User-Based Error Verification Method of Laser Beam Homogenizer

Jee Ho Song[1], Han Sol Shin[1], Tae Jun Yu[2], and Kun Lee[3](✉)

[1] Department of Information and Communication, Handong Global University, Pohang, Republic of Korea

[2] Department of Advanced Green Energy and Environment, Handong Global University, Pohang, Republic of Korea

[3] School of Computer Science and Electronic Engineering, Handong Global University, Pohang, Republic of Korea

kunlee@handong.edu

Abstract. In the laser homogenization experiment, there is a difference between the output from the pre-design and the output from the actual experiment. This is because, apart from the design mistake, the mistake of some lens placement during the lens assembly process greatly affects the final result. Unless there is a way to automate the alignment of all the lenses from the beginning, the only way to find and fix these errors is to re-arrange all the lenses. In this paper, we propose a new error verification method. To accomplish this, we first store all the output that can occur due to the change of the lens arrangement during the simulation process, and then use the machine learning to connect the relationship between the output images obtained from the actual experiment and the previously obtained data.

Keywords: Laser physics · Laser intensity · Data analysis · Contour Machine learning

1 Introduction

The laser is amplified by inductive emission and is used in various applications such as energy, new materials, semiconductors, and medical care required in the 21st century. In order to obtain a high output laser, Handong Intense Laser Lab (HILL) is studying to make the beam bundle into a rectangular parallelepiped shape (Fig. 1) for even energy distribution of the medium [1–3].

For Laser Beam Homogenizing experiment, several mirrors and lenses are used. However, unlike the mathematical approach, the results obtained through actual experiments are often different from those expected. The reason is that the laser, also referred to as the light, has the property which allows it to easily interfere with the surrounding environment. In this study, we propose a method to help the error verification and adjustment of experimental setup based on the case when the adjustment of each module (mirror, lens, etc.) is wrong. To do this, we try to learn the output images based on the parameters of the module through the deep learning algorithm and find out which output image of the experiment matches with the image using the parameters.

C. Stephanidis (Ed.): HCII Posters 2018, CCIS 850, pp. 206–210, 2018.
https://doi.org/10.1007/978-3-319-92270-6_28

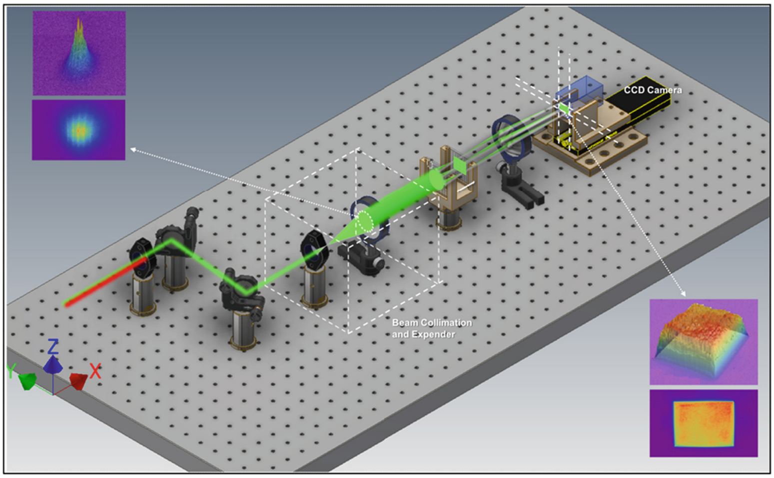

Fig. 1. Experimental setup for Laser Beam Homogenizing (HILL, 2017, used with permission).

2 Problem Description

As mentioned above, there are several parameters (focal length, mirror angle and so on) that are required for experimental setup for homogenizing. Figure 2(a) and (c) show the result when the focal length of the lens is different, and the remaining parameters are the same. And, (a) and (b) use the same focal length (F_C) lens but different position of CCD camera for image sensing.

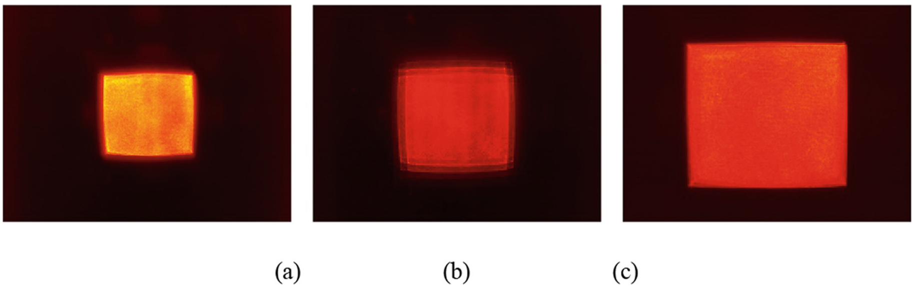

Fig. 2. Outputs with different parameters: (a) F_C = 32 mm, CCD = 0 mm, (b) F_C = 32 mm, CCD = −20 mm, (c) F_C = 60 mm, CCD = 0 mm

As can be seen from the results, some of the changes in some parameters result in different overall results. In particular, the parameters used in the experiments are the position and angle values of each module (two mirrors and four lenses, one lens array, and CCD) as shown again in Fig. 1. However, in order to adjust a total of 16 parameters, it must pass through the human hand. There are other ways to tune through the machine, but the installation cost is very expensive, and the possibility of machine failure is not negligible. It is almost impossible to adjust 16 parameters without mistakes. Therefore, we will study how to find faulty modules on the contrary, assuming there are errors.

3 CNN-Based Learning

There are several existing deep learning algorithms. Among them, CNN is the most widely known algorithm, designed to use minimal preprocessing (Fig. 3). Compared to other deep learning algorithms, it shows good performance in images and has the advantage of using fewer parameters [4–9]. Especially, we decided that it is suitable for the direction that we want in that the feature extraction and learning of images in the image are both possible.

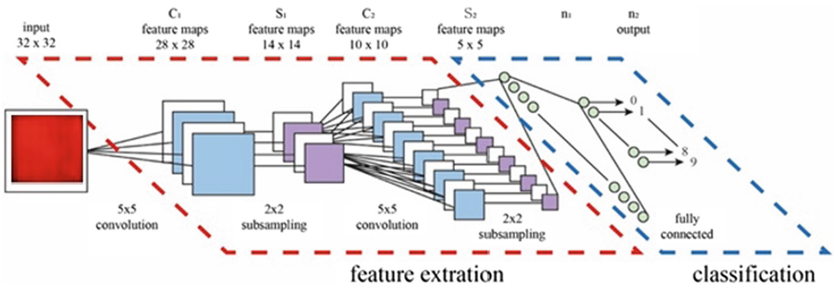

Fig. 3. Convolution neural network architecture model.

4 Proposed System

Using the advantage of identifying the partial features of CNN, we want to learn the output image to which the value applies in various cases of the parameters used in the simulation. The proposed system is shown in Fig. 4. Images to be learned include those that are not properly homogenized. Classification of images will be possible by characterizing edges and color (energy magnitude) related parts as shown in Fig. 5. At the end of the learning, we use the images obtained from the actual experiment as a training data set and derive the parameters of the matched learned image. Based on this parameter, we can expect the current state of the parameters of the modules used in the actual experiment. 1-layer and 2-layer of neural network for Laser Beam Homogenizer are shown in Figs. 6 and 7, respectively.

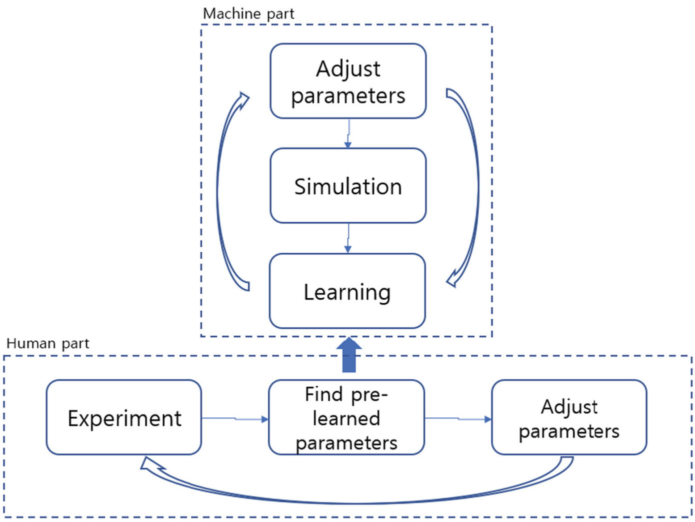

Fig. 4. Proposed method.

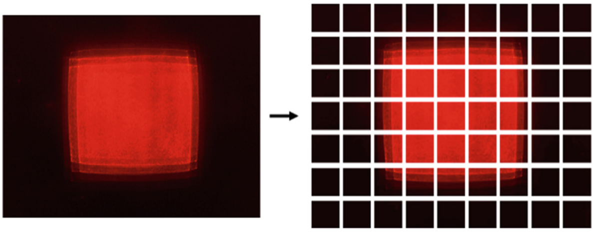

Fig. 5. Partial features of the image. (Color figure online)

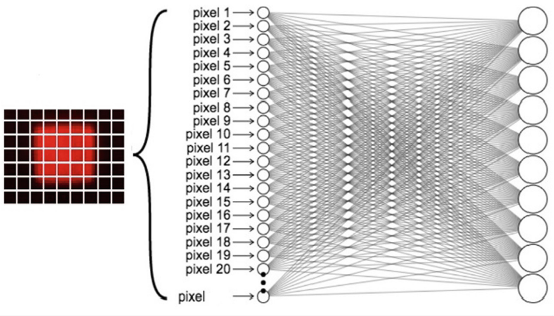

Fig. 6. l-layer neural network for Laser Beam Homogenizer

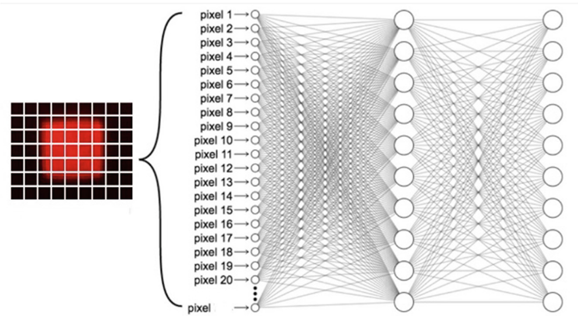

Fig. 7. 2-layer neural network for Laser Beam Homogenizer

5 Conclusion

In experiments involving human beings, the existence of errors is natural. We consider these errors as one piece of information and want to learn human error through CNN. Based on the proposed method, we use simulation images including errors as test data, and try to find error modules by seeding the images obtained through actual experiments. In future work, we will implement this method and provide a guide for the interaction between parameters of the experimental setup and the parameters required by the users.

Acknowledgments. This work was supported by the Industrial Strategic technology development program, 10048964, Development of 125 J•Hz laser system for laser peering funded by Ministry of Trade, Industry & Energy (MI, republic of Korea).

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