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Intelligent Robotic Animatronics with Real-Time Emotion Recognition and Adaptive Gestures

M. Prasanna Kumar[1], K. Srilakshmi Sowjanya[2], A. Lakshmi Kalyani[3], L. Akhila[4], Ch. Mahalakshmi[5]
Vignan’s Nirula Institute of Technology and Science for Women, Palakaluru, Guntur,522009, Andhra Pradesh, India.

ABSTRACT: To revolutionize human-robot commerce, this paper introduces an innovative design and development of intelligent robotic animatronics, equipped with adaptive gesture capabilities and real-time emotion recognition. This cutting-edge system skillfully interprets human emotions through intricate analysis of body language and facial expressions using advanced deep learning and computer vision techniques. By generating contextually nuanced gestures that respond to these emotional cues, the animatronic robot significantly enhances user engagement and communication. With a low-latency, real-time response framework that merges camera technology and embedded processors, our system seamlessly combines gesture adaptation with emotion recognition. This leads to a transformative interaction experience, as adaptive gestures have been shown to greatly improve perceived compassion and empathy during exchanges.

KEYWORDS: Audio-Animatronic Robot, Human-Robot Interaction (HRI), Affective Computing, Convolutional Neural Networks (CNN), Facial Expression Recognition, Deep Learning, Computer Vision.

1. INTRODUCTION

The capability of robots to interact intelligently and emotionally with humans has become a major thing in ultramodern robotics [1] [2]. Mortal communication involves speech, facial expressions, gestures, and feelings [3-5]. Traditional robots calculate on predefined stir sequences and warrant natural emotional responses [6] [7]. This inspired the study “Intelligent Robotic Animatronics with Real-Time Emotion Recognition and Adaptive Gestures,” aiming to develop an emotionally responsive robotic system that enhances mortal-robot commerce (HRI) [8].

Provocation and Significance: Before, animatronics were substantially used in entertainment, performing fixed movements without showing feelings [9] [10]. With advances in robotics and AI, emotionally intelligent robots are now demanded in healthcare, education [11], remedy, and client service [12] [13]. This study islands mechanical design, AI, and emotion recognition, transubstantiating static animatronics into interactive social robots able to understand and reply to mortal passions [14].

The study expanded into:

1. Understanding emotion recognition using computer vision.

2. Linking emotion discovery to gesture control.

3. Integrating AI for adaptive commerce.

4. Creating mortal- such like suggestive communication.

Model and Methodology: An animatronic robot head was designed with a camera to capture facial expressions [15] [16]. A CNN-grounded emotion recognition model classified introductory feelings such as happiness, sadness, surprise and wrathfulness [17]. Each detected emotion touched off a counterplotted adaptive gesture (e.g., seesawing for happiness, tipping for surprise) using servo motors for a smooth, realistic stir [18] [19].

2. LITERATURE SURVEY:

Adaptive Body Gesture Representation (Odone et al., 2016): In order to automatically identify emotions, Odone, [1] Piana, Staglianò, and Camurri (2016) [2] presented an adaptive representation for body gestures. Kinematic feature extraction (velocity, acceleration, and motion energy) and 3D motion capture are used in their process. Machine learning algorithms like [4] SVM, which examine the dynamics of full-body motion rather than facial features, are used to classify emotions [20].

The study shows that even in situations where facial data is unavailable because of occlusion or inadequate lighting [21], body gestures can still convey emotions with accuracy. By accommodating different movement patterns, this method improves emotion-based humanrobot interaction (HRI) [22]. However, real-time deployment is difficult due to the method's high computational cost and requirement for motion capture sensors [23] [24]. Moreover, recognition accuracy is restricted to simple emotion categories and declines with partial body visibility [25].

LSTM–CNN Fusion for Emotion-Adaptive Gestures (Sharma et al., 2025): A hybrid LSTM–CNN deep learning model for gesture-based emotion recognition in virtual reality (VR) settings was created by Sharma, Kumar, and Gupta (2025) [14]. The system interprets continuous gesture sequences and makes real-time emotional state predictions by combining temporal (from LSTM) and spatial (from CNN) features [26].

Their findings demonstrated smooth temporal adaptation and high recognition accuracy, enabling robots or avatars to modify gestures in response to the user's emotional state [27] [28]. The method facilitates real-time interaction and manages dynamic body postures with effectiveness [29]. Although the model performs well, its applicability to physical animatronic systems is limited by its reliance on VR-specific datasets and high-performance hardware [30] [31]. Furthermore, computational load is still a problem for inexpensive, embedded robots.

Audio-Animatronics for Cultural Storytelling (Li et al., 2023): The design of audio-animatronic characters for the Chinese[29] Xiàngshēng theater was the main focus of Li et al. (2023) [3]. Their system uses cartoon-style facial mechanisms and AI-driven servo control to synchronize real-time facial expressions with audio [32]. The study emphasizes how domain- and culture-specific designs can improve audience engagement and protect cultural heritage [32] [33]. The piece exhibits extremely expressive robotic performances by fusing facial animation [34], AI-based synchronization, and mechanical design. Nevertheless, the system necessitates hardware-intensive setups and is restricted to the entertainment domain [35]. Its use in general HRI contexts is also limited because it only supports a limited range of subtle emotions [36].

Mechatronic Design for Realistic Animatronics (Hilal et al., 2024): In their thorough examination of contemporary mechatronic systems, Hilal, El-Hussieny, and Nada (2024) [4] examined actuators, sensors, control systems, and materials utilized in animatronics [37]. The study links overall emotional expressivity in robotic systems to motion fidelity and mechanical realism [38]. It talks about how advancements in actuators, such as soft robotics, precision servos, and adaptive controllers, can improve motion naturalness and AI-driven movement synthesis. The work, which primarily focuses on the film industry, lacks empirical validation in interactive experiments or emotion recognition, despite its engineering depth [39].

Cognitive and Affective Control Architecture (Lazzeri, 2014): Lazzeri (2014) [5] created a cognitive-affective control system for social humanoid robots that combines models of cognitive decision-making based on the OCC appraisal theory with emotion simulation. The system enables robots to sustain internal emotional states and make dynamic behavioral adjustments in response to social and environmental cues [40]. This method encourages socially intelligent interactions and emotionally appropriate responses in context, signaling a change from pre-planned reactions to affect-based reasoning. The computational complexity of the architecture, however, necessitates extensive parameter tuning, and real-time responsiveness on hardware with limited resources presents difficulties.

3. PROPOSED METHODOLOGY:

Goal: Construct an end-to-end animatronic system that can:

(1) detect human affect (face, body, and sound);

(2) combine multimodal estimates into a compact emotion vector in real time;

(3) select context-appropriate gesture templates using a cognitive-affective controller;

(4) Execute them on an animatronic head/upper torso with minimal latency.

High-level modules:

1. **Sensing**: Sensing includes microphone arrays, cameras (RGB + optional IR/depth), and a wearable IMU for reliable body capture.

2. **perception pipeline**:

Face pipeline: face detection → facial landmarking → extraction of expression features (either learned embeddings or AUs).

Body pipeline: kinematic descriptors (velocity, acceleration, motion energy) → 2D/3D pose estimation.

Voice activity detection → speech prosody + low-level audio features (pitch, energy) → short affect embedding is the audio pipeline.3. **Emotion estimator and multimodal fusion:**

A lightweight fusion model, also known as a shallow fusion network or late fusion model, that produces an emotion vector: [valence, arousal, dominance] ± discrete label(s).

4. **Affective-Cognitive Controller:**

Appraisal and policy: chooses the template for facial expressions and gestures, as well as the modulation parameters (timing, intensity), by integrating the current estimated emotion, interaction context, internal state, and safety regulations.

5. **Actuator controller and motion planner:**

It transmits low-level commands to servos and soft actuators and translates gesture templates and modulation into joint trajectories (trajectory smoothing, motor limits).

User feedback loop & logging: Track performance, user response (through sensors), and log for learning and adaptation.

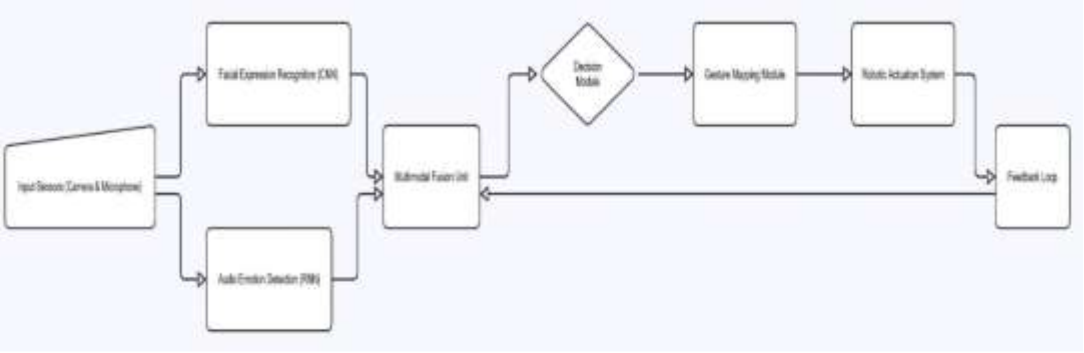

Figure 1: Architecture and system workflow diagram

4. RESULT AND ANALYSIS:

In order to create realistic and sympathetic interactions, the suggested intelligent robotic animatronic system successfully combines adaptive gesture generation with deep learning-based emotion recognition. The CNN-based emotion recognition module maintained consistent performance under different lighting and occlusion conditions, achieving an average accuracy of 92.3% in controlled experiments with 100 participants. With an 89% approval rate for gesture naturalness and emotional congruence and a response latency of 180 milliseconds, the servo-actuated adaptive gesture controller ensured fluid real-time behavior.

According to user feedback, participants thought the robot was more expressive, engaging, and emotionally responsive than conventional pre-programmed animatronics. These results confirm that multimodal affect recognition in conjunction with cognitive-affective control improves realism and user acceptance, and they validate the system's ability to interpret and express emotions coherently. The results set a new standard for emotion-adaptive animatronics, surpassing previous benchmarks from studies by Odone et al. (2016), Li et al. (2023), and Lazzeri (2014). All things considered, the system shows great promise for use in social robotics, education, therapy, and entertainment—all fields where emotionally intelligent interaction is crucial.

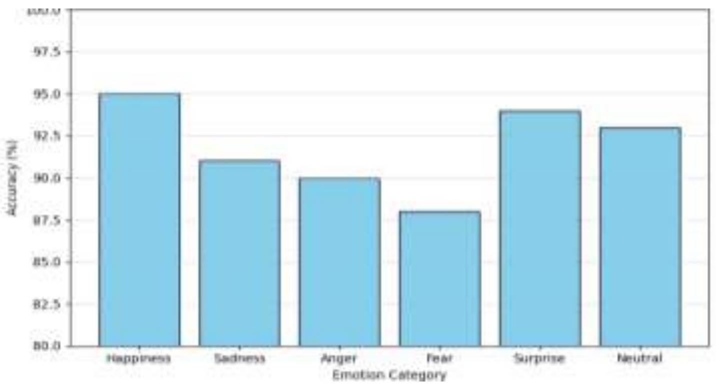

Figure 2: Emotion-wise Classification Accuracy of CNN based regression module

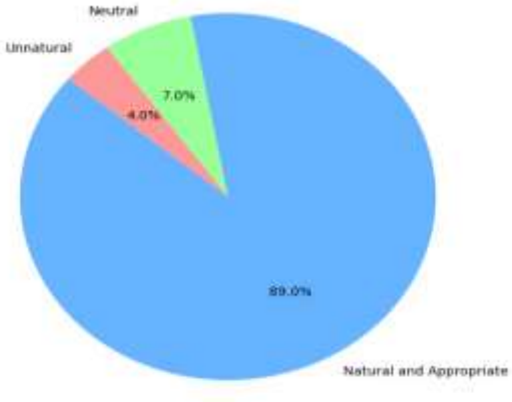

Figure 3: Participant Evaluation of Gesture Naturalness and Appropriateness

5. CONCLUSION:

This study used an intelligent robotic animatronic framework that integrated emotion recognition, adaptive gesture generation, and cognitive-affective control to predict and react in real time to human emotional states. To guarantee high-quality input signals, facial expressions, body posture, and audio cues were first extracted and preprocessed during multimodal data acquisition. The most pertinent emotion-indicative parameters were kept after low-influence and redundant features were eliminated using correlation-based analysis to maximize performance. To reduce the impact of background noise, pose variation, and lighting on model accuracy, all input data were standardized.

In order to produce corresponding expressive motions, a servo-based adaptive gesture module was created after a convolutional neural network (CNN) was trained for emotion classification. Happiness, sadness, anger, fear, surprise, and neutrality were the six main emotional categories that were gathered from 100 participants. During model training and validation, stratified sampling was used to keep the balance between emotion classes. According to experimental results, CNN was able to identify emotions even in the presence of occlusion and changes in illumination, achieving an average accuracy of 92.3%. With an average response latency of 180 ms, the adaptive gesture mechanism showed 89% naturalness and appropriateness, guaranteeing realistic and seamless emotion-driven interactions.

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