and adaptability across use cases. By synthesizing methods from both studies, a more comprehensive approach to texture-driven facial recognition systems could be envisioned. FRT uses various methods for collecting raw data; feature extraction is a frequently used approach, and is the second step in facial recognition after detection and before recognition (Bakshi, U., & Singhal, R. 2014, p. 2). Feature extraction algorithms operate by extracting features from an image, “These features encompass various aspects, including the distance between the eyes, the shape of the nose, the contour of the lips, and the pattern of wrinkles around the mouth.” (Daniel, 2023, Facial Feature Extraction. 2). This correlates with The Feature-Integration Theory Of Attention (FIT). FIT, proposed by Anne M. Treisman and Garry Gelade, is a theory that suggests that we need to focus on each item one at a time when multiple features, like color and shape, must be combined to identify or tell apart objects, it provides a foundational understanding of how the human brain combines individual features to perceive objects. This concept connects with my proposed skin texture-based facial recognition system, which relies on analyzing and integrating detailed surface-level features to achieve accurate identification. FIT explains that focused attention is required to combine separate attributes, such as shape, color, and orientation, into a unified perception of an object. Similarly, the proposed system must process individual texture details, such as pores, wrinkles, and skin patterns, to create a cohesive "texture map" for facial recognition. In traditional facial recognition systems, landmarks like eyes, nose, and mouth serve as primary identifiers. However, changes in these features (e.g., scars, swelling, or hair growth) often lead to errors, as these systems fail to adapt to altered appearances. FIT emphasizes that when features are not integrated correctly, perception errors, similar to misidentifications in facial recognition, occur. This aligns with the challenge of ensuring that separate skin texture elements are combined accurately in the system to maintain reliability despite facial changes. Moreover, FIT introduces the concept of "illusory conjunctions," where features are mistakenly combined when attention is insufficient. For the facial recognition system, this highlights the importance of precision during feature integration. Incorrect combinations of skin texture elements or associating patterns from different areas of the face could lead to false matches. The system must ensure that individual texture details are combined correctly to prevent such errors, which FIT suggests would require focused and deliberate processing. With people's appearances constantly changing, current solutions for identifying individuals despite facial changes rely on 2D and 3D approaches, each with its strengths and weaknesses. A 2D approach uses information theory to create a model based on the most significant data available on the facial surface. In contrast, a 3D approach constructs a facial geometry that represents the internal anatomical structure of the face rather than external factors (Dutta, n.d., p. 5). Both methods depend on facial landmarks, but they have inherent limitations. 2D methods are sensitive to external factors such as lighting, head positioning, and facial expressions. Meanwhile, 3D approaches, though more powerful (Matthews, I., Xiao, J., & Baker, S. 2007), rely on a person's underlying facial structure and may become less effective when individuals undergo face-altering conditions, such as surgery (Dutta, n.d., p. 5). Additionally, 2D methods are constrained by limited camera angles, requiring a person to face the camera within a 35-degree angle. On the other hand, 3D models focus on rigid facial features, such as the curves of the eye socket, nose, and chin, enabling identification up to a 90-degree angle. However, both approaches demonstrate challenges in maintaining accuracy under diverse or changing conditions (Dutta, n.d., p. 6).

SOLUTION

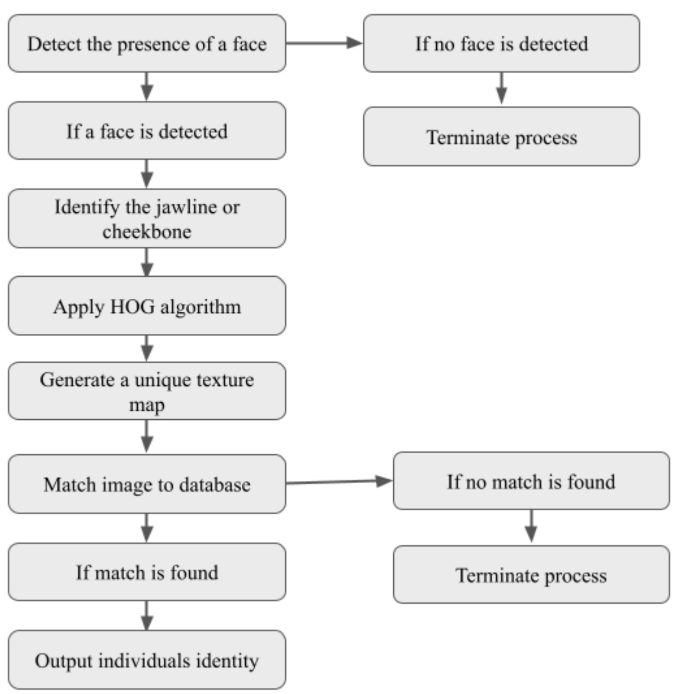
My solution is to use The Histogram Of Oriented Gradients (HOG), HOG is a simple and powerful feature descriptor that is robust for object detection because object shape is characterized using the local intensity gradient distribution and edge direction (Srujan, J. 2020, July 17). HOG operates by analyzing the direction of pixel intensity gradients in small sections of an image, (Shu, Ding, Fang 2011) creating a feature map that captures texture and structure, which will be adapted to analyze skin texture by using higher resolution cameras and smaller cell sizes to detect gradient changes, analyze pixel variations within the image, collect details such as pores and wrinkles across the skin to create a "texture map" for each person. A texture map is a digital representation of skin texture patterns based on pixel intensity variations, the system will focus on stable areas of the face, the jawline, and the cheekbone (Facial Identification Scientific Working Group [FISWG], 2021) to create unique texture patterns for each individual. These patterns will be compared to a database of images, enabling accurate recognition even in the presence of skin changes. My strategy addresses the limitations of relying on facial landmarks in scenarios involving facial changes, and the challenges of accurately identifying people after alterations to their appearance. By incorporating skin texture analysis, facial recognition systems can deliver more accurate identification outcomes even in cases of temporary problems such as blemishes or swelling, as well as permanent changes like surgery or scarring. Compared to traditional 2D and 3D methods, my solution eliminates key obstacles. For instance, it resolves issues like the inability to differentiate between individuals with extremely similar facial features (e.g., identical twins), limitations in recognizing faces turned at certain angles, or sensitivity to variations in lighting, head position, or facial expressions when compared to the image stored in the system's database. My approach improves upon current facial recognition technologies by leveraging the analysis of skin texture. This method focuses on stable, unique features such as pores, wrinkles, and fine texture details, which remain relatively unaffected by changes in lighting conditions, facial expressions, or makeup. Unlike existing 2D and 3D approaches that struggle with face-altering conditions or require controlled environments, my solution provides a strong and adaptable method of identification that remains effective even in active, real-world scenarios. By addressing these gaps, this method enhances both the accuracy and reliability of facial recognition systems, making them more versatile and applicable across diverse use cases.

APPROACH

The system begins with a camera that takes a photo and sends it into a pre-trained Haar cascade face detection algorithm. This algorithm identifies the presence of a human face. If no human face is detected, the program terminates. **Step 1:** Once a face is detected, the algorithm segments the image to isolate stable regions of the face, such as the jawline and cheekbone. **Step 2:** The HOG algorithm is applied to the segmented regions to analyze pixel intensity gradients. These gradients, evaluated in small sections (cells), capture the direction and magnitude of texture and structure. To improve precision, the system adapts HOG with high-resolution cameras and smaller cell sizes, enabling the detection of fine details like pores and wrinkles. **Step 3:** The extracted gradient data forms a "texture map," a digital representation of the skin's unique texture patterns based on pixel intensity variations. **Step 4:** The texture map is compared against a pre-existing database of stored maps using a pattern-matching algorithm. **Step 5:** If a match is found the system outputs the individual's identity. If no match is found, depending on the application's purpose, the texture map is either added to the database as a new entry or flagged for further review. The achievement of my proposal lies in its use of established algorithms adapted for a novel application in facial recognition. The process begins with a pre-trained Haar cascade algorithm integrated into a high-resolution camera. This ensures the program only proceeds if a human face is detected, providing a reliable foundation for the system. After detection, the system segments the image to isolate stable facial regions, such as the jawline and cheekbone. This step ensures consistency and accuracy in analysis. Next, the Histogram of Oriented Gradients algorithm is applied to the segmented regions. HOG captures pixel intensity gradients, highlighting texture and structure. By using higher-resolution cameras and smaller cell sizes, the system can detect finer details, such as pores and wrinkles. These details form a unique "texture map" for each individual, based on pixel intensity variations.



Woman in the image > Ebner, C, N. C. (2018). FACES



The texture map is then compared to a pre-existing database. Using proven database-matching techniques, the system identifies individuals even when their facial structure has changed. If no match is found, the texture map is either registered as a new entry or flagged for further review depending on the use. By adapting well-established algorithms to focus on skin texture, my proposal offers a possible solution to facial recognition challenges. It addresses the limitations of 2D and 3D systems while leveraging reliable methods to ensure practicality and accuracy.

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