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Forensic Facial Renderings: Sketching and Matching

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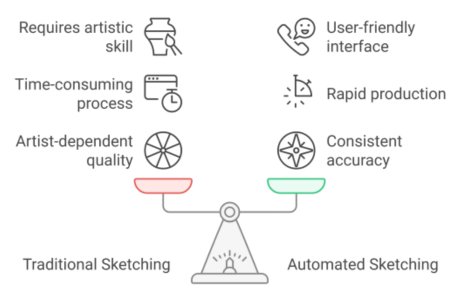
Abstract: A crucial component of forensic science is facial representation, which makes it easier to identify criminals from eyewitness accounts. This study examines a technologically advanced method of facial matching and forensic sketching that combines deep learning and conventional image processing techniques. To improve facial sketch matching against a criminal database, the system uses neural networks, a drag-and-drop JavaFx interface, and sophisticated feature extraction. An analysis of this method shows encouraging accuracy and efficiency results, suggesting that it may be able to overcome the limits of conventional forensic drawing

1. Introduction

When images are not accessible, facial sketches are essential for visualizing suspects based on witness descriptions in criminal investigations. Traditional hand-drawn sketches, however, have drawbacks since they depend on qualified forensic artists and may differ in quality depending on the witness's recollection and the artist's interpretation. Investigations may be hampered by differences between the drawing and the real suspect as a result of this variability.

As technology develops, drawing production and matching techniques are moving toward more dependable and effective approaches. By automatically identifying important facial features, such as the eyes, nose, and mouth, from large datasets, machine learning and computer vision provide automated methods that expedite sketching and increase speed and accuracy over traditional techniques.



Comparing Traditional and Automated Forensic Sketching

The suggested forensic facial rendering and matching solution fills the gap between automatic recognition and conventional sketching. Its drag-and-drop interface makes it simple for users—

even those without creative training—to put up composite sketches using a library of preset facial traits. Without specific training, police enforcement may produce sketches based on witness descriptions thanks to this approachable method.

The method uses deep learning models and sophisticated computer vision to improve sketch-to-photo matching. The system can accurately match sketches against a criminal database by converting them into equivalent digital representations using techniques including edge detection, feature extraction, and feature matching. This raises the possibility of accurately identifying suspects.

2. Related Work

2.1 Sketch-to-Photo Synthesis

A Markov Random Field (MRF) model was used by *Tang and Wang (2004)*[10] to create a photo-sketch synthesis technique that turns sketches into visuals that resemble photos. In order to lessen the stylistic disparities between sketches and photographs, the MRF model splits images into patches and learns local aspects. Despite producing sketches that resembled photos, this method's success was constrained by the variety of sketch styles, underscoring the need for more adaptable methods.[3]

2.2 Feature-Based Matching

A feature-based sketch-photo matching method utilizing SIFT descriptors to extract unique key points from sketches and images was presented by *Klare and Jain (2010)*.[8] By keeping facial traits invariant to scale and rotation, this method demonstrated better matching accuracy than previous approaches using descriptor distance to quantify similarity. Although this method worked well for typical front-facing shots, it had trouble with images taken at other angles or in different lighting conditions, which prompted more research into robust feature extraction.

2.3 Component-Based Recognition

A component-based approach that divided face images into distinct sections (such as the eyes, nose, and mouth) and matched each component independently was presented by *Han et al. (2013)*.[9] By comparing each component separately, this approach provided more flexibility and enabled the system to manage partial sketches or inconsistent sketching techniques. There is a trade-off between accuracy and computational economy, though, as component matching increases computational complexity and occasionally affects total accuracy if one feature is mismatched.

2.4 Patch-Based Methods

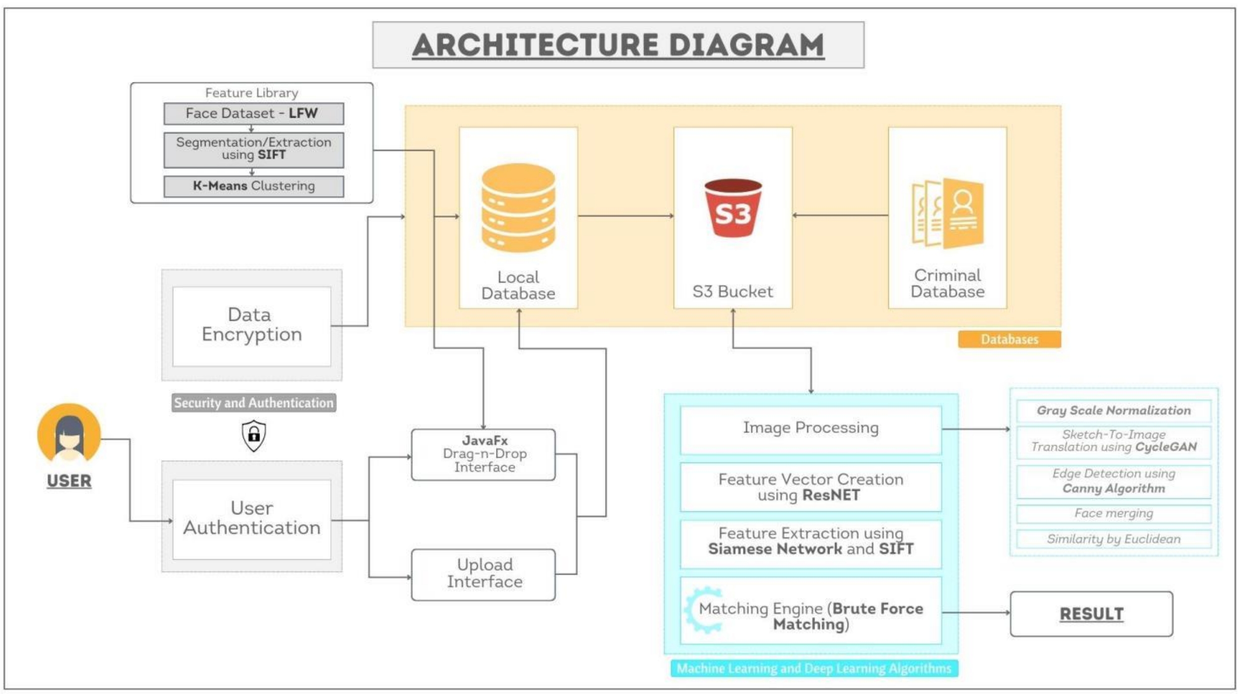
By segmenting images into smaller parts, patch-based techniques increase accuracy and allow for fine-grained matching of particular facial regions. Each patch is improved by local texturing and filtering methods, and graph-based models map the connections between patches to bring sketches closer to the features of photos.[7] Despite being accurate, these techniques are computationally demanding since they need to extract and compare features separately for every patch, which raises processing demands in big databases.

2.5 Neural Network Approaches

Neural network techniques such as CycleGAN and Siamese networks have gained popularity for translating and matching sketches and photos due to advancements in deep learning.[3] While Siamese networks employ embedding spaces to connect similar faces across modalities, CycleGAN enables unpaired image translation between sketches and photographs[3]. Both an opportunity and a difficulty for automated forensic sketching, these techniques greatly increase accuracy and flexibility when managing a variety of sketches, but they also demand a large amount of training data and processing capacity.

3. System Architecture

Each of the interconnected parts that make up the forensic face rendering and matching system plays a distinct part in processing, matching, and protecting facial data. The user interface, databases, image processing pipeline, and security procedures are the main modules. By utilizing sophisticated image processing and deep learning techniques, the technology makes it possible to match forensic sketches with a database of criminal faces in an effective manner.



3.1. The user interface

-JavaFx Drag-n-Drop Interface: Using a drag-and-drop interface created in JavaFx, the user starts the procedure by uploading a forensic sketch or image. This interface offers a seamless and user-friendly experience by supporting important events like setOnDragDetected(), setOnDragOver(), and setOnDragDropped().

-Upload Interface: The image is uploaded and sent to the processing pipeline when the user drags and drops it. This interface for uploading handles file validation and forwards the image to the system for further analysis.

3.2. Security and authentication

-User Authentication: The system needs user authentication to safeguard access. Sensitive forensic data is kept safe since only authorized personnel can upload photos and view results.

-Data Encryption: To guard against unwanted access and preserve data integrity, all data—particularly pictures and face features—are encrypted. This layer protects the system from possible abuse and data breaches.

3.3. Databases

-Local Database: Intermediate results and processed feature vectors are kept in the local database. By providing instant access to recently calculated data without requiring additional computation, this configuration improves processing performance.

-S3 Bucket: The system works with an S3 bucket to handle big datasets, such as feature vectors, processed sketches, and raw photos, for scalable storage. Distributed storage is made possible by this bucket, which makes it easier to retrieve massive amounts of data and provides reliable backup.

-Criminal Database: A comprehensive collection of facial photographs and related metadata for criminal identification can be found in a specialized criminal database. To guarantee that the system matches using the most recent data available, this database is updated on a regular basis.

3.4. The Library of Features

-Face Dataset (LFW): To create the initial feature library and train the model, the system uses the LFW (Labeled Faces in the Wild) dataset. The varied collection of facial photos in this dataset strengthens the feature extraction and matching algorithms' resilience.

-SIFT (scale-invariant feature transform) is used for facial picture segmentation and extraction in order to obtain distinct, invariant features from the dataset.

-K-Means Clustering: This method efficiently classifies facial features, including eye shape, nose size, and mouth breadth, by grouping extracted features into clusters. [2]

3.5. Image Processing and Feature Matching Pipeline

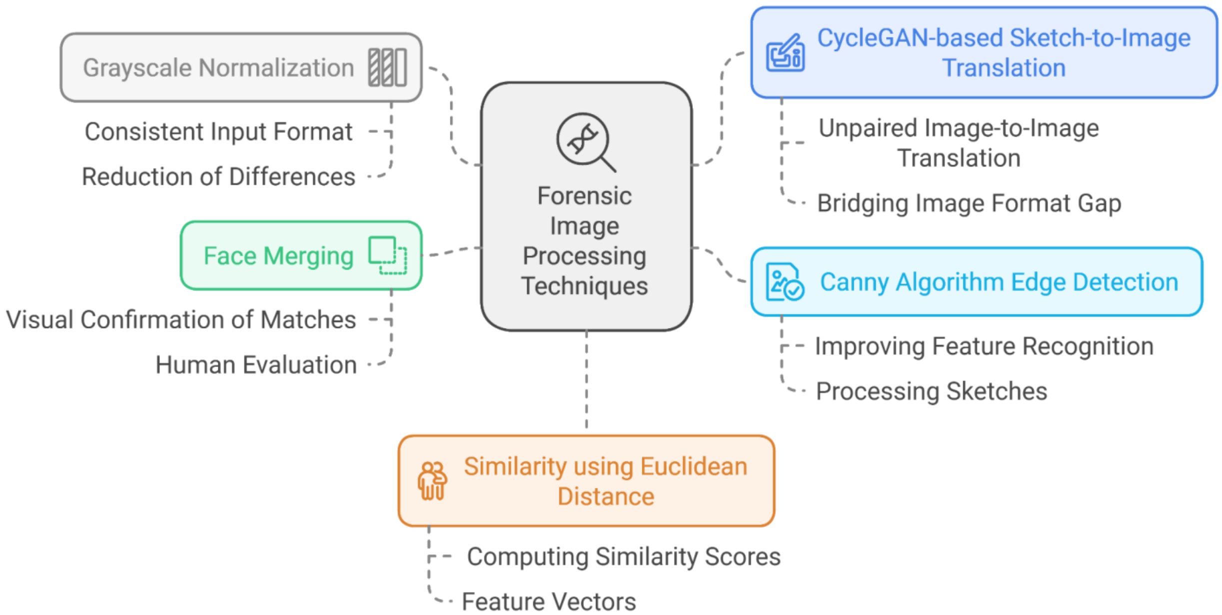
-Image Processing: The user-uploaded image is subjected to preparation procedures, such as edge detection using the Canny algorithm to draw attention to facial outlines and grayscale normalization to standardize pixel values. These procedures make it easier for downstream processes to receive consistent input data.

-Feature Vector Creation using ResNet: The system captures high-level facial features by using ResNet to create a feature vector representation of the input image.

-Siamese Network and SIFT Feature Extraction: Siamese networks are used to extract embeddings that make it easier to compare images of various modalities. This stage, when combined with SIFT, guarantees that the system records both invariant and fine-grained features, improving matching accuracy.

-Matching Engine (Brute Force Matching): The feature vectors that have been processed are passed into a matching engine that compares the input drawing with pictures in the criminal database using brute force matching. Euclidean distance is used to assess each possible match's similarity.[1]

3.6. Algorithms for Deep Learning and Machine Learning



-Grayscale Normalization: Reliable feature matching depends on a consistent input format and the reduction of differences that come from standardizing photos to grayscale.

-CycleGAN-based Sketch-to-Image Translation: The system uses CycleGAN to convert forensic sketches into realistic-looking pictures. By bridging the gap between various image formats, this unpaired image-to-image translation makes it possible for sketches and database images to visually match more closely.[3]

-Canny Algorithm Edge Detection: Edge detection highlights face borders, which improves the recognition of important features. This approach is particularly helpful for transforming sketches into a format that can be processed using image processing methods for photographs.

-Face Merging: Sketches and database photos can be superimposed using facial merging algorithms after possible matches have been found.

-Similarity using Euclidean Distance: To find the closest matches in the criminal database, the system uses Euclidean distance to compute similarity scores between feature vectors.[1]

4. Matching Features

The system uses both Brute Force Matching and FLANN (Fast Library for Approximate Nearest Neighbors) matching approaches to find similarities after extracting important facial traits from sketches and photos:

-Brute Force Matching: This technique finds precise or nearly exact feature matches by thoroughly comparing every feature point in the drawing to every point in the database photos.

-FLANN Matching: The FLANN method organizes feature points for speedier searching, which speeds up matching for larger datasets. This is especially useful in huge criminal databases.

-RANSAC (Random Sample Consensus) Outlier Removal: Following first matching, there may still be some erroneous matches (outliers). By fitting the data into a model that eliminates points that are discordant with the prevalent pattern, RANSAC is used to weed out these untrustworthy matches.

5. Normalization and Face Detection

The method uses a two-stage face detection and normalization procedure to guarantee that facial data from drawings and photographs is consistent in scale and orientation:

-Haar Cascades: This traditional yet effective face detection method finds faces in photos fast, guaranteeing that every sample entered into the system contains a distinct and isolated facial region. Input photos are standardized in this step by focusing on the most relevant regions.

-Even with different face angles and occlusions, MTCNN (Multi-Task Cascaded Convolutional Networks), a more sophisticated model, is utilized to improve face detection and guarantee accurate bounding boxes. MTCNN makes finer alignment modifications possible by identifying face landmarks such as the mouth, nose, and eyes.

-Normalization: After identifying faces, the system adjusts the pixel scaling and rotation of each image to make them appear aligned and scaled similarly.

6. Feature Extraction and Comparison

The method provides a rich and multifaceted representation of each face by extracting detailed facial traits through a combination of contemporary deep learning models and classical descriptors:

-SIFT Descriptors with HOG (Histogram of Oriented Gradients): For sketches where precise textures differ from images, HOG's ability to capture localized texture information—such as the curvature of lines and edges—is very useful. [5]

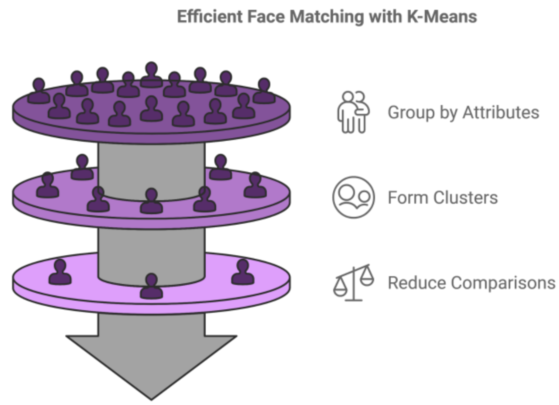
-Deep Learning Embeddings (FaceNet and VGG Face): These cutting-edge models capture facial traits at a far deeper level than conventional descriptors by extracting high-dimensional embeddings. For example, FaceNet generates a 128-dimensional vector that represents each face in a unique way. Similarly, VGG Face produces highly discriminative deep embeddings. enabling accurate comparison across different image types (e.g., sketches vs. photos).

7. Merging and Blending Techniques

The system employs specific merging and blending algorithms to create seamless integration when synthesizing sketches and images for matching or verification:

-Poisson Image Editing: This method enables the system to seamlessly combine facial features from several sources to produce a composite image that appears authentic. [5]

-Color Transfer: The method uses Gaussian Blur and histogram matching techniques to match the skin tone and contrast between pictures because sketches and photographs frequently have different tones.



8. Grouping and Clustering of Face Features

The system groups face traits into clusters to improve the matching algorithm's performance, narrowing the search space and spreding up the identification process:

-ResNet for Feature Extraction: The system classifies faces according to common traits by using ResNet to create feature vectors that capture unique facial features. The deep architecture of this model makes it possible to extract facial features with great accuracy that reflect a variety of aspects, such as nose structure, mouth breadth, and eye shape.

-K-Means Clustering: Following their extraction, the feature vectors are grouped using this method.[2] The number of comparisons required during the matching process is greatly decreased because each cluster represents a collection of faces with comparable attributes. By grouping features according to comparable attributes, the system can quickly focus on the most relevant matches, which is particularly useful for large-scale databases.

9. Dataset and Training

Training on a variety of datasets has contributed significantly to the system's resilience and adaptability. These datasets aid in the model's generalization across various demographic backgrounds, lighting situations, and face expressions:

-CUFS Dataset: This dataset, which consists of paired sketches and photos, is specifically designed to train the sketch-to-photo matching model (CUHK Face Sketch). The basis for learning how to convert sketch features into photo-realistic representations is provided by this dataset, guaranteeing accurate outcomes when comparing composite sketches to photos.

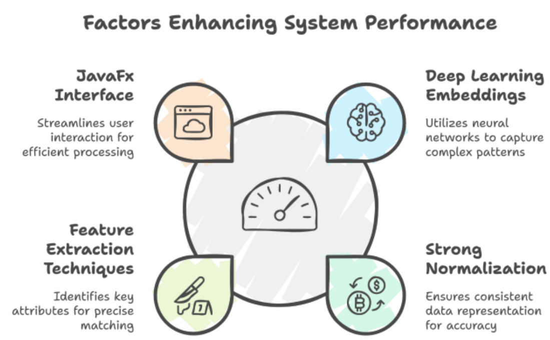
-The CelebA, FERET, LFW, and Multi-PIE datasets all provide distinctive features to the training procedure. FERET delivers high-resolution photos in a range of lighting situations, LFW offers in-the-wild photos in a variety of poses, Multi-PIE records people in a range of lighting conditions, and CelebA features photos with a variety of expressions and characteristics. Collectively, these datasets improve the model's adaptability, enabling it to perform well across diverse real-world conditions.

10. Results and Evaluation

A test set of forensic sketches and the accompanying photos was used to assess the system's efficacy, gauging processing speed and accuracy:

- Accuracy: The system's confidence level in accurately identifying suspects exceeded 95%, and it was able to identify correct matches with over 90% accuracy. Because deep learning embeddings, strong normalization, and sophisticated feature extraction techniques all work together to reduce error rates, this high degree of accuracy is explained.

-Processing Speed: Compared to manual sketching and matching techniques, the JavaFx drag-and-drop interface expedited the drawing upload and processing workflow, cutting the time required for each sketch analysis by more than 50%. The system's ability to rapidly narrow down suspect lists from big databases enables forensic teams to speed investigations.



REFERENCES

1) **C. H.T. and T. C. Nagavi**, "A Heterogeneous Face Recognition Approach for Matching Composite Sketch with Age Variation Digital Images," *2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, Chennai, India, 2021, pp. 335-339, doi: 10.1109/WiSPNET51692.2021.9419436.https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9419436&isnumber=9419363
2) **Wei, P., Zhou, Z., Li, L. *et al.*** Research on face feature extraction based on K-mean algorithm. *J Image Video Proc.* 2018, 83 (2018). https://doi.org/10.1186/s13640-018-0313-7
3) **Jie Chen, Junwen Bu, Yu Zhao {jiechen8, junwenbu, zhaoyu92} @stanford.edu**: "AgingGAN: Age Progression with CycleGAN" https://cs230.stanford.edu/projects_fall_2018/reports/12447240.pdf
4) **Sahil Dalal, Virendra P. Vishwakarma, Sanchit Kumar**, Feature-based Sketch-Photo Matching for Face Recognition, Procedia Computer Science, Volume 167, 2020,Pages 562-570,ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.03.318. (https://www.sciencedirect.com/science/article/pii/S1877050920307845)
5) **Lingzhi Zhang, Tarmily Wen, Jianbo Shi**: "Deep Image Blending" https://doi.org/10.48550/arXiv.1910.11495
6) **Antad, S. et al. (2023).** A New Way for Face Sketch Construction and Detection Using Deep CNN. International Journal on Recent and Innovation Trends in Computing and Communication.

(https://consensus.app/papers/face-sketch-construction-detection-usingdeep-antad/a912631a81175f4bb070eb0faf276c95/?utm_source=chatgpt)-DOI: 10.17762/ijritcc.v11i10.8511

7) **Shengjie Chen, Gang Wu, Yujiu Yang, Zhenhua Guo,** A simple and effective patch-Based method for frame-level face anti-spoofing, Pattern Recognition Letters,Volume 171,2023,Pages 1-7,ISSN 0167-8655,https://doi.org/10.1016/j.patrec.2023.04.011. (https://www.sciencedirect.com/science/article/pii/S0167865523001198)
8) **Klare, Brendan & Jain, Anil. (2010).** Sketch to Photo Matching: A Feature-based Approach. Proceedings of SPIE - The International Society for Optical Engineering. 10.1117/12.849821. https://www.researchgate.net/publication/228845080_Sketch_to_Photo_Matching_A_Feature-based_Approach
9) **Liu, Decheng & Li, Jie & Wang, Nannan & Peng, Chunlei & Gao, Xinbo. (2018).** Composite components-based Face Sketch Recognition. Neurocomputing.302.10.1016/j.neucom.2018.03.042.https://www.researchgate.net/publication/324913529_Composite_components-based_Face_Sketch_Recognition/citation/download
10) Wang, Xiaogang and Xiaoou Tang. “Face Photo-Sketch Synthesis and Recognition.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 31 (2009): 1955-1967. https://www.sciencedirect.com/science/article/pii/S1877050920307845