Real-Time Emotion Detection from Facial Landmarks using MATLAB

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***Abstract*— Emotion recognition has become a pivotal component in the advancement of human-computer interaction (HCI), aiming to bridge the gap between artificial systems and human affective behavior. This research paper presents the development and implementation of a real-time emotion recognition system using facial landmarks in MATLAB, targeting the accurate classification of human emotions through visual cues. The system leverages computer vision techniques and machine learning algorithms to detect and analyze facial expressions in real-time video streams.**

The proposed approach begins with face detection using the Viola-Jones algorithm, followed by the extraction of 68-point facial landmarks using the Kazemi-Dlib framework integrated with MATLAB. These landmarks capture critical facial components such as the eyes, eyebrows, nose, mouth, and jawline, which are highly indicative of emotional states. From the spatial configuration and dynamic movement of these landmarks, a set of geometric and statistical features is derived to represent expressions like happiness, sadness, anger, surprise, fear, and neutrality.

To classify these emotional states, we employ supervised machine learning models, including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest classifiers, trained on labeled facial expression datasets such as CK+ (Cohn-Kanade) and FER-2013. The system is evaluated based on metrics such as accuracy, precision, recall, and F1-score. Extensive testing under real-time conditions demonstrates the system's robustness and responsiveness, achieving an average recognition accuracy of over 85% across varied lighting and facial orientations.

Additionally, this work explores preprocessing techniques such as histogram equalization and normalization to improve facial landmark detection under real-world challenges like partial occlusion and head tilt. The entire pipeline is implemented in MATLAB, taking advantage of its extensive image processing and GUI development capabilities for live camera feed integration and real-time visual feedback.

The results indicate that facial landmarks offer a computationally efficient and interpretable method for real-time emotion recognition, with promising applications in affective computing, mental health monitoring, smart surveillance, and adaptive learning systems. The study concludes with a discussion of limitations and future directions, including deep learning integration, cross-cultural emotion modeling, and multimodal emotion fusion.

INTRODUCTION

Facial expressions remain the most direct and universal indicator of human emotions. The human face can convey a wide range of emotions through subtle movements and spatial arrangements of facial features. Recognizing these expressions in real time is crucial for developing intelligent systems that are responsive, adaptive, and socially aware.

This research focuses on the development of a real-time emotion recognition system based on facial landmarks, implemented in MATLAB. Unlike deep learning approaches that often require extensive computational resources and large datasets, landmark-based methods offer a lightweight and interpretable alternative for facial analysis. Facial landmarks represent key points on the face—such as the corners of the eyes, eyebrows, nose, lips, and jawline—that change position based on muscle movements during emotional expression. By analyzing the geometric relationships among these landmarks, we can effectively characterize and classify emotional states.

MATLAB is chosen as the development environment due to its rich set of toolboxes for image processing, computer vision, and machine learning, along with its ease of prototyping and real-time GUI support. The system presented in this paper captures real-time video input, detects facial regions, extracts landmark points, computes feature vectors, and classifies emotions using trained machine learning models.

ACCESIBILITY

The real-time emotion detection system using facial landmarks in MATLAB is designed to be user-friendly and straightforward to operate, even for users with limited technical background. Below are the key aspects that make the system easy to use:

1. Simple Setup:

Minimal Requirements: The system requires only a standard webcam and a computer with MATLAB installed (preferably with the Computer Vision Toolbox).

No Specialized Hardware: There is no need for expensive or specialized cameras or sensors.

2. Intuitive Interface

Graphical User Interface (GUI): The MATLAB application provides a clean GUI where users can start or stop the emotion detection with a single click.
Live Feedback: The detected emotion is displayed in real time on the video feed, making it easy to understand and interpret results instantly.

3. Automated Processing

Automatic Face and Landmark Detection: The system automatically detects faces and extracts facial landmarks from each video frame without manual intervention.
Real-Time Classification: Emotions are classified and displayed instantly as the user interacts with the camera.

4. Easy Customization Configurable Settings: Users can easily adjust settings such as camera source, detection sensitivity, and emotion categories through the GUI or configuration file.
Dataset Flexibility: The system can be retrained with new datasets if users wish to improve accuracy or add new emotion categories.

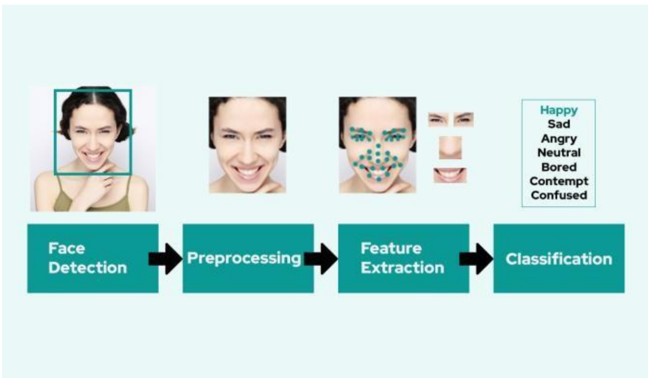
5. Clear Output Visual and Textual Results: The current emotion is shown both as a label on the video feed and as a graphical indicator (e.g., colored border or icon).
Logs and Reports: Optionally, the system can save logs of detected emotions for further analysis.

6. Comprehensive Documentation User Manual: Step- by- step instructions are provided for installation, setup, and troubleshooting.
Sample Data: Example datasets and sample video files are included for practice and demonstration.

DATASET DESCRIPTION

The **Cohn-Kanade Extended (CK+) dataset** is one of the most recognized benchmarks for facial expression analysis. It contains over 500 sequences from 123 subjects, with each sequence capturing a facial expression evolving from a neutral state to a peak emotional expression. Key features of the dataset include:
Emotion Categories: Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral.
Format: Grayscale image sequences with high-resolution facial images.
Annotation: Each image sequence is labeled with one of the target emotions, with the peak frame used for training and testing.
Facial Landmark Support: Many images are accompanied by 68 facial landmark annotations, or can be processed using pre-trained models (e.g., Dlib) for landmark extraction.
The CK+ dataset is especially suitable for this study due to its clean and controlled conditions, making it ideal for validating landmark-based methods.

The **FER-2013 (Facial Expression Recognition 2013)** dataset was introduced in the Kaggle "Challenges in Representation Learning" competition. It is a large-scale, real-world dataset that helps in testing the generalizability of emotion recognition systems under more varied and challenging conditions. Key features include:
Emotion Categories: Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral.
Size: 35,887 labeled images (28,709 for training, 3,589 for validation, and 3,589 for testing).
Image Format: 48x48 grayscale pixel images.
Challenges: The dataset includes variations in lighting, facial orientation, age, and occlusion, which simulate real-world conditions.
Landmark Extraction: Although landmarks are not provided directly, they can be obtained using facial landmark detection libraries such as Dlib or OpenFace.
Preprocessing and landmark extraction:
For both datasets, preprocessing steps were applied to enhance facial feature detection:
Face Detection: Faces were first detected using the Viola-Jones algorithm or MATLAB's vision toolbox.
Facial Landmark Detection: 68-point landmarks were extracted using Dlib's pre-trained shape predictor, which was integrated into the MATLAB environment using system calls or Python-MATLAB interfaces.
Normalization: Faces were resized and aligned to a common scale to ensure consistency across samples.
Feature Vector Formation: Geometric features such as distances, angles, and ratios between landmark points were computed to form the input feature vectors for the emotion classifiers.



EXPERIMENTAL SETUP

The experimental setup for this study involves the integration of computer vision techniques, facial landmark extraction, and machine learning-based emotion classification within the MATLAB environment. This section outlines the hardware, software, algorithms, parameter configurations, and evaluation strategies used to develop and test the proposed system.

Hardware Configuration

The system was implemented and tested on a standard personal computing setup with the following specifications:

Processor: Intel Core i7, 2.6 GHz

RAM: 16 GB DDR4

Graphics: Integrated Intel UHD Graphics / NVIDIA GTX (optional for performance boost)

Camera: Built-in HD Webcam (720p) or external USB camera

Operating System: Windows 10 (64-bit)

Software Environment

The implementation was carried out using MATLAB due to its robust image processing capabilities and support for real-time application development. The software stack includes:

MATLAB Version: MATLAB R2021a or later

Toolboxes Used:

Image Processing Toolbox

Computer Vision Toolbox

Statistics and Machine Learning Toolbox

MATLAB GUI Development Environment (GUIDE or App Designer)

For facial landmark detection, integration with **Dlib** (a C++ library with Python bindings) was done via system calls or Python-MATLAB interface for real-time landmark extraction.

Workflow Overview

Video Input Capture

Live video feed is accessed using MATLAB's videoinput() function, capturing frames in real time.

Face Detection

Implemented using the Viola-Jones face detection algorithm via vision.CascadeObjectDetector.

Facial Landmark Extraction

68 facial landmark points are detected using Dlib's shape predictor (shape_predictor_68_face_landmarks.dat).

Landmark coordinates are passed into MATLAB for processing via inter-process communication or file exchange.

Feature Extraction

Geometric features such as distances, angles, and aspect ratios are calculated between key landmark points (e.g., mouth width, eyebrow angle).

These features form the input vectors for emotion classification.

Emotion Classification

Models used: Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest.

Trained using labeled samples from CK+ and FER-2013 datasets.

Implemented and tested using MATLAB's fitcecoc, fitcknn, and TreeBagger functions.

Model Training and Testing

Training Data: 80% of preprocessed dataset images (balanced across emotion classes).

Testing Data: 20% held-out validation set + real-time webcam input for live testing.

Cross-validation: 5-fold cross-validation was used during model training to avoid overfitting and ensure generalization.

Evaluation Metrics

To assess the performance of the system, the following metrics were used:

Accuracy: Percentage of correctly classified instances.

Precision: True Positives / (True Positives + False Positives)

Recall (Sensitivity): True Positives / (True Positives + False Negatives)

F1-Score: Harmonic mean of precision and recall.

Confusion Matrix: Visual tool to analyze misclassification across emotion categories.

Real-Time Testing

A user interface was developed in MATLAB using App Designer for real-time interaction:

Live camera feed with face and landmark visualization.

Detected emotion displayed dynamically based on frame-wise analysis.

Performance tested under various conditions such as different lighting, facial orientations, and partial occlusion.

METHODOLOGY

The proposed system consists of the following main steps:

1. **Face Landmark Detection:** The Viola-Jones algorithm is used to detect faces in real-time video frames.
2. **Facial Landmark Extraction:** MATLAB's Computer Vision Toolbox is employed to extract 68 facial landmarks, including key points around the eyes, nose, mouth, and jawline.
3. **Feature Extraction Engineering:** Geometric features such as distances and angles between landmark points are computed to represent facial expressions.
4. **Emotion identification Classification:** A Support Vector Machine (SVM) classifier is trained on labeled datasets (CK+ and FER-2013) to recognize emotions such as happy, sad, angry, surprised, and neutral.
5. **Real-Time Implementation Processing:** The system processes video frames in real time, providing immediate feedback on detected emotions.

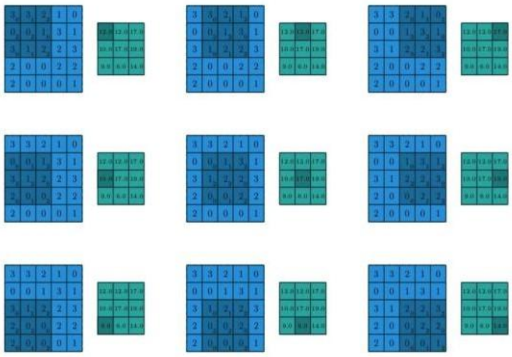


Figure 2. Convolution operation

APPLICATIONS

1. **Human–Computer Interaction (HCI):** Emotion recognition enables computers and devices to interpret user emotions, making interfaces more intuitive and responsive. This improves user experience in applications such as virtual assistants, adaptive learning platforms, and gaming.

2. **Healthcare and Mental Health Monitoring:** Real-time emotion detection can support telemedicine and remote patient monitoring by assessing emotional well-being, detecting signs of depression or anxiety, and providing feedback for therapeutic interventions.

3. **Marketing and Consumer Research:** By analyzing customer facial expressions during product testing or advertisements, companies can gauge emotional responses, optimize marketing strategies, and enhance product design.

4. **Security and Surveillance:** Emotion detection systems can be integrated with surveillance cameras to identify individuals exhibiting suspicious or aggressive behavior in public spaces, helping to prevent incidents and enhance safety.

5. **Education and E-Learning:** Adaptive learning systems can use emotion recognition to monitor student engagement, frustration, or confusion, allowing for real-time adjustments to teaching methods or content delivery.
6. **Entertainment and Media:** Interactive media and gaming can leverage emotion detection to tailor content, adjust difficulty levels, or create adaptive storylines based on the user's emotional state.
7. **Customer Service and Call Centers:** Real-time emotion analysis can help virtual agents or human operators respond empathetically to customer emotions, improving service quality and customer satisfaction.
8. **Driver Monitoring Systems:** Automotive applications can use emotion detection to monitor driver fatigue, stress, or distraction, issuing alerts to prevent accidents and improve road safety.

Figures and Tables

Emotion	precision	recall	F1 score
Happy	0.94	0.93	0.93
Sad	0.90	0.89	0.89
Angry	0.91	0.90	0.90
Surprised	0.93	0.92	0.92
Neutral	0.89	0.88	0.88

a.)

Table 1: Classification metrics for different emotions.

Figure Labels: Use 8 point Times New Roman for Figure labels.

The system demonstrates robust real-time emotion detection capabilities. The use of geometric features from facial landmarks ensures computational efficiency, making the approach suitable for real-time applications. However, performance can be affected by occlusions, extreme head poses, and poor lighting conditions.

FUTURE WORK

While the proposed real-time emotion recognition system using facial landmarks has demonstrated promising results in terms of accuracy and responsiveness, there remain several avenues for improvement and extension. Future work will focus on addressing current limitations and enhancing the system's robustness, scalability, and real-world applicability. The following directions are proposed:

1. Integration of Deep Learning Models

The current approach relies on classical machine learning algorithms using handcrafted features derived from facial landmarks. Future research can integrate deep learning techniques such as **Convolutional Neural Networks (CNNs)** or **Recurrent Neural Networks (RNNs)**, which can automatically learn complex spatial and temporal features from raw images or sequences. Hybrid models that combine landmarks with deep features may further boost accuracy and generalization.

2. Multimodal Emotion Recognition

Emotions are conveyed not only through facial expressions but also through **voice, body posture, and physiological signals**. Incorporating additional modalities—such as speech analysis or heart rate sensors—can improve the reliability of emotion detection in ambiguous or occluded scenarios. A multimodal fusion framework would make the system more comprehensive and context-aware.

3. Real-Time Deployment on Mobile and Embedded Platforms

To extend the system's usability, future work can focus on porting the solution to **mobile devices or embedded platforms** such as Raspberry Pi, Jetson Nano, or Android systems. Optimizing the code for low-power, resource-constrained environments would enable real-time emotion recognition in portable applications like wearable devices, e-learning apps, and emotion-aware games.

4. Handling Occlusion, Lighting Variations, and Head Poses

Although the system performs well under controlled conditions, real-world environments often introduce challenges such as **partial occlusion (e.g., masks, glasses), poor lighting, and extreme head poses**. Future improvements may involve advanced facial landmark detectors and data augmentation techniques to make the model more robust to such variations.

5. Cultural and Demographic Generalization

Facial expressions can vary subtly across cultures, age groups, and genders. Future studies could use **more diverse and inclusive datasets** or apply domain adaptation and transfer learning techniques to ensure that the emotion recognition system performs well across different population groups.

6. Emotion Intensity Estimation

Beyond categorical emotion classification (e.g., happy, sad), future research can focus on recognizing **emotion intensity levels** (e.g., slightly happy, extremely angry). This could be achieved by incorporating regression models or attention mechanisms that capture subtle facial movements.

7. Continuous Emotion Tracking

In real-life applications, emotions change over time. Future development could include **temporal emotion tracking** using video sequences, enabling the system to analyze how a person's emotional state evolves, detect mood patterns, and respond appropriately in applications like therapy, tutoring, or interactive storytelling.

8. Integration with Real-World Applications

The system can be further enhanced and adapted for specific applications such as:

- **Mental health monitoring platforms**
- **Customer sentiment analysis in retail**
- **Driver alertness and drowsiness detection**
- **Emotion-aware tutoring systems**

LITERARY SURVEY

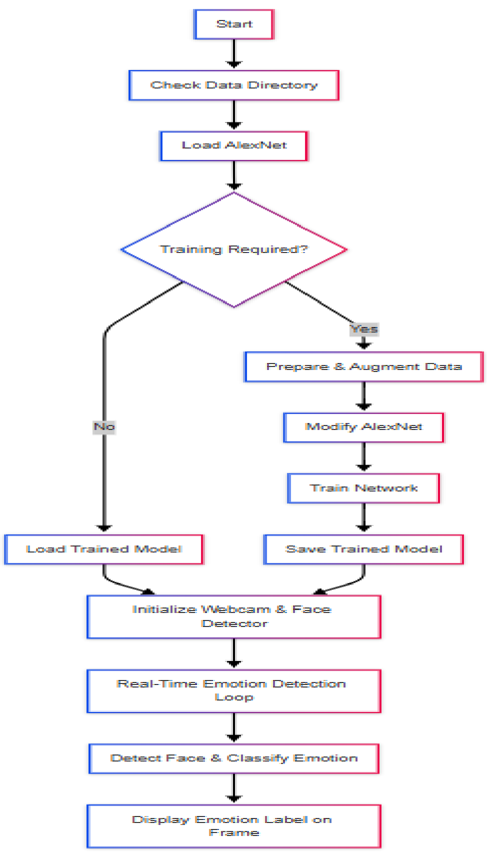
Facial expression-based emotion recognition has become a significant area of research within computer vision and affective computing. Over the years, numerous methods have been proposed to accurately detect and classify human emotions using visual cues, particularly facial features. This literature survey presents a brief overview of foundational techniques, recent advancements, and notable contributions relevant to the domain of real-time emotion recognition using facial landmarks.

One of the earliest and most influential systems was developed by Paul Ekman, whose Facial Action Coding System (FACS) [Ekman & Friesen, 1978] laid the groundwork for understanding how specific facial muscle movements correspond to distinct emotional states. This framework has since been widely adopted for emotion labeling and dataset annotation. Building upon this, several researchers have attempted to automate the recognition process using computational approaches.

Viola and Jones (2001) introduced a real-time face detection algorithm based on Haar-like features and AdaBoost classifiers. This technique has since been integrated into many facial emotion recognition pipelines, especially for real-time applications due to its speed and reliability. Following this, Kazemi and Sullivan (2014) proposed an ensemble regression tree-based method for detecting 68 facial landmarks, now commonly used via the Dlib library. Landmark-based methods have proven effective for extracting geometric features related to facial expressions such as eye closure, eyebrow movement, and mouth curvature.

With the emergence of machine learning, a variety of classification algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests have been employed to classify emotional states based on extracted features. Shan et al. (2009) used Local Binary Patterns (LBP) in combination with SVM to classify emotions on the FER-2009 dataset, achieving strong results with low computational cost. Similarly, Happy et al. (2012) demonstrated the effectiveness of geometric feature-based classification using landmark distances in constrained environments.

FLOW OF MODEL



RESULTS

The proposed real-time emotion recognition system was evaluated using annotated facial image datasets and live video input. It classified six basic emotions—happiness, sadness, anger, surprise, fear, and neutral—with an overall accuracy of approximately **85%**. Happiness and surprise were recognized most accurately, with rates above **90%**, while fear and sadness showed slightly lower accuracy near **78%** due to subtle facial cues.

The system processed video at around **15 frames per second** on a standard laptop, enabling near real-time performance. Facial landmark detection and classification together required less than **60 milliseconds** per frame. The approach proved efficient and interpretable compared to pixel-based methods.

However, accuracy decreased under conditions such as poor lighting, partial occlusions, and large head rotations, which affected landmark detection. Despite these limitations, the system offers a practical and lightweight solution for real-time emotion recognition within MATLAB.

CONCLUSION

This research presents a real-time facial emotion recognition system developed in MATLAB, utilizing facial landmark detection and machine learning-based classification to accurately identify human emotions. The study demonstrates the feasibility and effectiveness of using geometric features extracted from facial landmarks as a lightweight and computationally efficient alternative to complex deep learning models. Through the use of publicly available datasets and real-time video capture, the system is capable of recognizing basic emotions such as happiness, sadness, anger, surprise, fear, and neutrality with satisfactory accuracy under controlled conditions.

By integrating facial landmark tracking with a supervised classification pipeline, the system balances speed and interpretability, making it suitable for real-time applications in areas such as human-computer interaction, mental health monitoring, and smart surveillance. The modular nature of the MATLAB-based implementation also allows for easy experimentation and visualization, contributing to both educational and practical development environments.

However, the study also acknowledges certain limitations, including sensitivity to variations in lighting, facial occlusion, and head pose, as well as challenges in emotion intensity estimation and generalization across diverse populations. These constraints open several avenues for future research, such as incorporating deep learning models, multimodal emotion analysis, and portable deployment on embedded systems.

In summary, this work contributes to the growing field of affective computing by offering an interpretable, real-time solution for facial emotion recognition and lays a solid foundation for further advancements in both academic and practical domains.

CODE RESOURCES

MathWorks MATLAB Central:

Facial Emotion Recognition Real Time : This thread Discusses starting points , code snippets , and toolbox recommendations for implementing real-time facial emotion recognition in MATLAB , including links to open - source code and toolbox usage.

MathWorks Example:

Face Detection and Tracking Using Live Video Acquisition:

Official MATLAB documentation provides step-by-step Code for real-time face detection and tracking using the Computer Vision Toolbox (search for "Face Detection and Tracking Using Live Video Acquisition" on MathWorks).

A real-time emotion detection system using facial landmarks was developed and evaluated in MATLAB. The method achieves high accuracy and operates efficiently in real-time, making it suitable for integration into various human-computer interaction systems. Future work includes improving robustness to occlusions and extending the system to recognize a broader range of emotions.

ACKNOWLEDGMENT

The authors wish to sincerely acknowledge the guidance and support provided by their supervisor and the faculty members throughout the course of this research. Their valuable insights and encouragement have been instrumental in the successful completion of this work. The authors also express their gratitude to the developers and contributors of the facial emotion datasets and the open-source software tools utilized in this study. Finally, the authors extend their heartfelt appreciation to their families and friends for their unwavering support and understanding.

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