GENERATIVE ACTION SYNTHESIS FOR EMOTION REPLICATION IN ROBOTIC AGENTS VIA CONDITIONAL GANS, HIERARCHICAL TRANSFORMERS, AND STOCHASTIC POLICY GRADIENTS WITH FOKKER-PLANCK-KOLMOGOROV STABILIZED DYNAMICS

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January 27, 2025

ABSTRACT

This paper introduces Generative Action Synthesis (GAS), a novel method for imbuing robots with human-like emotional expression during task execution. GAS leverages conditional Wasserstein GANs (cWGANs) for action generation conditioned on emotional embeddings, guided by expert demonstrations and refined via Hamiltonian Monte Carlo. A temporal-hierarchical transformer (THT) synthesizes actions while a Von Mises-Fisher mixture model (vMF-MM) resolves ambiguities. The framework also employs stochastic policy gradients for dynamic adjustment based on real-time feedback and task requirements, with Fokker-Planck-Kolmogorov equations ensuring emotion stability. This approach, integrating generative models with reinforcement learning and structured emotional embedding, enables robots to exhibit a range of emotional behaviors, including anger, humor, and empathy, leading to more natural and adaptable human-robot interactions. Practical implications include advanced applications in caregiving, customer service, and other social domains, highlighting its significance in the development of emotionally intelligent robots.

***K*eywords** Generative Action Synthesis · Robots · Emotion Replication · Generative Adversarial Networks · Reinforcement Learning · Emotional Personas · Temporal-Hierarchical Transformers · Von Mises-Fisher Mixture Model · Hamiltonian Monte Carlo · Stochastic Policy Gradients

1 Introduction

The development of robots capable of exhibiting human-like emotional behavior is a complex endeavor, requiring sophisticated techniques to synthesize actions that convey specific emotional personas. This research addresses this challenge through Generative Action Synthesis (GAS), a novel framework that leverages advanced artificial intelligence to enable robots to replicate human emotions such as anger, humor, and empathy. The framework integrates expert demonstration learning, generative adversarial networks (GANs), and reinforcement learning to produce emotionally resonant and context-aware robotic behavior. A crucial aspect is the use of emotion embeddings that capture the relationships between different emotional states allowing for nuanced and realistic transitions. Key concepts within GAS include conditional Wasserstein GANs (cWGANs) for action generation, temporal-hierarchical transformers (THT) for sequence modeling, and Von Mises-Fisher mixture models (vMF-MM) to resolve action ambiguity.

Feedback loops utilizing Hamiltonian Monte Carlo (HMC) refine generated actions, while stochastic policy gradients enable dynamic behavior adjustments. A central challenge involves ensuring both the task efficacy and the consistency of emotional expressions during extended interactions, necessitating the use of Fokker-Planck-Kolmogorov equations to

Table 1: Emotional Persona Embeddings

Persona		
Name	Feature Vector	Description
Anger	$\sigma(W_a[\text{assertiveness}, \text{urgency}]^T + b_a)$	Expresses assertiveness and urgency.
Empathy	$\sigma(W_e[\text{caring}, \text{support}]^T + b_e)$	Displays caring and supportive behavior.
Humor	$\sigma(W_h[\text{playfulness}, \text{wit}]^T + b_h)$	Exhibits playful and witty actions.
Frustration	$\sigma(W_f[\text{irritation}, \text{disappointment}]^T + b_f)$	Demonstrates irritation and disappointment.
Neutral	$\sigma(W_n[\text{calm}, \text{composed}]^T + b_n)$	Exhibits calm and composed behavior

model the temporal evolution of emotional states. The objective is to create robots that not only perform tasks efficiently but also adapt their behavior to mirror human emotional nuances, thereby facilitating more intuitive and effective human-robot interaction. The research questions addressed in this paper focus on how to effectively synthesize actions that accurately reflect specific emotional personas, how to handle action ambiguity in emotional contexts, and how to maintain emotional stability over time. The methodology employs a hybrid approach combining cWGANs, THT, vMF-MM, and reinforcement learning, along with emotional embeddings that allow for smooth transitions between emotional states. The significance lies in creating emotionally intelligent robots suitable for applications requiring complex social interactions. The paper is organized to detail the GAS framework, its key components, the technical underpinnings, and provides a conclusive overview of its potential impact on human-robot interaction.

2 Generative Action Synthesis

Generative Action Synthesis (GAS) provides a framework for imbuing robots with the ability to express emotions through their actions, using expert demonstrations of behavior coupled with emotional personas represented mathematically. This approach enables robots to not only complete tasks but to also express nuanced emotional states like anger, humor, or empathy, facilitating more natural and adaptive interactions. Central to GAS is the use of advanced AI models, such as generative adversarial networks (GANs) and reinforcement learning, to generate action sequences conditioned on the current state of the robot and the desired emotional persona, ensuring that actions are both realistic and emotionally expressive. The framework incorporates probabilistic modeling to address inherent ambiguity in action selection, using feedback loops to refine generated actions and ensure they align with both task goals and emotional expectations. To synthesize actions that reflect specific emotional states, it's essential to understand the underlying distributions governing these actions. This necessitates the ability to capture and sample from the space of possible action sequences conditioned on both the current state and desired persona. Consider the complex interplay between robot state, emotional context, and subsequent actions; this relationship can be captured by a formulation that allows for a probabilistic mapping between these variables. A mathematical construction that formalizes this relationship offers a robust approach for generating these actions within the GAS framework.

The synthesized actions are generated through temporal hierarchical transformers (THT). THTs process sequences of robot states and corresponding emotional personas through a multi-layered attention mechanism, thus enabling contextual understanding of the sequence, thus facilitating effective action generation that reflects emotional states. The THT's architecture allows the system to learn long range dependencies, thereby ensuring coherence in actions sequences. Action selection ambiguity is resolved through a Von Mises-Fisher mixture model (vMF-MM), which is adept at capturing multimodal action distributions associated with emotional personas and choosing the most appropriate action for any given state. Furthermore, feedback loops powered by Hamiltonian Monte Carlo (HMC) are used to refine the outputs of the generator by comparing generated actions to expert examples. Stochastic policy gradients are also deployed for dynamic prompt injection, which ensures the robot's behavior adapts based on real-time feedback and task needs. The model is also designed to maintain stability of the expressed emotion over time through dynamic equation. Emotional states are inherently complex and often represented as abstract concepts. Understanding how these states influence action and their relationships to one another is crucial for a robot to behave in an emotionally intelligent manner. This understanding can be structured through a set of relationships represented below, which maps emotions to an underlying feature space, providing a framework to learn the associated behavioral nuances and facilitate smooth transitions across the emotional spectrum.

The structured embedding space allows the robot to navigate through different emotional personas and facilitate a seamless blend between them when required. This also enables it to perform emotional transitions effectively and also prevents emotion drift over time during long tasks. The representation of emotional personas as embeddings captures the semantic relationships between them and also allows continuous transitions between different states. Furthermore,

using the described methods, the robot can create and display more nuanced behavior. The ability of the robot to adapt to its environment and changing circumstances is crucial for the overall effectiveness of the GAS framework. Reinforcement learning techniques allow the system to learn how to behave optimally while expressing a given emotion, further refining its behavior in response to its interactions with the environment and task objectives. It is essential to visualize this interaction between the environment, the robot, and the generated behavior. The interaction is crucial for the robot to adapt and refine its actions based on feedback.

3 Literature Review

This research introduces Generative Action Synthesis (GAS), a novel method for robotic emotion replication using advanced AI. The core methodology centers on training robots via expert demonstrations where actions are paired with emotional personas represented as mathematical embeddings. Action generation is achieved through a specialized AI model, adaptable to assigned personas, resolving ambiguity using a probabilistic model and refining outputs through iterative feedback. The system uses emotional embeddings to ensure smooth transitions between emotional states, and dynamic adjustments via reinforcement learning. The framework integrates conditional Wasserstein GANs (cWGANs) with Boltzmann policy entropy regularization. The GAN loss function balances discriminator and generator outputs with a gradient penalty. The generator synthesizes actions through temporal-hierarchical transformers (THT), modeled as a product of softmax functions over multi-head attention. To manage action selection ambiguity, a Von Mises-Fisher mixture model (vMF-MM) assigns probabilities over a latent space based on the given persona. Refining the generator's outputs is done through Hamiltonian Monte Carlo (HMC) by minimizing a KL divergence loss. Furthermore, dynamic adjustments are introduced through stochastic policy gradients, maximizing returns. Emotion stability is enforced through Fokker-Planck-Kolmogorov equations describing state transitions. The framework's key findings emphasize the ability of robots to perform tasks while also demonstrating a range of human-like emotions. The literature, while demonstrating the feasibility of combining complex AI models for robotic emotion generation, has some gaps. The current research heavily relies on expert demonstrations, which can be labor-intensive and may not capture the full spectrum of human emotional expression. Additionally, the system's dependence on reinforcement learning may lead to biases influenced by the reward function. The use of GANs can lead to instabilities and challenges in training. The framework also assumes a well-defined structure for emotional persona, which can be subjective and complex. Further, while the use of a probabilistic model helps in mitigating ambiguity, there is limited evidence of how the model would perform under unforeseen scenarios that were not covered in the training data. Existing works also do not explore the robustness of these systems to adversarial attacks or whether the system would maintain emotional consistency over extended interactions. Finally, existing research on combining multiple personas and transitions are not clear on how such system may scale in complex situations. Future research directions should focus on diversifying training data, exploring unsupervised learning techniques, and devising more robust algorithms for handling unforeseen scenarios. Incorporating feedback from user interactions could improve emotional accuracy and the development of robust methods to tackle adversarial attacks and drift in emotional consistency is also critical. Finally, methods to test the scalability of emotional combinations in multiple personas will be important.

4 Data

The research leveraged a dataset of expert demonstrations, with each action paired with an emotional persona represented as a mathematical embedding, to train the robots. This data was crucial for learning how to generate actions that align with specific emotional expressions. The use of simulated data offered advantages in terms of controllability and scalability, allowing the researchers to explore a broad spectrum of scenarios without the constraints of real-world data acquisition. Theoretical models, such as conditional Wasserstein GANs, Boltzmann policy entropy regularization, and Von Mises-Fisher mixture models, provided the foundational basis for the AI algorithms. The initial data was primarily used for training and evaluating performance. Empirical validation, involving real-world experiments with robots, is a planned step to test the effectiveness and generalization capabilities of the proposed framework. Data was also used in the feedback loop to refine actions by comparing it with expert demonstrations.The insights gained from the initial experiments, both simulated and real, will guide adjustments to the models and improvements to the architecture, and will facilitate ongoing development and further research into advanced emotional modeling for robotics. Data is essential to measure emotion stability over time using Fokker-Planck-Kolmogorov equations.

5 Use case and Business potential

The Generative Action Synthesis (GAS) framework offers significant business potential by enabling robots to perform tasks with nuanced emotional expressions, leading to improved process optimization and cost reduction through

enhanced human-robot interaction. This technology facilitates innovation in automated systems, particularly in decision-making processes where understanding and adapting to human emotional cues are crucial. The ability to provide enhanced customer solutions with empathetic interactions and scale operations while maintaining consistent emotional responses creates a competitive advantage. Further, GAS allows for richer data insights into human-robot dynamics, thereby increasing productivity through emotionally aware collaborative work. Employee well-being can be improved by delegating emotionally demanding tasks to robots. The framework also offers potential for improved compliance by ensuring consistent and appropriate responses. Additionally, future research can explore sustainability benefits. Quantifiable metrics related to efficiency, satisfaction, and innovation resulting from the implementation of GAS will be crucial for assessing its ROI, but current limitations include the complexity of reliably replicating full emotional ranges and the need for robust validation against diverse user groups. Future research directions should focus on refining the emotional modeling, enhancing generalization capabilities, and exploring the ethical implications.

6 Result and Metrics for Evaluation

The evaluation of the Generative Action Synthesis (GAS) framework involves rigorous quantitative and qualitative analyses aimed at demonstrating its efficacy in replicating human emotions through robotic actions. The process begins with generating robotic action sequences conditioned on varying emotional personas, using a training dataset comprising expert demonstrations paired with specific emotional embeddings. The performance of the action generator, denoted by G, which employs temporal-hierarchical transformers (THT), is primarily evaluated using metrics derived from the Wasserstein GAN (WGAN) loss. Specifically, the convergence of the GAN's discriminator loss and the generator loss over training epochs is carefully monitored, with lower loss values indicating improved action synthesis fidelity. Furthermore, gradient penalty (GP) values are tracked to ensure stable GAN training. To evaluate the diversity and quality of the generated action sequences, the Frechet Inception Distance (FID) is computed between the distribution of expert actions and the distribution of actions synthesized by the GAS framework. Lower FID scores suggest better similarity and therefore superior performance of the generator in capturing the underlying patterns of expert actions under different emotional personas. Another key metric is the Kullback-Leibler (KL) divergence between the generated action space and a latent representation of the emotion using Hamiltonian Monte Carlo (HMC), demonstrating a low KL divergence between the action space and the emotion space signifies a more aligned emotional expression. This is important since, this process uses the Von Mises-Fisher mixture model (vMF-MM) to resolve ambiguity in action selection. The accuracy of this probabilistic model in choosing appropriate actions, given an emotion persona, is evaluated through quantitative analysis of the probabilistic selection accuracy, ensuring that the most suitable action is consistently chosen for a given persona. The stochastic policy gradient method which injects dynamic prompts modeled through dynamic reinforcement learning is quantified using reward metrics, where the goal is to maximize the discounted cumulative reward as the robot adapts its behaviors. In addition, the stability of the robots emotional behavior over long tasks is determined via analysis of the emotional embeddings evolution, using Fokker-Planck-Kolmogorov equations. The key performance indicators (KPIs) include: (1) GAN convergence rates, (2) FID scores for action quality, (3) KL divergence for emotion alignment, (4) probabilistic action selection accuracy (5) policy performance via cumulative reward and (6) emotion stability. Statistically, paired t-tests are conducted to determine significant differences between action performance with and without emotion conditioning. In addition, regression analysis is utilized to quantify the relationship between the complexity of the task and the stability of emotional expressions. The importance of thorough data collection is paramount since the quality of the training dataset directly influences the ability of the model to accurately learn to associate specific actions with emotional states. Also robust statistical analysis is key to validate the generalizability of results. This rigorous methodology provides an objective assessment of the effectiveness of the GAS framework in replicating emotionally driven behaviors in robots. The impact of AI-driven solutions like GAS offers significant potential benefits, including the development of more human-like robots for caregiving, customer service, and social applications. A limitation would be the generalization capabilities to unforeseen tasks, or if there are gaps in the training data. Further research should focus on enhancing the framework's robustness to novel scenarios and improving generalization across various applications.

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