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Review Article

Prediction of Image of Polystyrene using AI Model to Match Experiments

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Abstract

In this paper we predict the image of the polystyrene to match experiments for the first time. We consider five different sizes of the polystyrene. We use the features of four different sizes of the polystyrene for training our model. The training parameters are color, structure, geometry, grating number in the x-y direction, the number of gratings in the x direction and y direction, respectively. We use human perception method in our artificial intelligence model. We use computer image parameters in the model. The image properties are pixel dimension in x-y directions and Dot Pixels Per Inch (dpi) for the polystyrene. Our Similar Index (SSIM) for the image is calculated using the human visual method, image properties and geometry. We obtain good accuracy. Our model can be used to polymers. Our work can find applications in sensors, imaging, Computer Aided Design (CAD) and printing.

Introduction

Prediction of the image using computer models are challenging. The image of the object obtained from the camera matches the object in the isometric view. The physics used in the camera are complex. The electrical, optics, object, electronics, ink used to obtain the image from the object and interact with the forces and produce the image in the format to store in the camera. The electronics, semiconductor and many interactions are available in the storage tank inside the camera. The memory card in the camera is the storage tank. The memory card in the camera generates the camera image to display on the camera screen. This is not new. The isometric view of the image is produced in this form. The digitization of the image is also part of the camera capability. To model the isometric view of the camera image using software is the novelty of our work. We consider polystyrene polymer material [1-4]. The prediction of the image has to be accurate to match the camera image. Then, the next logical scope of the future work is towards the 2D and 3D printing of the camera image. The future to use frame rate and consider multiple camera images to produce the object with good accuracy should be made available.

Artificial intelligence helps to understand the generation of the image to match the experiments. Artificial intelligence is broader modelling platform to introduce the task to meet. The sub divisions of the artificial intelligence are the machine learning and deep learning. Machine learning is the ability of the machine to learn and use their structure to complete model for the object property. Deep learning is the capability of the machine to connect the object properties that are available in the object. The deep learning involves neural networks. The data in the object from the literature informs the model to give many of its properties. The data driven neural networks match the simulations to data in the literature. The physics informed neural networks uses the relations for the object using classical laws to match the experiments. Many properties of the object are well documented for the polymer [5-10].

The graph neural networks use the structure of the polymer to understand the color, gratings, spacings, vents, mass and geometry in digital language. The graph neural networks help predict the polymer properties [11-15]. Computer vision uses the computer to understand and predict the polymer image properties stored in the computer [16,17]. The artificial intelligence model to predict image using human perception instead of neural networks are needed [18-22]. The structure, color, grating spacings and number of gratings are important in the Similarity Image Index (SSIM). The ability of the model to match the image properties in the computer that includes the pixel dimensions and Dots Pixels Per Inch (dpi) are needed.

In this paper, we consider human perception model to generate and predict the image of polystyrene polymer to match experiments [23-27]. Our artificial intelligence model for the first time does not use neural network but predicts from physics of human perception vision models. We match the polystyrene structure, color, grating spacings, number of gratings, image properties that includes the computer pixel dimensions and dpi with SSIM good accuracy. We use the image properties from 4 different sizes of the polystyrene. We use them for the training data. We predict for size 5 of the polystyrene the image that matches experiments. (Figure 1) shows the schematic arrangement of the polystyrene that is photographed using camera. The different sizes of the polystyrene are considered. We model the image properties and match the model with experiments to good accuracy.

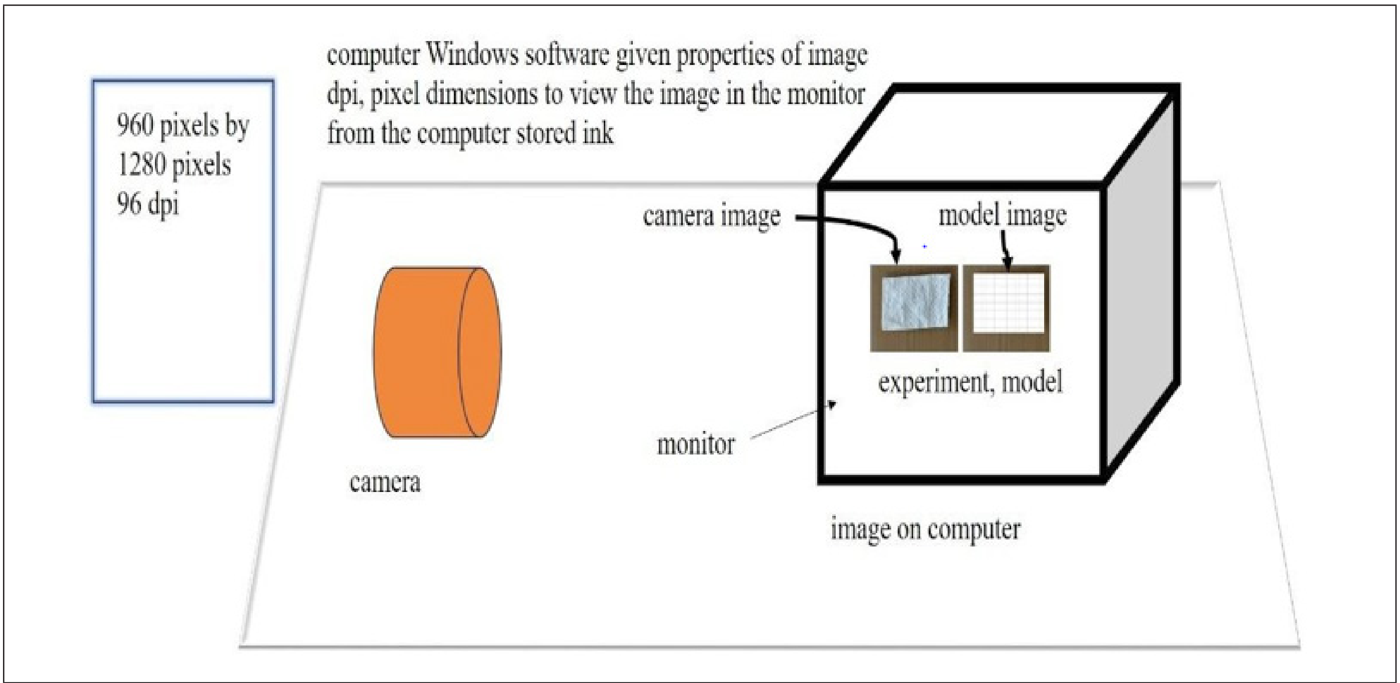

Figure 1: Schematic of the predict generate image of the polystyrene and compare with camera image.

The rest of the paper is outlined as follows. Section 2 discusses the materials and methods. The model and simulation details are given in section 3. A detailed discussion is provided in section 4. Finally, conclusions are presented in Section 5.

Materials and Methods

We purchase the polystyrene from Lakshmi electricals and hardware, India. We purchase the OM system camera from Kesari Scientific Chemicals, India. The camera has features for microscopy imaging. The polystyrene is cut using cutter. The cutter is purchased from Nimibind, India. We code using python. We model and run the code in Windows power prompt shell.

Physics informed AI simulation having human visual perception method

In the model, we consider grating number and grating spacing distance in horizontal x and vertical y directions. In the experiments the number of gratings in the x direction are 28 for the side that have length of 7.6 cm as shown in Figure 2a. The experiment number of gratings in the y direction are 17 for the side that have width of 4.6 cm as shown in Figure 2a. The grating number in x and y direction observed in the experiments matches the simulations as shown in Figure 2b. The grating spacing in the experiments for size 5 of the polystyrene are measured using plastic scale. The experimental grating spacing in the x direction is 3.2 mm and the grating spacing in the y direction is 2.7 mm. The theoretical grating spacing in the x direction is calculated using Eq (1).

$$\text{Grating spacing x direction } = \frac{L}{G_x} \quad (1)$$

where L is the length of the size 5 of the polystyrene and G_x is the number of gratings in the x direction.

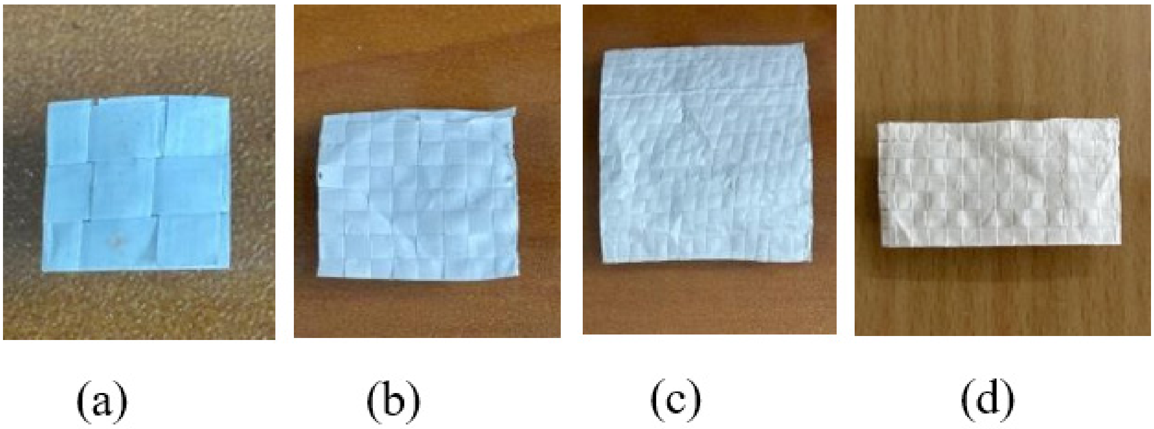

Figure 2: images of the polystyrene for various sizes.

The theoretical grating spacing in the y direction is calculated using Eq (2).

$$\text{Grating spacing y direction} = \frac{B}{G_y} \quad (2)$$

where B is the width of the size 5 of the polystyrene and G_y is the number of gratings in the y direction.

The theoretical grating spacing in the x direction is 3.2 mm and the grating spacing in the y direction is 2.7 mm that matches the experiments. The accuracy is good. We measure the pixel dimension of the experiment image. Pixel is defined as the single point of color on the monitor screen of the computer. The pixel can be regarded as the ink size used to display digital image on the monitor screen of the computer. We measure the Dot Pixels Per Inch (dpi) of the experiment image. The experiment image dpi are 96 pixels per inch. We model the dpi to match the experiments. We define the pixel using standard.

The pixel per cm (P) is given in Eq (3).

$$P = \frac{N_x}{2.54} \quad (3)$$

Where N_x are the number of pixels. Here N_x are 96. 2.54 is the relation between 1 inch and 2.54 cm.

The pixel dimensions for the experiment image are 960 pixels by 1280 pixels. We model the pixel dimensions hard code in python to 960 pixels to 1280 pixels to match experiments. We obtain good accuracy. Hence, we use more pixel ink than dpi to produce the simulation image that experiments. This reveals dpi 96 and pixel dimensions 960 pixels by 1280 pixels are two different storage pixel ink tanks in the central processing unit of the computer that can be independently used to display the experiment image on the monitor screen of the computer. Our model matches the experiments. The color of the simulated image is incorporated by human visual perception method. It is considered white in the Red, Blue and Green (RGB) color palette in the python. The weave pattern to make the gratings are coloured to (200, 200, 200) color code in python. This is equivalent to light Gray. We learn the polystyrene material dimension for size 5, color, weave grating lines color, physics of pixel dimension in x and y directions, dot pixel per inch, pixel per cm, grating number in the x and y direction for the size 5 of the polystyrene, grating spacings in the x and y direction for the size 5 of the polystyrene, colour, weave grating lines and weave colour of images provided for size 1 to size 4 in the model. Hence, we develop the model from the human visual perception method that learns the detailed parameter given. The model developed is physics informed AI simulation to predict image for the size 5 of the polystyrene.

The similar index of the image is calculated using Eq (4).

$$\text{SSIM} = f_{actual} - f_{model} \quad (4)$$

where SSIM is the similar index of the image. f_{actual} is the function for the actual image given in Eq (5).

$$f_{actual} = f\ (color, grating\ spacings, number\ of\ gratings, dpi, pixel\ dimensions) \quad (5)$$

where f is the function that includes the physics of color, grating spacings, number of gratings, dot pixel per inch, pixel dimensions in x and y directions, respectively. f_{model} is the function for the actual image given in Eq (6).

$$f_{model} = f_{sim}\ (color, grating\ spacings, number\ of\ gratings, dpi, pixel\ dimensions) \quad (6)$$

where f_{sim} is the function used in the simulation that includes the physics of color, grating spacings, number of gratings, dot pixel per inch, pixel dimensions in x and y directions, respectively.

The SSIM value is good in our method. The human visual perception and physics from ai simulation parameters used during training and predict image matches the actual image from the experiments.

Results and Discussion

Figure 2 shows the images of different sizes of the polystyrene. Figure 2a shows the polystyrene of length 8 mm width 8mm and thickness 0.082 mm. Figure 2b shows the size 2 of polystyrene of length 2 cm, width 2 cm and thickness 0.082 mm. Figure 2c shows the size 3 of length 4.5 cm, width 4.5 cm and thickness 0.082 mm. Figure 2d shows the size 4 of length 4 cm, width 2 cm and thickness 0.082 mm.

Figure 3 shows the comparison between the experiment size 5 of the polystyrene and physics informed AI predicted image simulation. The size 5 of the polystyrene have length 7.6 cm, width 4.6 cm and thickness 0.082 mm. The predicted image from physics informed AI simulation have pixel dimensions 960 by 1280 same as the experiments. The accuracy is good. We calculate the SSIM without Gaussian blurs method. We develop codec having human visual perception method only.

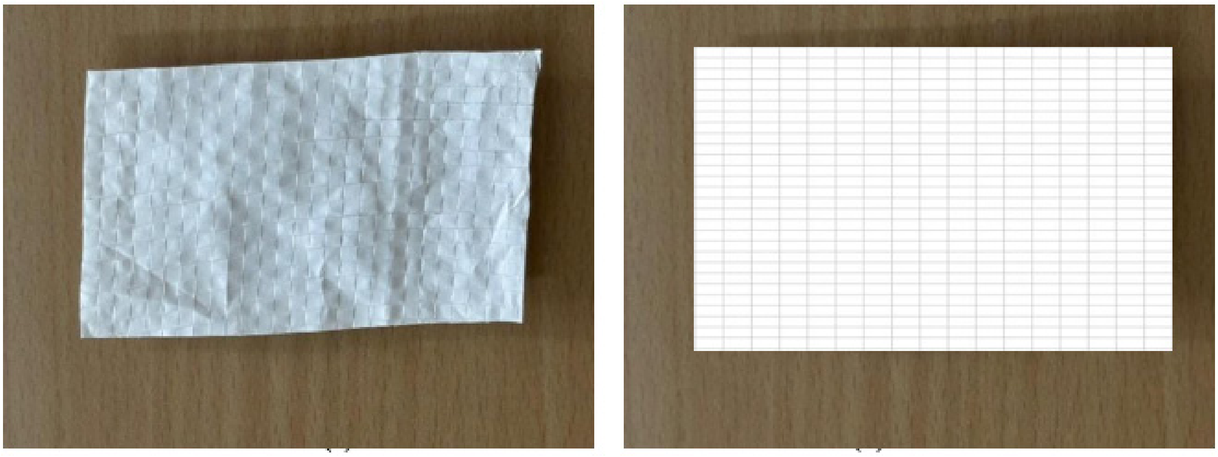

Figure 3: Comparison of the experiment polystyrene image and the computer model.

Conclusions

To conclude, we predict the image for size 5 of the polystyrene to match good accurately with the experiments. We use human visual perception method and physics from ai models. Our training models use the parameters of the experiment image for size 1 to size 4. The pixel image properties are also included in the model. We calculate the similarity index of the image using equations and obtain good accuracy. Our work can easily be extrapolated to many polymers and objects.

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Author Contributions

Nandigana V. R. Vishal: Conceptualization, Data curation, Formal analysis, investigation, methodology, resources, software, supervision, validation, visualization, writing – original draft, writing – review and editing.

Conflicts of Interest

The authors declare no conflict of interest.

Data Availability

The data from the current study are available from the corresponding author upon reasonable request.

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