Automatic Design of Optical Multilayer Films with Deep Reinforcement Learning

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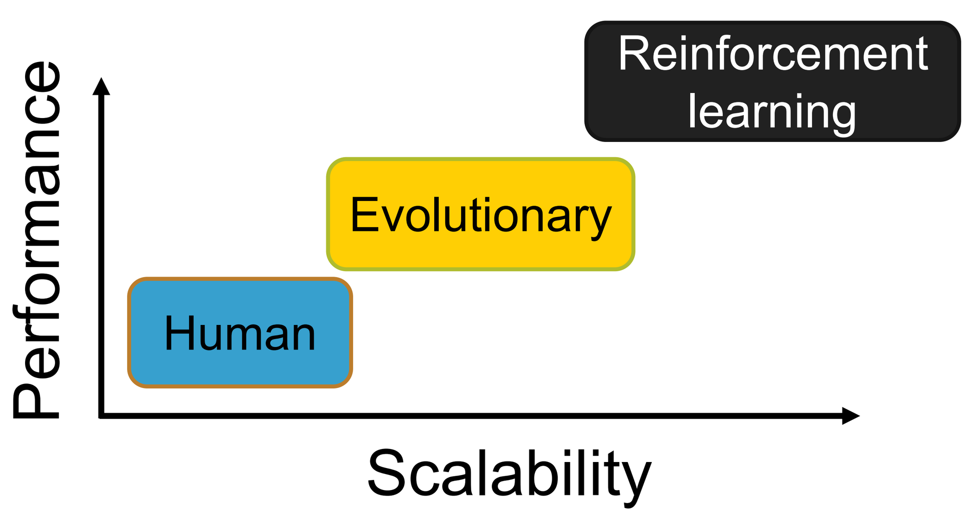
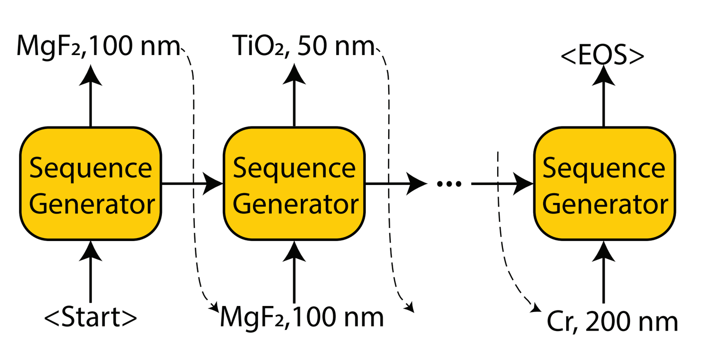
Motivation

- Optical multilayer films are widely used in energy and lighting applications.
- Optical designs are often based on human experts, and the design process could be slow and suboptimal.
- Deep reinforcement learning could automate the design process and might lead to better designs.

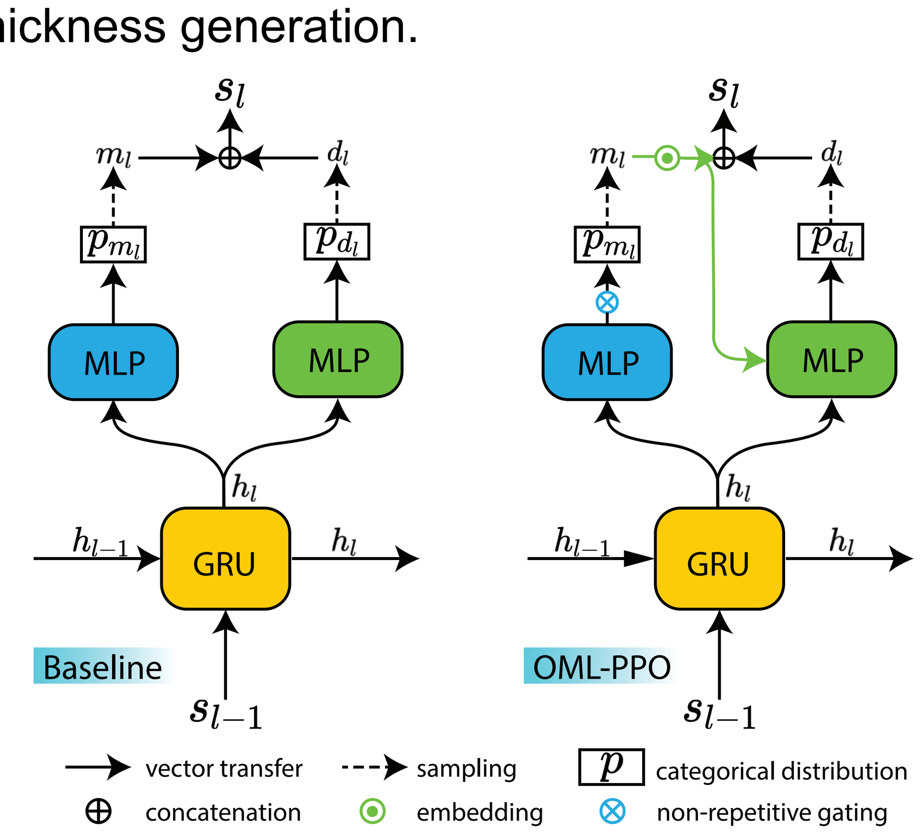


Design as Sequence Generation

- Optical multilayer films can be represented as sequence. Thus, we can leverage sequence generation methods for optical multilayer design.



- Sequence generator architecture with non-repetitive gating and auto-regressive material-thickness generation.



DRL Training

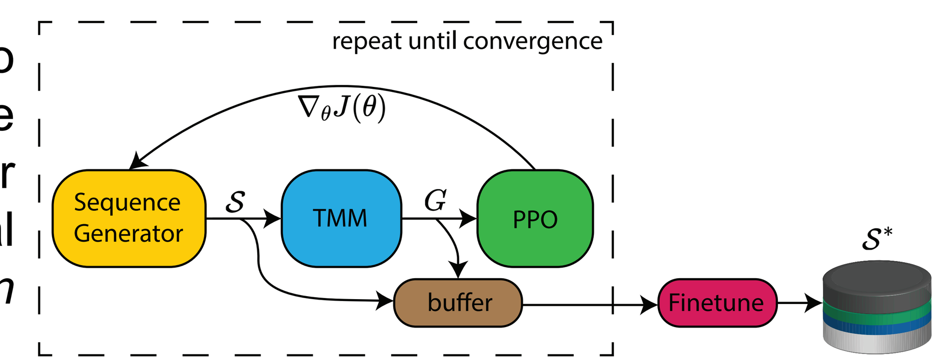
- Reward function is the mean absolute error between target spectrum and generated spectrum.

$$G(\mathcal{S}) = 1 - \frac{1}{K}\sum_{k=0}^{}\frac{1}{J}\sum_{j=0}^{J-1}\left|T^{\mathcal{S}}(\lambda_j, \delta_k) - \tilde{T}(\lambda_j, \delta_k)\right|$$

- We apply *Proximal Policy Optimization* for training the sequence generation network.

$$g = \nabla_\theta \mathbb{E}_{\mathcal{S}\sim\pi_\theta}[\min(r(\theta)A_{\theta_v}(\mathcal{S}), \mathrm{clip}(r(\theta), 1-\epsilon, 1+\epsilon)A_{\theta_v}(\mathcal{S}))]$$

- *Active search* is applied to output the final design. We also finetune the layer thicknesses of the final design with *quasi-Newton* method.



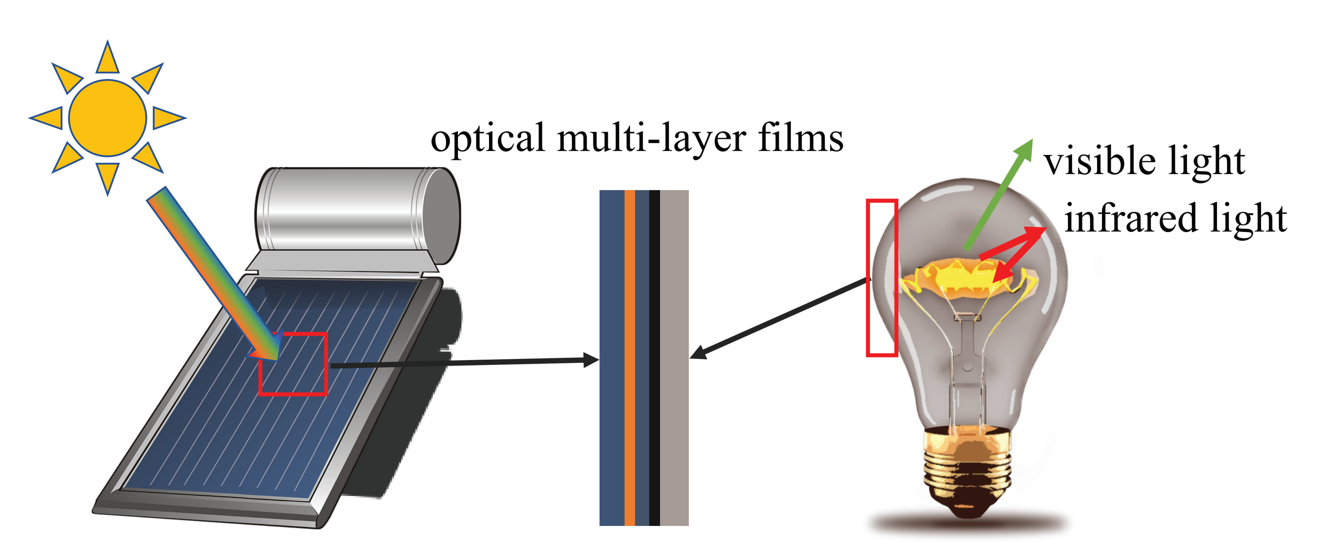
Algorithm 1: OML-PPO

Input: target $\tilde{T}$, number of epochs K, batch size B, maximum length L
Output: Optical multi-layer sequence $\mathcal{S}^*$

1. Initialize sequence generator parameters θ;
2. Initialize critic network parameters θ_v;
3. Initialize best design $\mathcal{S}^*$;
4. **for** $k = 1, \ldots, K$ **do**
5. $\quad \mathcal{S}_i \sim \mathtt{SampleDesign}(L, B, \theta)$;
6. $\quad \mathcal{S}^* \leftarrow \mathtt{SelectBest}(\{\mathcal{S}_i\}, \mathcal{S}^*, \tilde{T})$
7. $\quad \theta, \theta_v \leftarrow \mathtt{PPOUpdate}(\{\mathcal{S}_i\}, \theta, \theta_v)$;
8. **end**
9. $\mathcal{S}^* \leftarrow \mathtt{QuasiNewton}(\mathcal{S}^*, \tilde{T})$

Applications

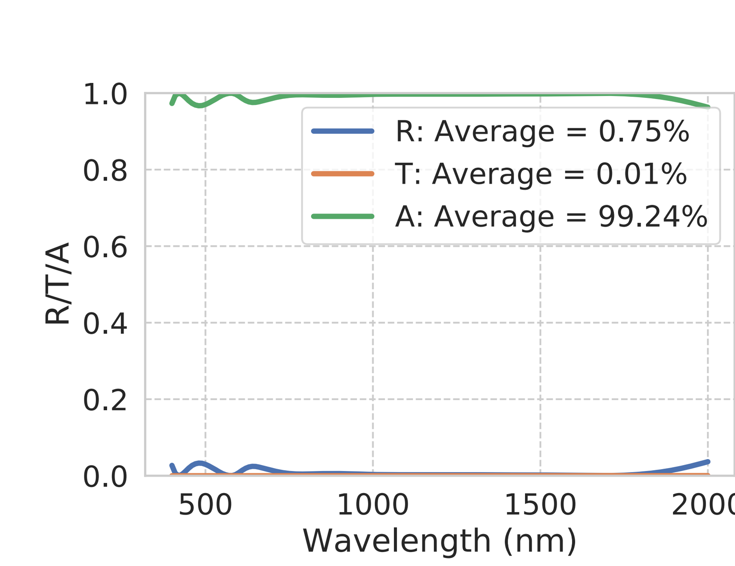
- The proposed method is applied to two tasks: 1) designing perfect solar energy absorbers; 2) designing incandescent light bulb filters for improved lighting efficiency in the visible light range.

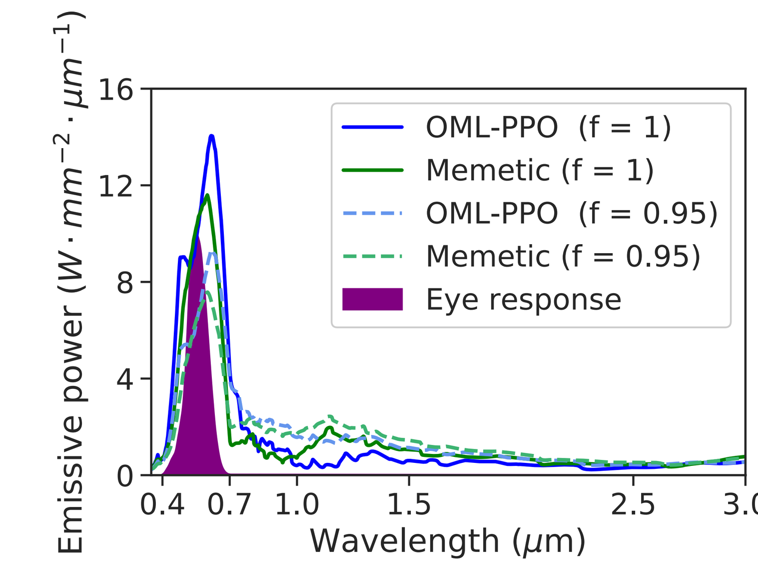


Application 1: solar thermal panels
Application 2: incandescent light bulb

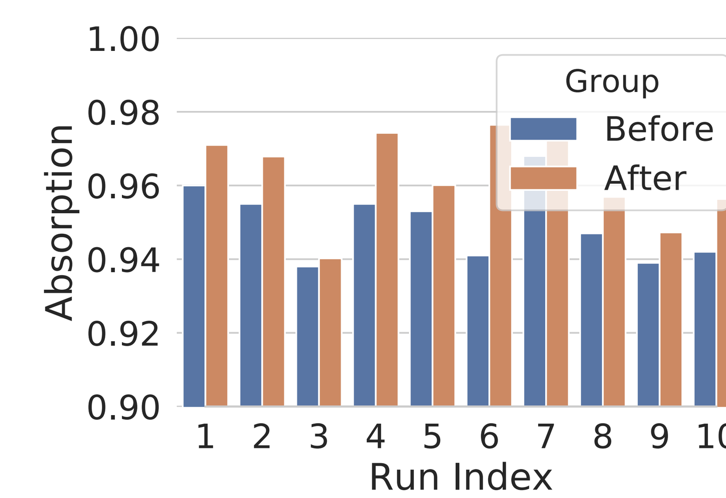
Results

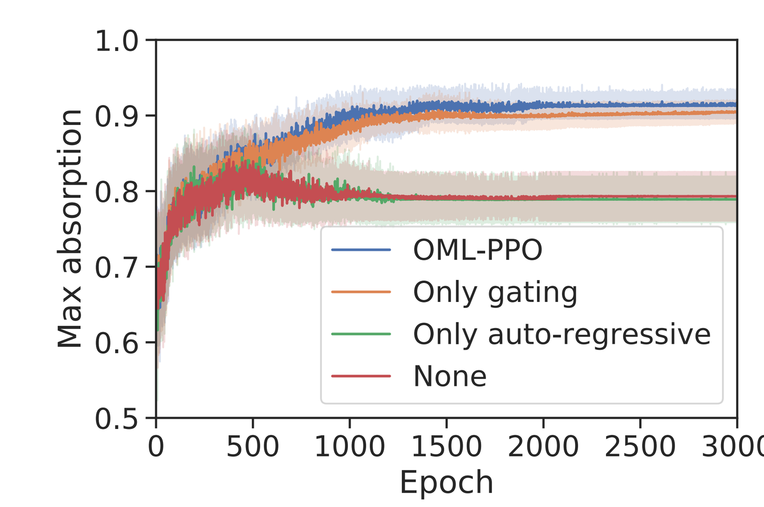
- On the perfect absorber task, the proposed method designed a 14-layer structure with 99.24% absorption. The proposed method outperforms a state-of-the-art memetic algorithm (Shi et al, 2017).





- Through ablation study, we find that thickness finetuning and non-repetitive gating significantly improve the design performance.





Conclusion

- Deep reinforcement learning can be successfully applied to optical multilayer designs.
- Customized neural network architecture for the optical sequence generation task can significantly improve the design performance.
- The proposed method can be applied to other optical design tasks that involve multiple layers.
- We plan to study meta reinforcement learning to efficiently solve related optical design tasks.

References

1. Haozhu Wang, Zeyu Zheng, Chengang Ji, and L Jay Guo. Automated optical multi-layerdesign via deep reinforcement learning. *Mach. Learn.: Sci. Technol.*, 2020.
2. Shi, Y., Li, W., Raman, A. and Fan, S., 2017. Optimization of multilayer optical films with a memetic algorithm and mixed integer programming. *ACS Photonics*, 5(3), pp.684-691.

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