Multiobjective coevolutionary training of Generative Adversarial Networks

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ABSTRACT

This article presents a multiobjective evolutionary approach for coevolutionary training of Generative Adversarial Networks. The proposal applies an explicit multiobjective optimization approach based on Pareto ranking and non-dominated sorting over the coevolutionary search implemented by the Lipizzaner framework, to optimize the quality and diversity of the generated synthetic data. Two functions are studied for evaluating diversity. The main results obtained for the handwritten digits generation problem show that the proposed multiobjective search is able to compute accurate and diverse solutions, improving over the standard Lipizzaner implementation.

CCS CONCEPTS

• **Computing methodologies → Bio-inspired approaches**; *Neural networks*; *Unsupervised learning*.

KEYWORDS

Generative Adversarial Networks, multiobjective optimization, coevolutionary algorithms, image generation

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1 INTRODUCTION

Generative Adversarial Networks (GANs) are computational intelligence methods to learn generative models [6]. A GAN comprises two neural networks (a generator and a discriminator) that compete during the learning process. The generator is trained to produce synthetic data indistinguishable from real data. The discriminator is trained to differentiate between real and generated data. GANs have been successful in a wide range of tasks, such as producing images and videos. GANs training is a challenge, due to many unstable dynamics or pathologies, such as oscillation, mode collapse, discriminator collapse, and vanishing gradients [1].

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Evolutionary computation (EC) has yielded promising results for GAN training. Evolutionary algorithms (EAs) and coevolutionary algorithms (CEAs) have been applied to optimize the GAN parameters or to define spatial systems to enhance the learning process. In general, EC-based GAN training methods guide populations of neural networks toward convergence, providing comparable and better results than baseline GAN training methods.

This article focuses on spatially-distributed competitive CEAs for GAN training, such as Lipizzaner [7], which have shown robustness to GAN training pathologies. These methods provide a framework to define a spatial topology (e.g., a two-dimensional toroidal grid or a ring) to locate the individuals of two populations (a population of generators and a population of discriminators), i.e., pairs of generator-discriminator are placed in each cell of the spatial topology. Besides, neighborhood relationships between cells and migration policies allow the definition of subpopulations and signal propagation across the topology. Thus, a cellular algorithm is applied to optimize the parameters of the generators and the discriminators by applying gradient-based training.

The EA in Lipizzaner is guided by a single objective fitness function, defined by the minmax loss applied in GANs. The minmax loss focuses on optimizing the quality of the samples produced by the generator. However, this optimization process does not consider the diversity of the synthetic samples, which could lead to generators being unable to represent the whole distribution of the real data and provoke pathological situations such as mode collapse.

This article proposes applying a multiobjective optimization (MO) approach for the spatially-distributed competitive CEA training in Lipizzaner. An explicit strategy is applied to train generative models that produce high-quality and diverse samples, which defines the two objectives of the proposed optimization (training) method. The proposed approach is implemented over Lipizzaner and validated in a state-of-the-art benchmark based on the MNIST database of handwritten digits, commonly used for training and validation of image processing systems.

The main research questions (RQ) that guide the research are *RQ1:* is it possible to extend the CEA implemented in Lipizzaner using multiobjetive optimization methods, to improve the robustness of the training process and the diversity of the generated data ? and *RQ2:* does the multiobjective CEA improves over the baseline Lipizzaner implementation in terms of diversity, without reducing the quality of generated data?

The main results indicate that the proposed MO evolutionary training approach allows the GAN to train generative models that produce accurate and diverse samples, significantly improving over the standard Lipizzaner implementation.

2 EVOLUTIONARY GAN TRAINING

This section presents the GAN training problem, its resolution by applying CEA, and reviews related works.

2.1 Coevolutionary GAN training

GAN training is modeled as a two-player game (generator vs. discriminator) solved by gradient-based optimization on the GAN minmax objective [6]. In contrast, competitive CEA GAN training entails two populations (of generators and discriminators) that coevolve against each other towards convergence, while addressing the minmax objective.

Lipizzaner applies the CEA approach, coevolving populations of generators and discriminators. The individuals are located in the cells of a toroidal grid. Overlapping neighborhoods establish the migration among the cells. Each cell has two competitive subpopulations defined by the individuals in the cell and the ones gathered from the neighborhood. Training occurs in pairs throughout the subpopulations by applying stochastic gradient descent (SGD) with a minmax objective. Gaussian mutation is applied to adjust the SGD training parameters during the evolution. After each training epoch, the competing subpopulations are updated with copies of the best generator and discriminator from each neighborhood cell.

2.2 Related work

Wang et al. [9] evolved a population of generators for GAN training. Several mutation operators and cost functions were studied to avoid mode collapse. The Determinantal Point Process (DPP) loss function was proposed by Elfeki et al. [5] to mitigate mode collapse, pushing the generator to create diverse data. The loss function avoided mode collapse for image datasets, without affecting the image quality. Wang et al. [10] applied structure similarity index in a Deep Convolutional GAN to improve smoothness and consistency for the palmprint recognition problem. The approach obtained accurate error rates, outperforming existing methods.

Zhang at al. [11] proposed a MO approach to improve diversity and reduce repetitive phrases in dialogue generation. Multiple discriminators were used to capture different aspects of linguistics, and policy gradient for optimization. Results over Cornell Movie and Open Subtitles improved over baseline generation methods.

MO-EGAN [2] optimized three functions: i) minimax, from standard GAN training, ii) an heuristic to maximize the log probability of the discriminator to separate distributions; and iii) a least square function that does not suffer vanishing gradient. MO-EGAN computed accurate results and avoided mode collapse on two synthetic datasets from 2D Gaussian mixture distributions.

HypervolGAN [8] balanced multiple loss functions for GAN training via (single objective) convex combination of losses with regularization terms, and maximizing hypervolume with a standard EA. Results for the image super resolution problem, considering pixel, perceptual, and adversarial losses, showed a better computational efficiency of HypervolGAN in comparison with other GAN-based training methods, whereas generating good quality samples.

No explicit MO approaches have been proposed for GANs training, except for MO-EGAN. Although MO has been applied for ensembles of generators, this article presents the first explicit MO for the CEA GAN training in Lipizzaner.

3 MULTIOBJECTIVE CEA GAN TRAINING

The proposed algorithm is Coevolutionary Non-dominated Sorting Evolution Strategy (Co-NSES), which adapts the non-dominated sorting schema in NSGA-II [3] to the CEA applied by Lipizzaner. Pareto dominance was included in the selection scheme, considering non-dominated ranking by fronts. The evolutionary operators are reformulated to consider Pareto dominance and the replacement strategy implements the μ+λ evolutionary model, where parents compete with offspring for survival.

Co-NSES implements multidimensional objective functions, adapts the evolutionary operators to consider the multidimensional objective functions, and implements new survival operators. The strategy design pattern was applied to encapsulate different algorithmic variants and allow them to be easily configured at runtime.

The MO problem in CEA GAN training proposes the simultaneous maximization of diversity and fidelity of generated synthetic samples. The diversity evaluation is based on GDPP [5]. The cost function $\mathcal{L}^{DPP}$ has two factors: diversity magnitude and diversity structure $\mathcal{L}^{DPP} = \sum_i \left\|\lambda real^i - \lambda fake^i\right\|_2 - \sum_i \lambda^{*i} \cos\left(v^i_{\text{real}}, v^i_{\text{fake}}\right)$, where λreal^i and λfake^i are the i^{th} values kernels eigenvalues and λ^{*i} the normalized version using min-max to scale the cosine similarity between eigenvalues v^i_{fake} and v^i_{real}. The generator cost function is $\mathcal{L}_g = \mathbb{E}_{z\sim p_z}[\log(1 - D(G(z)))] + \mathcal{L}^{DPP}$.

4 EXPERIMENTAL EVALUATION

This section describes the empirical analysis of the proposed Co-NSES algorithm for GANs training.

4.1 Evaluation metrics

MO metrics are applied to evaluate the Co-NSES algorithm: number of non-dominated solutions in the Pareto front (ND), generational (GD) and inverted generational distance (IGD), spread, and relative hypervolume (RHV). The quality of images is evaluated considering density, coverage, and Fréchet Inception Distance (FID).

4.2 Parameters setting

The parameter settings studied the RHV results of Co-NSES, regarding fidelity and diversity. The parameters and candidate values studied were: number of generations (ng): 100 and 200; mixture mutation scale (ms): 0.01 and 0.05, initial learning rate (L_0): 0.0002 and 0.0005; mutation rate (mr): 0.0001 and 0.0005; mutation probability (mp): 0.5, and 0.25. The best results were computed using $ng = 200$, $ms = 0.01$, $L_0 = 0.0002$, $mr = 0.0001$, $mp = 0.5$.

4.3 Evaluation

The proposed Co-NSES algorithm was evaluated for generating images from the MNIST dataset [4] (28×28 pixels grey-scale images of handwritten digits). The batch size for training was set to 100, and the GAN was trained during 200 epochs, the same values used in the standard (single objective) Lipizzaner [7]. The evaluation studied the grid dimension considering the studied MO metrics and the quality of results. A comparison with the standard (single objective) Lipizzaner is performed. In all experiments, 30 executions of Co-NSES were executed. Statistical tests were applied to analyze the result distributions.

Table 1: MO metrics results for Co-NSES using different grid sizes

grid	ND ↑			RHV ↑			GD ↓			IGD ↑			spread ↓		
	median	IQR	best	median	IQR	best	median	IQR	best	median	IQR	best	median	IQR	best
2×2	4.0	0.0	4.0	0.530 $^{\mathbf{2/5}}$	0.099	0.758	2.151 $^{\mathbf{2/5}}$	0.023	2.119	2.185 $^{\mathbf{2/5}}$	0.038	2.223	0.417 $^{\mathbf{1/5}}$	0.111	0.215
3×3	9.0	1.0	9.0	0.528 $^{\mathbf{1/5}}$	0.056	0.633	2.150 $^{\mathbf{2/5}}$	0.026	2.106	2.145 $^{\mathbf{0/5}}$	0.086	2.213	0.398 $^{\mathbf{1/5}}$	0.161	0.255
4×4	11.0	3.8	16.0	0.622 $^{\mathbf{4/5}}$	0.058	0.703	2.203 $^{\mathbf{0/5}}$	0.019	2.168	2.192 $^{\mathbf{3/5}}$	0.042	2.276	0.336 $^{\mathbf{1/5}}$	0.160	0.179

Multiobjective search. Table 1 reports the results of the studied MO metrics for Co-NSES. Overall, RHV results improved when using larger grid sizes. Co-NSES computed accurate values of GD and IGD metrics, with slightly better results in 3×3 and 4×4 grids. Good spread results were obtained in the two smaller grids.

The pairwise Wilcoxon rank sum test was applied to analyze the statistical significance of the computed results distributions. The small superscript in black indicates how many times the computed median value is better (with statistical significance) than the other median values, according to the performed pairwise tests.

Figure 1 presents the Pareto fronts computed by Co-NSES for the studied grid sizes. The reference (best known) Pareto front is also presented in blue, to properly evaluate the quality of the computed non-dominated solutions. Co-NSES properly sampled the central region of the Pareto front, computing good approximations to the ideal vector and in the 4×4 grid. Overall, the computed Pareto fronts improved notably when using the 4×4 grid size.

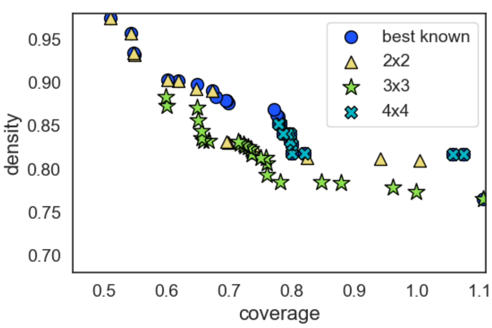


Figure 1: Pareto fronts for the studied grid sizes

Results quality. Table 2 reports the median and IQR results for the three studied metrics (density, coverage, and FID), for the closest solution on the computed Pareto front to the ideal vector. This solutions provides a balanced trade-off between the considered objective functions. Median and IQR are reported since the application of the Kruskal-Wallis statistical test allowed rejecting the hypothesis of results following a normal distribution.

Table 2: Quality results for Co-NSES using different grid sizes

grid	density ↑			coverage ↑			FID ↓		
	median	IQR	best	median	IQR	best	median	IQR	best
2×2	0.81	10^{-4}	0.89	0.70	10^{-3}	1.00	175.60	1.56	88.36
3×4	0.77	10^{-3}	0.81	0.85	10^{-4}	1.11	116.03	1.01	72.76
4×4	0.80	10^{-3}	0.82	**0.96**	10^{-3}	1.07	**87.23**	0.44	65.54

Results in Table 2 indicate that Co-NSES mainly focused on diversity when using the smaller grid. In the 3×3 grid the population increased and the diversity of evolved generators allowed computing better coverage values. Coverage values significantly improved when using the 4×4 grid. The quality of results, evaluated by the FID metric, follows the same pattern of notably improving when using a larger grid size. FID values reduced up to 50.3% in the 4×4 grid with respect to the results in the 2×2 grid. The computed improvements on coverage (higher values are better) and FID (lower values are better) are statistically significant for the 3×3 grid, and especially when using a 4×4 grid. Numbers marked in bold in Table 2 represent the best computed values for each metric, for which statistical significance is supported by the results of the Wilcoxon test.

Figure 2 presents the boxplots from the results distributions for coverage, density, and FID computed by Co-NSES for different grid sizes. Another relevant analysis is reported, studying the distance of the best trade-off solution computed by each method to the ideal vector. This study allows determining the proximity to the Pareto front for that solution that provide a balanced trade-off between the problem objectives.

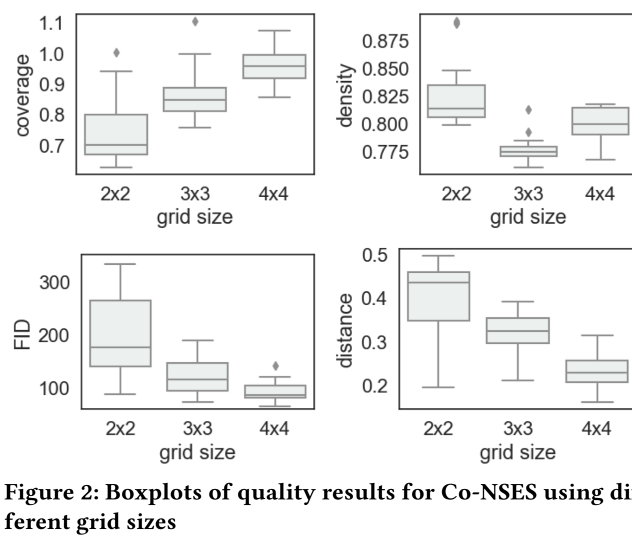


Figure 2: Boxplots of quality results for Co-NSES using different grid sizes

Comparison with standard Lipizzaner. The proposed Co-NSES was pcompared with the standard (single objective) Lipizzaner implementation for the studied quality metrics (density, coverage, and FID) and the 4×4 grid.

The boxplots in Figure 3 summarize the results distributions computed using Co-NSES and Lipizzaner. Results clearly demonstrate that the proposed Co-NSES implementations improved over the baseline single objective Lipizzaner. The computed improvements on median values were up to 30% in coverage, up to 5% in density, and up to 33% in FID. Overall, Co-NSES significantly improved over the standard Lipizzaner.

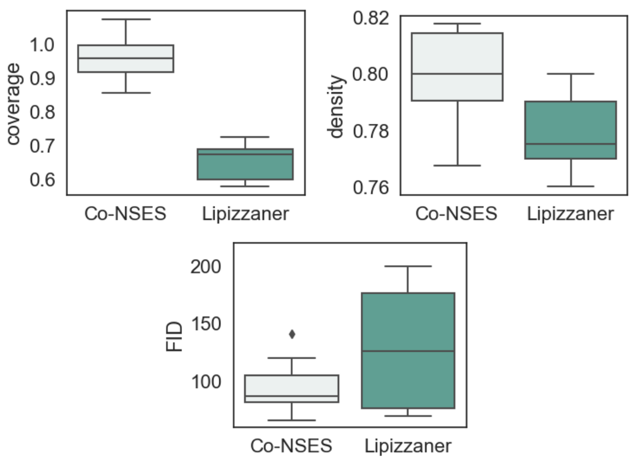
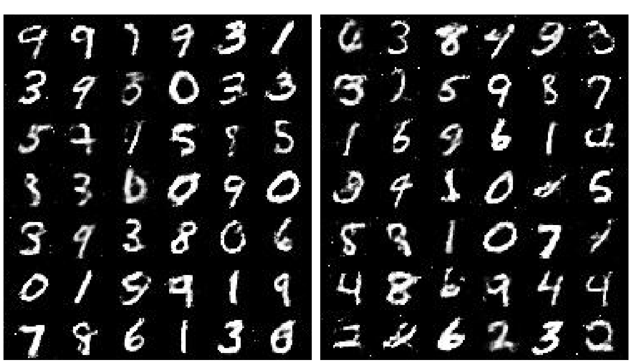


Figure 3: Boxplot comparing the distributions of results computed for the non-dominated solutions of Co-NSES and standard Lipizzaner for the 4×4 grid

Sample generated images. Figure 4 presents samples produced by Co-NSES. The presented samples improve diversity and coverage over samples during training. In turn, one of the main motivations of this research, i.e., avoiding mode collapse, is successfully accomplished by introducing a MO scheme to explicitly consider diversity. These results confirm that Co-NSES trained generative models simultaneously considering fidelity (quality) and diversity of the samples.



(a) Generated sample 1 **(b) Generated sample 2**

Figure 4: Samples of generated images

5 CONCLUSIONS

This article presented a multiobjective optimization strategy for the COEA training method of Generative Adversarial Networks implemented in Lipizzaner. An explicit MO approach based on Pareto ranking and non-dominated sorting was implemented to enhance GAN training by simultaneously optimizing the quality and diversity of the generated synthetic data. A specific variant of Lipizzaner was implemented, considering a specific function for evaluating diversity.

The proposed approach was validated for the handwritten digits generation problem, evaluating the MO search, the analysis of diversity functions, and the comparison with the single objective Lipizzaner implementation. The main results demonstrated that the proposed MO search is able to compute accurate and diverse solutions, improving over the standard Lipizzaner implementation. The coverage and quality of generated results improved up to 30% and 33%, respectively.

The main lines for future work are related to extend the experimental validation of the proposed MO approach, and conceive and implement different MO strategies to improve over the computed results by applying specific concepts of MO optimization. The approach should be validated over other standard datasets to analyze the generalizing capabilities of the proposed MO GAN training strategy.

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