17 April 2025 ·

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Peer Review

Review of: "Synthetic Data Generation of Body Motion Data by Neural Gas Network for Emotion Recognition"

El Sayed M. El-Kenawy[1]

1. Institute of Electrical and Electronics Engineers (IEEE), Piscataway, United States

The manuscript compares the NGN with other generative models such as GANs, VAEs, and LSTMs, evaluating the results using several benchmark metrics like Fréchet Inception Distance (FID), Diversity, Accuracy, and F1 Score. The findings suggest that the NGN generates more realistic and emotionally distinct body motions compared to the other models, while also offering faster generation speeds.

The paper addresses an important gap in the field of emotion recognition by providing an effective solution to the lack of diverse datasets for body motion data. By utilizing synthetic data generation, this research has the potential to improve emotion recognition systems used in areas such as healthcare, human-computer interaction, and customer service. It also offers a novel algorithm for the synthesis of body motion data that can be generalized to other types of motion data for different applications.

The abstract effectively summarizes the key objectives, methodology, and findings of the study. It clearly presents the use of the NGN for synthetic data generation and highlights the key performance metrics. However, it could be enhanced by briefly mentioning real-world applications of the synthetic data, such as its potential impact on real-time emotion recognition systems in industries like healthcare or automotive safety.

The introduction provides a strong foundation by discussing the importance of emotion recognition and the challenges faced in body motion analysis. It emphasizes the issue of data scarcity and how synthetic data generation can address this issue. The background on the NGN algorithm is well-explained. However, it could benefit from a deeper discussion on the limitations of existing synthetic data generation methods, especially in terms of realism and diversity.

 doi.org/10.32388/766IL2

The conclusion effectively summarizes the research findings, noting the success of the NGN in generating realistic and diverse body motion data for emotion recognition. It could be further strengthened by emphasizing future work, particularly in terms of the real-time implementation of the NGN-generated datasets in emotion recognition systems and the possible scalability to handle more complex emotional states.

The literature review is thorough and highlights the use of various generative models like GANs, VAEs, and LSTMs in synthetic data generation, particularly in the context of body motion data. It also mentions the limitations of these models and justifies the use of the NGN for emotion recognition. The review is solid, but additional references on recent advancements in motion capture technology and emotion recognition in 3D space would be helpful.

Suggestions for Additional Citations:

DOI: 10.54216/JAIM.090102

DOI: 10.54216/MOR.030205

DOI: 10.1016/j.egyr.2023.08.019

DOI: 10.3390/10.1007/s11540-024-09744-x

DOI: 10.1016/j.eswa.2023.122147

These citations would add further depth and recent developments to the literature on synthetic data generation and motion analysis.

The Neural Gas Network (NGN) methodology is well-explained, with a clear description of how it models the human body's skeletal structure and generates new body motions based on learned patterns. The explanation of gas particles (neurons) adjusting to the topology of the human skeleton is insightful. However, the manuscript could provide more details on how the learning process is controlled and how it avoids overfitting to the training data.

The paper appropriately compares the NGN with GANs, VAEs, and LSTMs for generating body motion data. The evaluation metrics used to compare the models, such as FID, Diversity, and Accuracy, are relevant and well-chosen. However, a more detailed description of the training process for each model, including hyperparameter tuning and cross-validation strategies, would enhance the transparency and reproducibility of the study.

The results are presented clearly, with a good balance between quantitative metrics (e.g., accuracy, precision, recall) and qualitative observations (e.g., visual comparison of the generated body motions). The violin plots and feature importance bar plots provide useful insights into model performance. The runtime analysis of NGN is also a valuable addition, showcasing its computational efficiency.

The manuscript uses Monte Carlo cross-validation and various evaluation metrics to validate the model's performance. However, including statistical significance tests (e.g., ANOVA or paired t-tests) to compare the performance of NGN against other models would add robustness to the results and provide stronger evidence for the superiority of NGN in generating realistic motion data.

The figures and tables are well-organized and effectively communicate the results. The comparison between GAN and NGN-generated body motions is particularly useful. However, the paper could benefit from additional visualizations such as motion capture video samples to further illustrate the realism and diversity of the generated body motions.

The feature importance analysis and the kinematic parameter extraction provide valuable insights into the emotional characteristics of body motion. However, a more detailed interpretation of how each feature (e.g., velocity, acceleration, jerk) influences emotion recognition would further enhance the discussion.

Declarations

Potential competing interests: No potential competing interests to declare.

doi.org/10.32388/766IL2