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Peer Review

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

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This study presents a novel application of the Neural Gas Network (NGN) algorithm for generating synthetic body motion data aimed at improving emotion recognition systems. The approach addresses the common challenge of data scarcity in emotion recognition by leveraging NGN to generate diverse and realistic body motion datasets. The generated motion data is then used for emotion recognition, with the synthetic data compared against existing generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Long Short-Term Memory (LSTM) models. The paper demonstrates that NGN outperforms existing models in terms of diversity, fidelity, and generation speed, making it a promising method for emotion recognition tasks.

The significance of this study lies in its ability to generate large, diverse, and realistic synthetic datasets, which are critical for training emotion recognition models. The NGN-based approach not only addresses the issue of data scarcity but also improves the quality of synthetic motion data by capturing complex human body motion dynamics. The paper's results could have profound implications in fields such as healthcare, where emotion recognition can be used to monitor patient mental states, and in human-computer interaction, where more empathetic AI systems can be developed.

The abstract effectively summarizes the research objectives, methodology, and key findings. It introduces the NGN algorithm and its application in generating synthetic body motion data for emotion recognition. However, the abstract could be more concise, particularly in the explanation of the comparison with other generative models. The mention of specific metrics (e.g., FID, Diversity, Precision) is useful but could be briefly summarized to focus on the main contributions.

Streamline the abstract to focus more on the novel aspects of the study and the key results.

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Mention the comparison with other models in a more concise manner.

The introduction provides a strong rationale for emotion recognition and discusses the challenges of data scarcity in this domain. It successfully ties the importance of synthetic data generation to the advancement of emotion recognition technologies. However, the research gap could be articulated more clearly, with a stronger emphasis on how the NGN method specifically addresses the limitations of existing approaches.

Clarify the specific research gap and explicitly highlight how the NGN method addresses these challenges.

Include a more direct statement of the research question or hypothesis.

The literature review covers a wide range of generative methods for emotion recognition, including GANs, VAEs, and LSTM. While it provides a good overview of existing methods, it could benefit from a more detailed comparison of these methods in the context of body motion data synthesis. Additionally, the review could be expanded to include more recent studies in synthetic data generation and emotion recognition.

Suggestions:

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

Include recent studies on synthetic data generation for emotion recognition.

The methodology is well-detailed and explains how NGN is applied to synthesize body motion data for emotion recognition. The explanation of how the NGN algorithm works, particularly how it maps the human skeletal structure and generates new postures, is clear. However, the explanation of hyperparameter tuning for the NGN model and how the quality of synthetic data is evaluated could be expanded.

Provide more details on how hyperparameters for the NGN algorithm (e.g., the number of gas particles and learning rate) are tuned.

Clarify the evaluation process for the synthetic data, including how it compares to real-world data.

The methodology is solid, and the application of NGN for synthetic body motion generation is well-justified. However, there is limited discussion on how the model's performance could be further optimized. For example, how can the NGN algorithm be fine-tuned for different emotional expressions, and are there any limitations to the approach in terms of scalability?

Discuss potential optimizations for the NGN model to improve its performance further.

Address the scalability of the NGN algorithm, particularly in larger datasets or real-time emotion recognition systems.

While the NGN model's basic structure is well-explained, additional details on the training process and hyperparameter tuning would add value. For instance, how does the selection of the number of neurons (gas particles) affect the quality of the generated motion data?

Provide more information on the process of hyperparameter tuning and its impact on model performance.

Consider including a section on model convergence and stability over different iterations and hyperparameter settings.

The results are presented clearly and include relevant performance metrics such as FID, Diversity, Precision, and MCC. The comparisons between the NGN-generated data and other models are valuable. However, more detailed statistical analysis could strengthen the validity of the results.

Include statistical tests (e.g., paired t-tests) to confirm the significance of the performance differences between the NGN and other models.

Add a discussion of the computational efficiency of each model, as this is important for real-world applications.

The metrics used in the evaluation, such as FID, Diversity, and MPJPE, are appropriate for measuring the quality of generated body motion data. However, additional metrics like ROC-AUC or Precision-Recall curves could provide more insights into model performance, especially in emotion classification.

Consider adding more evaluation metrics like ROC-AUC and Precision-Recall curves to evaluate the model's performance in real-world scenarios.

Provide more detailed discussions on the interpretation of these metrics in the context of emotion recognition.

The figures and tables are clear and effectively support the findings. The comparison of NGN with GAN-generated body motions in Figure 3 is particularly insightful. However, the figure captions could be more detailed, explaining the significance of each comparison in greater depth.

Provide more context in figure captions, particularly in Figures 2 and 3, to ensure the reader understands the significance of the visual differences between NGN and GAN-generated motions.

Add more visualizations that demonstrate the real-world applicability of the synthesized data in emotion recognition systems.

Declarations

Potential competing interests: No potential competing interests to declare.