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Research paper

Application of image-based acquisition techniques for additive manufacturing using canny edge detection

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Abstract

Edge is an indispensable characteristic of an image, defined as the contour between two regions with significant variance in terms of surface reflectance, illumination, intensity, color, and texture. Detection of edges is a basic requirement for diverse contexts for design automation. This study presents a guideline to assign appropriate threshold and sigma values for the Canny edge detector to increase the efficiency of additive manufacturing. The algorithm uses different combinations of threshold and sigma on a color palette, and the results are statistically formulated using multiple regression analysis with an accuracy of 95.93%. An image-based acquisition technique system is designed and developed for test applications to create three-dimensional objects. In addition, a graphical user interface is developed to convert a selected design of a complex image to a three-dimensional object with the generation of Cartesian coordinates of the detected edges and extrusion. The developed system reduces the cost and time of developing an existing design of an object for additive manufacturing by 20% and 70%, respectively.

1. Introduction

The industries of the current technological era are highly innovative and research-oriented for robust production. Most of the processes and activities in the job role are automated to reduce the work stress of the employers and to improve the safety and quality of the end product. Conventional machining processes, including lathe, boring, milling, and drilling with specified cutting tools, according to defined temperature and velocity specifications, are used to remove material in order to achieve desired geometry rarely implemented in industries with the development of technology. Recent innovations allow additive manufacturing in various sectors of industries, including aerospace, automotive, health care, and product development with high reliability and easy production.

Federal Aviation Administration (FAA) has allowed the use of additive manufacturing for part productions in a commercial jet engine [1] while FAA certified fabricated structural parts of Boeing 787 using additive technology [2] were displayed in 2017 Paris Air Show. In addition, additive manufacturing is established in developing customized surgical implants and models to assist surgeons with guidance during emergencies in an operation and pre-operative assessments.

Additive manufacturing not only uses thermoplastic polymers for reliable manufacturing but also uses polyvinyl alcohol, which is a water-soluble component, to create temporary support structures. Furthermore, additive manufacturing uses metals, including gold, silver and titanium, and ceramics such as alumina and tricalcium phosphate in civil construction study. Varieties of glass products are created with baked alternate layers of powdered glass and adhesives. In addition, researchers are currently developing human organs using bio-inks fabrication while bone structure supporters, made out of silicon, zinc and calcium phosphate, are already existing in the medical field.

Additive technology is a significant improvement in technology, allowing the designers to incorporate complexity in development. It improves the strength and durability of the prototype while providing minimum restrictions in designing for product designers. Various additive manufacturing processes have been developed over the last decade. Material extrusion is the most common process where spooled polymers are extruded through a heated nozzle. The heated nozzle is mounted on a movable arm in horizontal direction while the base moves vertically, allowing the melted material to be built in layers. The developed products show reliable results depending on the control of temperature and the use of chemical bonding agents. Directed energy deposition (DED) uses the same technique but with various materials such as ceramics and metals where the nozzle is replaced by an electron beam gun or laser mounters five-axis arm.

The material jetting process uses a print head similar to a two-dimensional (2D) inkjet printer but moves in all three axes to create three-dimensional (3D) objects. In addition, there are other techniques such as binder jetting where print head uses powdered material and a liquid binder, laminated object manufacturing (LOM), and ultrasonic additive manufacturing (UAM). However, LOM is highly used in visual modeling since it uses alternative layers of paper and adhesive while UAM employs ultrasonic welding with thin metal sheets.

Powder bed fusion (PBF) technology is used in various additive manufacturing processes, including direct metal laser sintering (DMLS), selective laser sintering (SLS), electron beam melting (EBM), selective heat sintering (SHS), and direct metal laser melting (DMLM). However, all the processes follow the fundamental stages of the production of three-dimensional objects.

Additive technology uses digital objects defined by computer-aided-design (CAD) software to create thin layers of objects with supporting files. This determines whether the nozzle path has to deposit the material upon the basic layer with full or partial melting mode. Three-dimensional objects are formed with fusion of each layer together. Although the creation of digital objects reduces cost, time, and money by replacing the intermediate steps such as the creation of dies and molds, the developed additive manufacturing technology can constantly be improved and increased inefficiency.

The use of image analysis with recent advancement in science and technology to overcome time limitations and human errors is manifold in industrial automation. However, the use of this technique is restricted in certain domains, including manufacturing industries, production factories, and educational institutes, due to the requirement of proficiency and expertise knowledge in computer vision and artificial intelligence.

Manufacturing industries undergo the tremendous task of designing an object in a virtual environment, even though objects with identical features exist in the real world. The design engineers in industries focus on designing an object for manufacturing from the fundamental stage. It consumes time and increases the operating cost, including the working hours of designers, and demands required facilities. Further, interior architectures require the use of contrasting colors and different shapes to decorate the environment, while graffiti illustrators and wall painting artists need to duplicate and use certain features available in the environment for an appealing task. In addition, fashion designers manually represent various ideas, while with the aid of image processing techniques, the requirements can be automated. Factory supervisors and store managers require details on entry and exit data of different vehicles, raw material purchases, which can also be analyzed with vehicle detection using the proposed technique.

Edge detection followed by color detection in image processing applications complicates the allocated task and increases the computational load. Potential users who have limited knowledge of computer programming in industries struggle to complete a task due to a lack of experience in image processing applications. A feasible method to design and manufacture basic objects by extracting desired designs from the environment is an essential necessity.

2. Related studies

Locating sharp discontinuities in an image by detection of edges is vital in the recognition and classification of objects to reduce the quantity of data by filtering out the ineffectual information while preserving the required structural property in an image. There are various edge detection techniques developed and revised, including but not limited to Canny Operator [3], Sobel Operator [4], Robert Operator [5], Robinson Operator [6], Marr - Hildreth Operator [7], and Prewitt Operator [8]. However, it had been concluded in researches [9-13] that in general, the performance of the Canny operator for edge detection is consistent and precise in comparison to other advanced edge detectors.

However, it had been concluded in researches [9-13] that, in general, the performance of the Canny operator for edge detection is consistent and precise in comparison to other advanced edge detectors. The optimal Canny edge detection algorithm focuses on specific attributes to exhibit an efficient edge detection method. It has a low error rate by which it ensures that edges occurring in the images are not missed while no responses are produced by non-edges. Further, the distance between the edge pixels and the actual edge of an image is minimized, and only one response is generated for a single edge. Thus, it is the most practical and commonly used algorithm for edge detection with a multistage process.

The Canny edge detector eliminates the presence of noise by using a simple mask of Gaussian filter at first. Gaussian smoothing is performed using the standard convolution method where a convolution matrix, which is much smaller than the actual image, slides over the original image, manipulating a square of the pixel at a time. After completion of noise removal and image smoothening, the edge strength is found using the gradient of the image.

The Sobel operator performs a 2D spatial gradient measurement to determine the approximate absolute gradient magnitude. It highlights the region with high spatial derivatives allowing the algorithm to trace along the edge in the edge direction and suppressing any pixel that is not at the maximum. The remaining pixels that have not been suppressed are reduced by hysteresis, in which it uses two threshold values. If the magnitude is below the lower threshold value, it is set to zero while if the magnitude is above the higher threshold, it is made as an edge. However, if the threshold magnitude of a pixel is in between the lower threshold value and the higher threshold value, it is set to zero unless there is a path from this pixel to another pixel with a gradient above a higher threshold. The Gaussian filter that is used as the pre-processing method to blur the image is determined by the parameter sigma in the Gaussian function [14] given by Eq. (1).

$$h(x,y) = \exp(-(\frac{\pi(x^2+y^2)}{\sigma})) \quad (1)$$

The parameter σ (sigma) determines the width of the filter. The blur increases with the increase of sigma values. However, if the value of sigma is higher, the faint edges will not be detected. This will lower the sensitivity to noise. In addition, the localization error of the detected edges will

increase resulting in lower reliability. In contrast, if sigma is low, the noise too will be detected as edges.
Thresholding is the technique used to select an optimal grey-level threshold value for separating the object of interest in an image from the background based on grey level distribution. It creates a binary image of a grey-level image by converting all the pixels below a certain threshold value to zero and all the pixels above to one. If f(x,y) is the threshold function of g(x,y) at global threshold T, it can be defined as described [14] in Eq. (2).

$$f(x,y) = 1 \; if \; g(x,y) \geq T \\ \quad = 0 \; otherwise \tag{2}$$

Global thresholding is solely based on the characteristics of all pixels in the image, unlike local thresholding which divides an original image into several sub-regions and chooses various thresholds T for each sub-region reasonably. However, if the value of the threshold is lower, in general, more edges will be detected along with noise and irrelevant edges. Conversely, if the threshold value is high, subtle edges will be ignored. Thus it is crucial to use appropriate threshold and sigma value for canny edge detection. However, the guideline to understand the selection of threshold and sigma values for images with diverse content is vague. Thus it is significant for users of the different domains to be able to use this technique for their applications.
There have been researches [15-25] focusing on different aspects of edge orientation, noise environment, and edge structure of canny edge detection to improve the accuracy. However, none of the studies concludes a guideline to interpreting values for threshold and sigma. A nonparametric and unsupervised method of automatic threshold selection is presented [26] in which an optimal threshold value is selected to maximize the separation of resultant classes in grey levels. This method is incorporated with canny edge detection for better accuracy in recent researches [27-32].
The application of canny edge detection is a promising solution to various industrial sectors such as glass production, ceramic manufacturers, traffic controls, and electronics [33-39]. However, additive manufacturing, unlike other technologies, requires significant threshold value selection. Industry 4.0 technologies [40] consider additive manufacturing as one of the primary enabling factors which require continuous growth towards modernization in industries.
Additive manufacturing technology is rapidly growing since it has the ability to manufacture complex parts with limited cost. In addition, it allows the selection of materials depending on the applications, strength, and required durability. The stability of an additive manufacturing process is based on melt pool geometry, and it is vital to monitor and process the control. Even though currently melt pool boundaries are extracted using intensity-based image processing through grey scale, selection of the corresponding threshold is challenging due to disturbance in the environment, flares, speckles, and intensity based noise. Thus a guideline for the selection of threshold and sigma for additive manufacturing is a basic requirement.
Diverse applications of researches focusing on additive printing of complex chocolates [41] and foods, in general, focuses on precision and accuracy [42]. Eijnatten et al. [43], in their research study on image segmentation methods for computer tomography scan of bones, discuss applications of medical additive manufacturing using global thresholding. The study suggests that future researches require development in image segmentation methods. Mohammed [44] reviewed applications of 3D printing technologies in oceanography, while a review on additive manufacturing of custom orthoses and prostheses ensures the requirement of improvement in the existing technology [45]. Recent researches ensure the importance of improvement in additive manufacturing [46-51]. However, it is difficult for the creative artist to communicate the design for production to a computer programmer who has different background knowledge. Nevertheless, if there is a robust way to convert a real life object to a design to be manufactured automatically, the workload and computational cost can be reduced.

3. Methodology

A guideline for the selection of threshold and sigma values for canny edge detection of various colors and brightness level images is required to automate the edge detection application efficiently in industries. Considering the applications of reverse engineering, the image-based acquisition technique is developed by capturing multiple views of two-dimensional images of the existing product and creating the 3D model of the object.

3.1. Design and development

The main frame of the developed model is fabricated by fused deposition modeling (FDM) technique while the camera is allowed to be connected to both interior and exterior surfaces depending on the object of interest. The designed apparatus is shown in Fig. 1 with the components as tabulated in Table 1.

3.2. Research experiment

The research experiment to study the relationship between the sigma and threshold values based on the color of the images, including intensities, is designed with the reference image, as shown in Fig. 2. The objective of the study is to detect the edge of a specific color of an image with corresponding threshold and sigma values and with regard to the brightness level.
An Intensity value of each color on the palette is considered on a scale of 0 to 255 in terms of red, green, and blue [52] and on a scale of 00 to FF in hexadecimal [53-55]. The research experiment uses the most common pixel format of byte image where the number is stored as an 8-bit integer giving a range of possible values from 0 to 255. This research experiment considers the intensity value of black as 0, the intensity value of white as 255 and analyzes the RGB value of each color of the reference image.
The research is developed with consideration to the relationship between the intensity of the image and detection of the edges in terms of threshold and sigma values. The threshold and sigma values are chosen as in Table 2 to develop the statistical relationship among the variables. Three sigma values are chosen with good variation to find the respective threshold values within the range of 0.01 to 0.99 for different colors to disappear from the palette, thus detecting the rest of the edges. Similarly, a constant threshold value of 0.5 is chosen with a variety of sigma values.
The intensity values of red, green, and blue pixels are used as three independent variables to create a relationship among the variables. Multiple regression analysis provides a prediction of the value of a criterion variable based on the value of other explanatory variables.
Since the dependent variables are measured on a continuous scale and are continuous, this analysis can be used in this research study. Multiple regression models create a relationship between the experimental variables and the response variable by formulating an equation with experimental data. This model is being used successfully in various recent researches [56-62] for better prediction with minimum error. Multiple regression model is used in this study to develop the research results to calculate the minimum value of threshold and sigma values for the failure of edge detection of various colors. The graphical user interface is a requirement of the users who have limited knowledge of computer programming for ease of tasks.
If the guideline can be deduced from the research results, it can be used to select any random design from the environment to perform edge detection. In addition to the manufacturing industries, even the artists and designers can use the developed research study to perform edge detection of the specific part of a complex image.

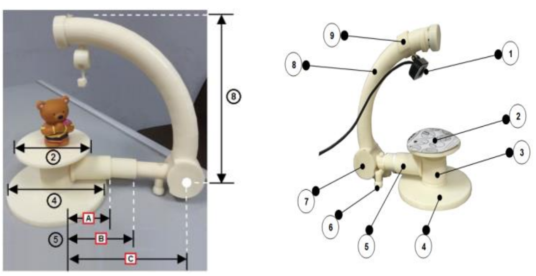

Fig. 1. The developed image-based acquisition technique model.

Table 1. The components of the developed model.

No.	Components
1	Capturing device
2	Rotary platform of diameter 10 cm
3	Linear arm joint
4	Circular base of diameter 15 cm
5	Linear adjustable arm with joint length, (LA = 5.5 cm, LB = 9.5 cm, LC = 15 cm)
6	Positioning legs
7	Curvature arm joint
8	Curvature adjustable arm with joint, length L = 22 cm.

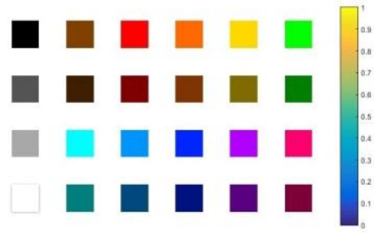

Fig. 2. The reference image for edge detection.

Table 2. Selection of variables.

Research experiment	Sigma values	Threshold values
Design 01	0.1	0.01 to 0.99
Design 02	1.1	0.01 to 0.99
Design 03	2.3	0.01 to 0.99
Design 04	0.1 to 2.5	0.5

3.3. Research application

Development of the guideline to detect certain intensity in a defined brightness for canny edge detection provides a high technical solution for additive manufacturing in automated industries. The graphical user interface allows the users to select the specific intensity of an image to be detected with edges. This selected area of the design is later considered to be the whole image for the following process of automated manufacturing as in Fig. 3.

According to the figure, firstly, a three-dimensional image is required for manufacturing. Currently, a CAD model is being used by developing from the elementary level. Instead, this study uses an image taken with the required design to be developed into a three-dimensional object with the aid of generated guidelines for the selection of threshold and sigma values. The graphical user interface not only allows the user to upload an image but also allows the user to adjust the threshold and sigma values with respect to the developed guideline to create an output image. The selected output three-dimensional image is converted into a format that can be read by an additive manufacturing device such as standard tessellation language. The image from the developed system is easier to convert to standard tessellation language than that of a three-dimensional computer-aided drawing since the developed system only focuses on the edges. This allows layering the object into slices and then feeding it into the existing additive manufacturing systems.

The detected edges are considered as the contour of the object to be developed and the Cartesian coordinates of the contour are used to generate the toolpath for automated control machines, including lathes, mills, grinders, and routers. In addition, they can also be used to increase the efficiency of the computer numerical control (CNC) machining process and laser-based additive manufacturing.

Additive manufacturing requires an input with 3D design. However, the toolpath with a detected edge has only two coordinates in both the x and y-axis. Thus, the extrusion technique is included for designing in three dimensions. The extruded 3D image is later given as the input to the 3D printer for additive manufacturing with desired materials such as acrylonitrile butadiene styrene (ABS) or polylactic acid (PLA) using existing 3D printers. In addition, this approach can also be used in various other types of additive manufacturing.

4. Results and discussion

The research results are considered in two major categories of constant sigma with varying threshold and constant threshold with varying sigma to understand the relationship between the variables. Later, the graphical user interface and the application of the developed guideline in additive manufacturing are discussed with limitations and delimitations of the study.

4.1. Constant sigma with varying threshold

The order of the disappearance of detected edges using the canny filter on the color palette with constant sigma with a varying threshold is recorded. However, the detection of edges for the intensity of the black color palette is constant. Thus it is not considered in formulating the equation using a multiple regression model. However, for better clarity of the image and precise edge detection, the images are inverted as in Fig. 4 with white background for a sigma value of 2.3.

The threshold values, at which failure of edge detection occurs for different sigma values of 0.1, 1.1, and 2.3 for different intensity levels of the colors, are tabulated and graphically represented in Fig. 5. The graph is drawn with consideration to the order of failure of the detected edges on the horizontal axis. The results show that the lower brightness fails in the detection of edges initially with low threshold values while the color palette with high brightness images requires high threshold values to fail. However, the threshold values vary with the brightness of the image and require interpolation for a variety of applications.

The residual output for different threshold values along with the predicted threshold values at sigma 1.1 is shown in Fig. 6.

The regression statistics calculates the standard error of the predicted threshold values with respect to the actual threshold values using the developed guideline as 0.0448 with the coefficient of multiple determination for multiple regression as 93.97%. The general formula for the algorithm is thus generated using multiple regression analysis with a 95% confidentiality limit. The developed algorithm exhibits 95.93% accuracy with minimum root mean square error.

4.2. Constant threshold with varying sigma

Sigma value in an image corresponds to the clarity of the detected edges. Smaller sigma values result in sharp corner edges. However, with higher sigma values at a constant threshold of 0.5, curved edges are generated as output. Fig. 7 shows an output image with a sigma value of 0.1 and a threshold value of 0.5. The detected edges are sharp and similar to the original image. Fig. 8 shows the difference at the edges with a sigma value of 10 and the same threshold value of 0.5. The sharpness of the edges depends on the sigma value and the detected edges of the square generated a circle instead of the square at a sigma value of 25. This variation can be applied accordingly to adjust the desired design of an image as required. This not only provides fillet and chamfer features in the design but can provide a more artistic view of an existing object.

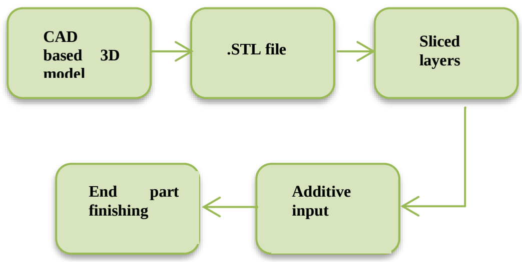

Fig. 3. The process flow of additive manufacturing.

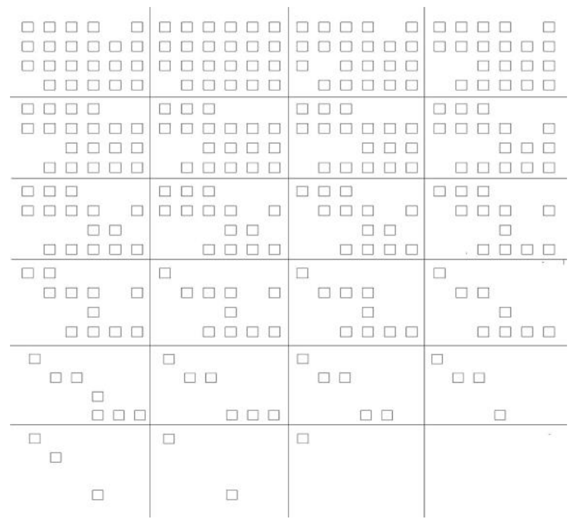

Fig. 4. The inverted output image with different threshold values for sigma 2.3.

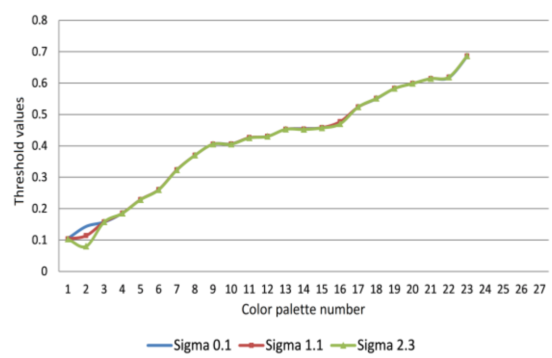

Fig. 5. Variation in selected threshold values for selected sigma values.

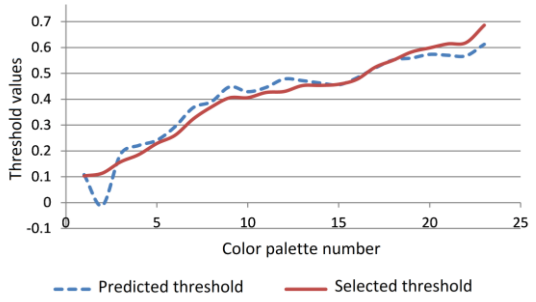

Fig. 6. Residual output for different threshold values.

4.3. Applications of image-based acquisition technique

Various images with significant colors are selected and tested with the developed apparatus, as shown in Fig. 9.
However, for larger objects and objects that cannot be fit onto the rotating table, Images are taken as shown in Fig. 10 by attaching the image capturing device to the exterior area.

4.4. Graphical user interface

The developed guideline and generated statistical equations allow the users to select the required design of a complex image for manufacturing without even designing the 3D model of the design. The graphical user interface is developed using MATLAB with which the users insert the RGB values of the desired part of the image to extract the corresponding edges.
The interface allows the users to upload an image of their interest and produces an output of the selected design depending on the provided threshold and sigma values. The user interface includes artistic attributes, including color pixel display in input requirement selections to create a user-friendly environment for users who have less knowledge of programming. The black design of a light color shoe is selected here in the user interface for extraction for development, as shown in Fig. 11.

4.5. System development

The design is detected with appropriate threshold values with which the design is modified according to the desired designing process. Sigma values are changed with consideration to the requirement of the sharpness of the edges.

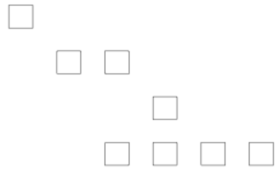

Fig. 7. The output image with sigma 0.1 and threshold 0.5.

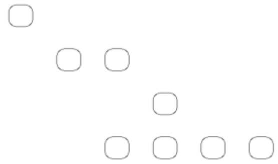

Fig. 8. The output image with sigma 10 and threshold 0.5.

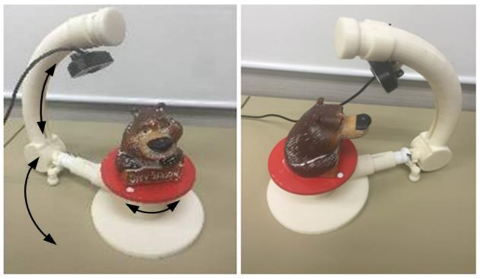

Fig. 9. Different orientation of the selected object on the developed model.

Fig. 10. Different orientation of the capturing device placement for larger object.

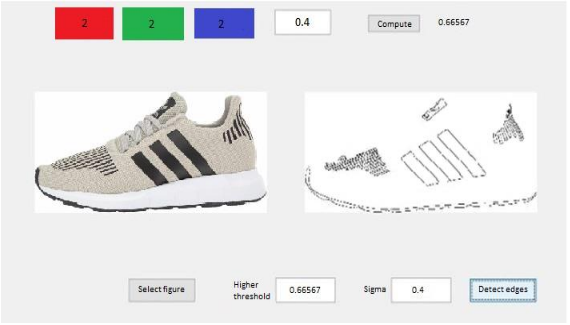

Fig. 11. The user interface of the system.

Various changes at the edges are allowed to be incorporated into the design with the developed user interface. The output image can be viewed and altered until the user gains satisfaction. Once the design is finalized, the toolpath of the selected design can be generated with Cartesian coordinates.

Toolpath is a series of locations of coordinates followed by a cutting tool during the machining process. Roughing toolpath in computer-aided designing and computer-aided manufacturing programming phase allows the cutting tool to remove most of the amount of material possible with good accuracy and efficiency. This is detected by the variation in edge pixels and the background pixels. Missing pixels are introduced in between two pixels if required, and the final toolpath is generated.

The generated toolpath can be used for various manufacturing techniques depending on the functionality of the machines. In addition, the toolpath can also be used as an input for the extrusion algorithm to create a three-dimensional image from a two-dimensional image. This allows uniform extrusion for additive manufacturing. This not only reduces the job role of designing an image before manufacturing but increases the efficiency of additive manufacturing. Fig. 12 shows the extruded image of the desired design which can be interpreted in standard tessellation language for additive manufacturing. The generated output shows that any two-dimensional image can be converted into a three-dimensional design for additive manufacturing using the proposed technique.

4.6. System testing

Five users with average knowledge on designing and image processing designed a specific part of the existing design from the environment using both a developed approach, computer-aided design, and drafting technology. An image of the existing design was taken and using the developed approach, the edges were detected based on the desired colors. Later, different values of sigma and threshold were used to improve the design, and the final design was converted into a three-dimensional image as an input for additive manufacturing. The same users were also requested to generate a three-dimensional image of the existing design using computer-aided software. The time taken by the users for both techniques is shown in Fig. 13.

The average time taken using the developed approach was 12 min while the use of computer-aided design and drafting technology took 40 min. This indicates that the developed approach reduces the time taken for designing by 70%.

This reduces the workload of employees and stress and encourages them to actively participate in work. The cost can also be reduced by 20% with lesser requirements of professional designers and management depending on the applications. Even though this approach reduces the workload of designers with drafting existing designs from the environment and outperforms the existing designing techniques, the creative designing tools are limited.

Further, designs with the same hues and intensities cannot be extracted separately. The approach also requires an additional camera or mobile phone with camera features for system implementation. However, the system can be used effectively based on applications of the manufacturing and production industries.

The guideline developed using the research study is limited to the brightness level and color intensities used in formulating the statistical equation. The selected values of sigma and threshold are the delimitations of the study.

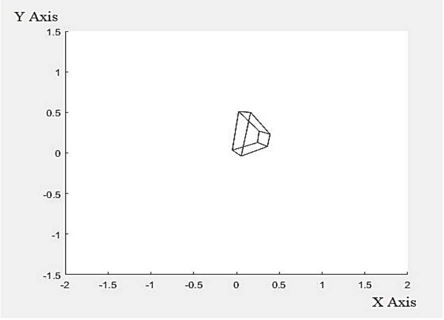

Fig. 12. The extruded output image of the system.

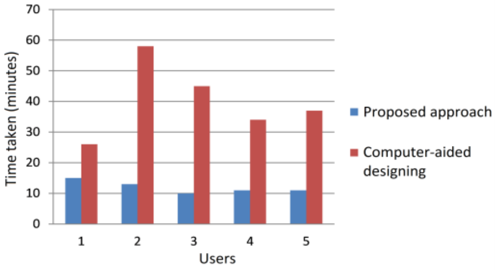

Fig. 13. The time taken by the users for proposed and existing computer-aided designing approach.

The generated guideline can be improved using machine learning models such as support vector machine (SVM) and deep learning models, including artificial neural network (ANN), to increase the efficiency of the prediction. SVM even though is effective in high dimensional spaces and has a clear margin of separation, fails to perform with a large dataset, which requires high training time. In addition, SVM is sensitive to noises. If a small dataset with minimum noise can be generated, this technique can improve the accuracy of the developed guideline. ANN is one of the main tools in deep learning inspired by the learning procedures of the human brain. ANN requires higher computational power and has the ability to work with complex tasks. However, the users have no access to the decision-making process of the neural network even though they can fine-tune the answers. Furthermore, this requires more training datasets. Nevertheless, more images with different brightness levels and various color intensities can be considered for improvement.

5. Conclusions

This research study focuses on providing a guideline to choose threshold and sigma value for users who are not experts in image processing in manufacturing industries such that the advancement in technology can be used in various industries regardless of requirement for computer specialists. The proposed approach uses different combinations of threshold and sigma to generate the desired design with an accuracy of 95.93%. The proposed approach reduces the workload of designers by 70% in the production industry by allowing them to choose the desired design from a complex two-dimensional image. Extrusion and generation of Cartesian coordinates from images without a requirement of designing objects improves the production methodology of the industries. Further, it reduces the demand for designing engineers and the operating cost of the industries. It contributes not only to the production industry but food industries, artistic creations, entertainment-based companies, and interior architectural firms, which focus on designing and manufacturing desired designs.

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