

Starting points generation for freeform reflective imaging system design using neural network based deep-learning

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1. Introduction

Using freeform optical surfaces is a revolution in the field of imaging system design. Such systems have important applications in the area of virtual reality and augmented reality, light-field and high-performance cameras, microscopy, spectroscopy, and other applied physics researches. We propose a framework of starting points generation for freeform reflective imaging systems using back-propagation (BP) neural network based deep-learning. Good starting points of specific system specifications for optimization can be generated immediately using the network. The amount of time and human effort as well as the dependence on advanced design skills reduce significantly.

2. Method and design example

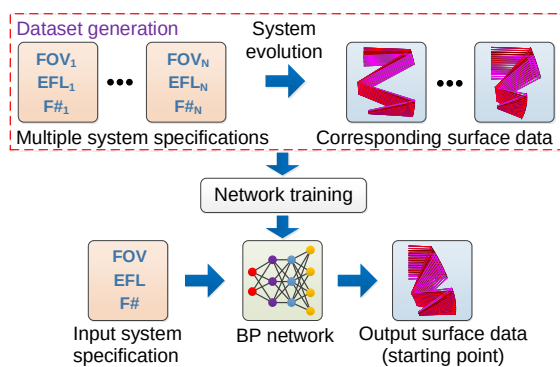


Fig. 1. Illustration of the design framework.

The diagram of the design framework is shown in Fig. 1. For a given system folding geometry, the entire framework consists of the following steps. The first step is to generate a number of “base systems” within a given range of system specifications. The system data of these systems and the corresponding freeform surface locations and coefficients (surface shape) are taken as the input and output parts respectively in the dataset. Here, the field-of-view (FOV) in x and y directions (XFOV and YFOV), effective focal length (EFL) and F-number (F#) are used to describe the system specification. The generation process of the corresponding base systems with good imaging performance starts from an easy-designed base system with non-advanced specification. A principle is proposed to guide the careful and automated generation of the rest of the base systems: Each base system $BaseSys_i$ is optimized starting from the specific system that has the most similar specifications to $BaseSys_i$ among the base systems that have already been obtained. Following this principle, specific system evolution approach can be determined to obtain all the base systems.

Then, the feed-forward BP neural network can be trained using the obtained dataset. For a specific design task, the surface locations and coefficients (good starting point for further optimization) can be output directly when the given system data are input to the network. The time-consuming starting point exploration or complicated analytical/numerical design process are not needed.

We use the design of the Wetherell-configuration [1] freeform off-axis reflective triplet to validate our proposed design framework. The range of the system parameters are: $4^\circ \leq XFOV \leq 9^\circ$, $4^\circ \leq YFOV \leq 9^\circ$, $80\text{mm} \leq EFL \leq 120\text{mm}$, $1.5 \leq F\# \leq 4$. $N=3888$ different system specifications are sampled. The freeform surface type is XY polynomials up to the fourth order with no base conic. The BP network have two hidden layers with 30 and 40 nodes respectively. Tansig and purelin are taken as the transfer function for the hidden and output layers respectively. When we have obtained this network, for a specific system specification input within the system data range, corresponding surface data of a system with acceptable imaging performance can be output immediately in general. The corresponding system can be taken as a very good starting point for further optimization. Output systems of several typical system specifications generated by the network are plotted in Fig. 2 as examples.

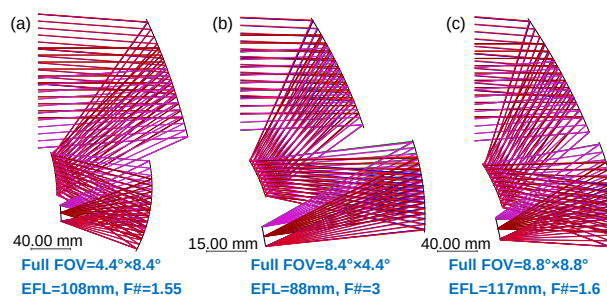


Fig. 2. Output systems of several typical system specifications

3. Conclusions

This research highlight the powerful ability of deep learning in the field of freeform imaging system design. Similar design framework can also be used in the design of imaging systems using phase elements such as diffractive optics and metasurface.

Acknowledgements

This work is supported by National Key R&D Program of China (2017YFA0701200), National Natural Science Foundation of China (61805012), and Beijing Institute of Technology Research Fund Program for Young Scholars.

References

[1] W. B. Wetherell and D. A. Womble, U.S. Patent 4,240,707.