Generating Magnetic Skyrmion Ground States with Generative Adversarial Networks

Bozhidar Trenchev, Srinandan Dasmahapatra, Marijan Beg, Ondrej Hovorka, Natalie Downing

University of Southampton

btrenchev1@gmail.com

UNIVERSITY OF Southampton

Magnetic Skyrmions

Skyrmions are topologically protected non-trivial field configurations [1] observed in chiral magnetic materials [2]. Their **stability, nanometer size** and **coherent dynamics** [3] make them attractive candidates for applications such as **race-track-like memories** [4] and **reservoir computing** [5].

Skyrmionic states such as those on *Fig. 1* are explored by **minimizing** the **total energy** of a random initial magnetisation configuration. Current numerical methods are **far from exhaustive** and **computationally expensive**.

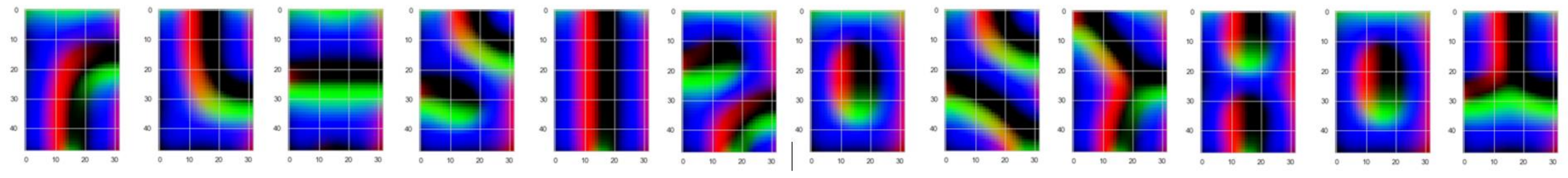


Fig.1 Example training skyrmion samples of size (48, 32) generated with the micromagnetics simulation software Ubermag with OOMMF as computational backend.

Computational Micromagnetics

The **magnetization field** $\mathbf{M}(\mathbf{r}) = M_s\hat{\mathbf{m}}(\mathbf{r}) \in \mathbb{R}^2$ (a hat denotes a unit length vector) is computed using a **finite-difference method** where $\mathbf{r}$ is restricted to a 2D lattice grid of size (48, 32) or (144, 96).

The **energy** of the system is computed as

$$E[\hat{\mathbf{m}}] = \int [w_{\text{ex}}(\hat{\mathbf{m}}) + w_{\text{dmi}}(\hat{\mathbf{m}}) + w_z(\hat{\mathbf{m}})]\, \mathrm{d}^2\mathbf{r} \qquad (1)$$

where $w_{\text{ex}}(\hat{\mathbf{m}}),\ w_{\text{dmi}}(\hat{\mathbf{m}}),$ and $w_z(\hat{\mathbf{m}})$ are the symmetric exchange, the Dzyaloshinskii-Moriya and the Zeeman energy densities respectively.

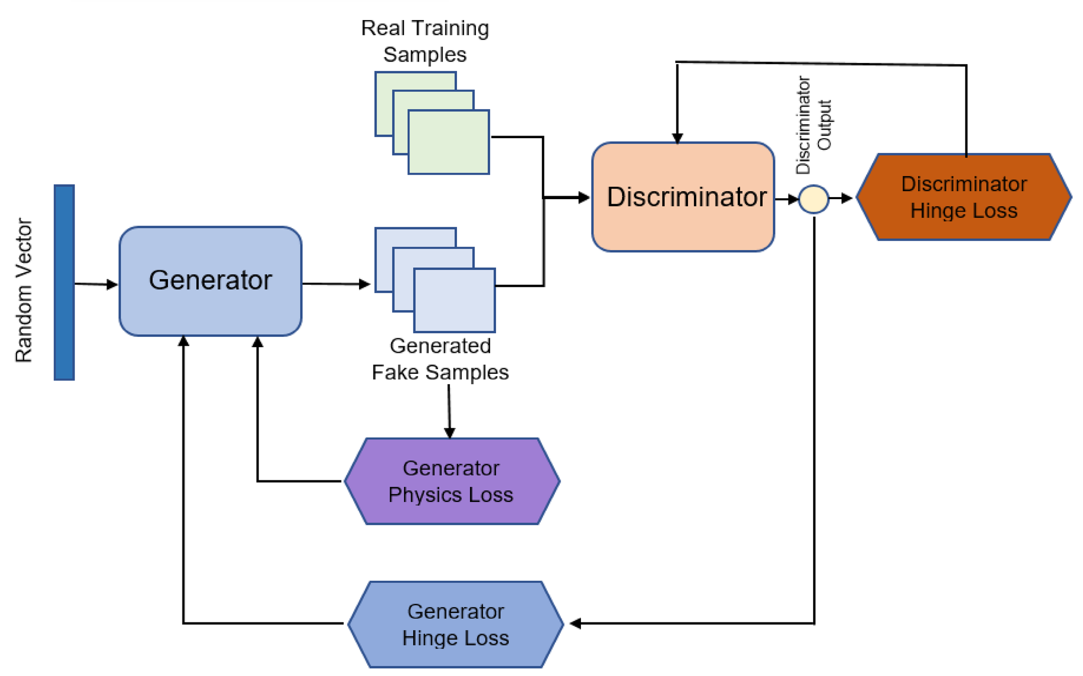
The first variational derivative of the energy functional $E[\hat{\mathbf{m}}]$ with respect to $\hat{\mathbf{m}}$ is called the **effective field** $\mathbf{H}_{\text{eff}}(\hat{\mathbf{m}})$. The magnetisation field dynamics is governed by the **Landau-Lifshitz-Gilbert (LLG) equation** [6]:

$$\frac{d\hat{\mathbf{m}}}{dt} = -\frac{\gamma_0^*}{1+\alpha^2}\hat{\mathbf{m}} \times \mathbf{H}_{\text{eff}} - \frac{\gamma_0^*\alpha}{1+\alpha^2}\hat{\mathbf{m}} \times (\hat{\mathbf{m}} \times \mathbf{H}_{\text{eff}}) =: \ell(\hat{\mathbf{m}}, \mathbf{H}_{\text{eff}}(\hat{\mathbf{m}})) \qquad (2)$$

where γ_0^* is the modified gyromagnetic ratio and α is the Gilbert damping, dependent on the skyrmion-hosting material which for this study was chosen to be **FeGe** [7] , whose $\alpha = 0.1$. Let $\mathbf{L}_\times := \hat{\mathbf{m}}(\mathbf{r}) \times \mathbf{H}_{\text{eff}}$. A dynamically **steady state** (equilibrium state) is reached when $\mathbf{L}_\times$ is close to 0.

PhysGAN

Our network **PhysGAN**, implemented in Tensorflow and Keras, **reduces the search space** from a random initialisation using the **minimax** game with a **hinge loss** and a **physics loss** which helps reduce the energy of the generated samples and keep them consistent with the FeGe micromagnetic model.



We seek to **generate** viable **equilibrium configurations** using several custom **Generative Adversarial Networks** [8] that incorporate some of the micromagnetic **physical laws** into their architectures via **physics-aware loss functions**.

Physics Losses

Every L_{phys} loss is computed for a mini-batch of generated samples and reduced to a single number.

- E **loss:** the average $E[\hat{\mathbf{m}}]$;
- $\mathbf{L}_\times$ **loss:** the average of $(\mathbf{L}_\times)^2$ or the norm $|\mathbf{L}_\times|$ or $|\mathbf{L}_\times|^2$;
- **Combined loss:** $\alpha E + \beta|\mathbf{L}_\times|^p$ for $p = 1, 2$;
- **LLG loss:** the average of $\ell(\hat{m}, \mathbf{H}_{\text{eff}}(\hat{\mathbf{m}}))^2$ or the norm $|\ell(\hat{\mathbf{m}}, \mathbf{H}_{\text{eff}}(\hat{\mathbf{m}}))|$ or $|\ell(\hat{\mathbf{m}}, \mathbf{H}_{\text{eff}}(\hat{\mathbf{m}}))|^2$.

Training Strategies

1. Train the Generator only on L_{phys};
2. Train the Generator with both L_{phys} and hinge loss with the Discriminator;
3. First perform hinge-loss-only training or strategy 2 training for several epochs, then train only on L_{phys}.

The training data consists of equilibrium-state skyrmion magnetizations, 'seen' by the network as images.

Evaluation

For every combination of strategy and L_{phys}, samples were generated from a newly-instantiated PhysGAN trained for 1000 epochs. Results were checked **how physically plausible** they were according to the following criteria:

- Are the **samples diverse** and visually **similar** to the **training data**;
- Is the L_{phys} being **reduced** over the epochs;
- Is the average energy density E (AED) and the average cross product $\mathbf{L}_\times$ (ACP) of a batch of generated samples close to reference values computed from the training data which are AED: -8.19×10^4, ACP: $[1.76, 6.78, 1.83] \times 10^{-4}$.

Results

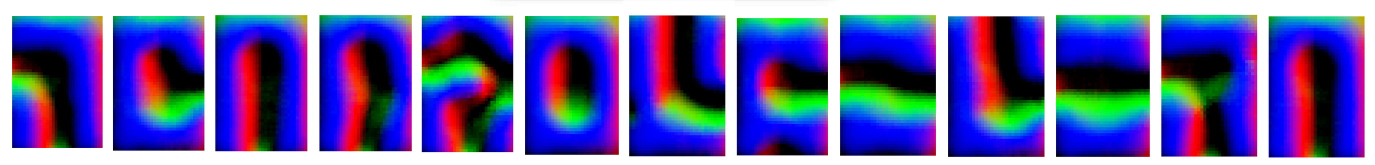


Fig. 2 Output of size (48, 32) of a PhysGAN trained with E loss and strategy 2 for 1000 epochs. AED: -7.7×10^4; ACP: $[-2623, 1820, 820]$.

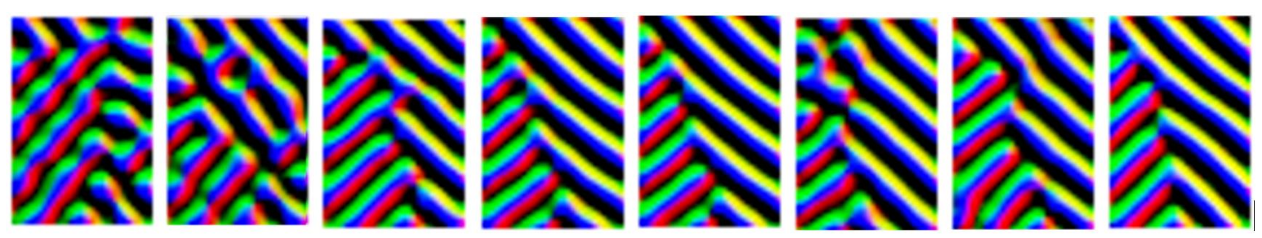


Fig. 3 Output of size (144, 96) of a PhysGAN output (AED: -10^5); trained with strategy 3 on E loss for 100 epochs. Samples from left to right are from epoch 6 to 41 with step of 6. It is noticeable how the Generator finds a more optimal state as the training progresses.

Results

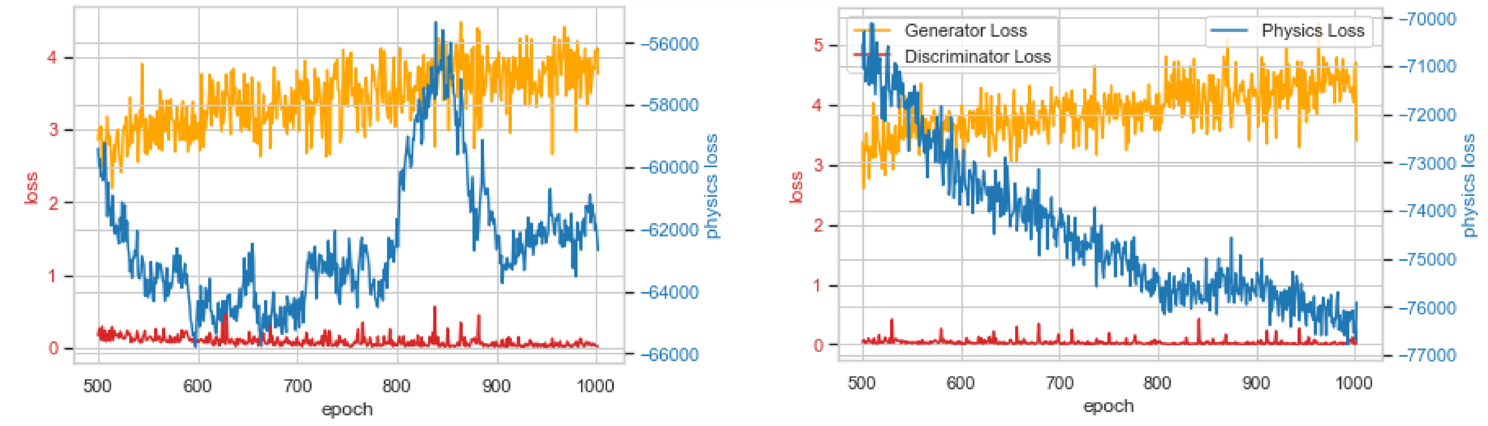


Fig. 4 Left: The average hinge losses and E loss for the last 500 epochs of the training of 10 PhysGANs with only hinge loss, the E is calculated as a score, not applied to the generators' gradients. One such PhysGAN had AED: -6.6×10^4, ACP: $[-2268, 160, -6512]$. Right: The losses of the training of 10 PhysGANs with E loss and strategy 2 for the last 500 epochs.

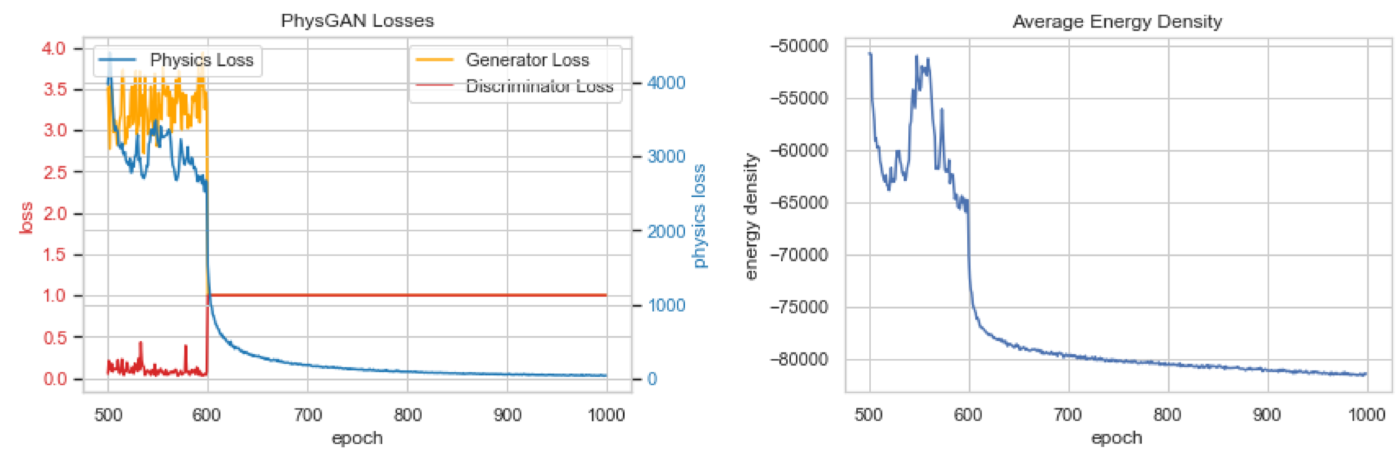


Fig. 5 Left: The losses of a PhysGAN; last 500 epochs; trained with strategy 3 and $|\mathbf{L}_\times|^2$. Switch to $|\mathbf{L}_\times|^2$-only-training at 600th epoch. AED: -8.2×10^4, ACP: $[98, -2070, 913]$; Right: AED.

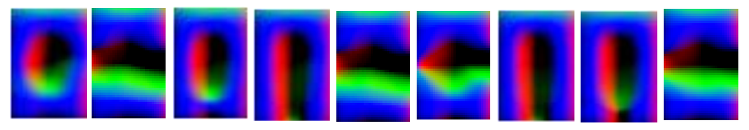


Fig. 7 Output of the *Fig. 5* PhysGAN. More diverse samples.

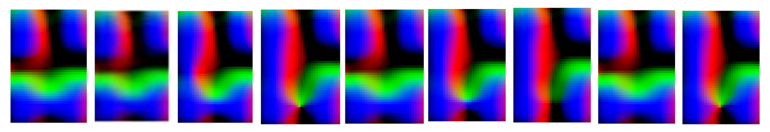


Fig. 8 Output of a PhysGAN trained with strategy 3 and $|\ell(\hat{\mathbf{m}}, \mathbf{H}_{\text{eff}}(\hat{\mathbf{m}}))|$ loss. Less diversity.

Training with **strategy 1** always led to **mode collapse**. The PhysGANs trained with **strategy 2 and 3** generated **diverse samples** which looked **similar to** the **training data** as shown in *Fig 2* and *Fig. 3*. The Discriminator and Generator losses maintain **equilibrium** as seen in *Fig. 4*, whilst reducing the L_{phys} . Strategy 3 also had better L_{phys} reduction, **smoother samples**, but **partial mode collapse**. All losses are good at reducing AED, but the $\mathbf{L}_\times$ and LLG losses reduce the ACP more. Inclusion of L_{phys} makes the generated skyrmions **more consistent** with the **physics** model.

Conclusion

The proposed PhysGAN shows promising although not yet perfect results regarding physics data generation. Future work improvements:

- **Conditional PhysGAN**;
- Vary the parameters dependent on the material. Check what magnetizations arise. This might assist the discovery of **new** helimagnetic **materials**;
- Apply the core ideas of the PhysGAN to **other scientific domains**.

References

[1] T. H. Skyrme, "A unified field theory of mesons and baryons,"Nuclear Physics, vol. 31, no. C, pp. 556–569,1962.
[2] S. Mühlbauer, B. Binz, F. Jonietz, C. Pfleiderer, A. Rosch, A. Neubauer, R. Georgii, and P. Böni, "Skyrmion lattice in a chiral magnet," Science, vol. 323, no. 5916, pp. 915–919, 2009.
[3] N. Nagaosa and Y. Tokura, "Topological properties and dynamics of magnetic skyrmions," Nature Nanotechnology, vol. 8, no. 12, pp. 899–911, 2013.
[4] R. Tomasello, E. Martinez, R. Zivieri, L. Torres, M. Carpentieri, and G. Finocchio, "A strategy for the design of skyrmion racetrack memories," Scientific Reports, vol. 4, no. 1, p. 6784, 2014.
[5] D. Pinna, F. Abreu Araujo, J.-V. Kim, V. Cros, D. Querlioz, P. Bessiere, J. Droulez, J. Grollier, "Skyrmion gas manipulation for probabilistic computing," Phys. Rev. Applied, vol. 9, p. 064018, 2018.
[6] T. L. Gilbert, "A phenomenological theory of damping in ferromagnetic materials," IEEE Transactions on Magnetics, vol. 40, no. 6, pp. 3443–3449, nov 2004.
[7] M. Beg, M. Albert, M.-A. Bisotti, D. Cortés-Ortuño, W. Wang, R. Carey, M. Vousden, O. Hovorka, C. Ciccarelli, C. S. Spencer, C. H. Marrows, and H. Fangohr, "Dynamics of skyrmionic states in confined helimagnetic nanostructures," Physical Review B, vol. 95, no. 1, p. 014433, jan 2017.
[8] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative Adversarial Networks," jun 2014