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Study on Wire and Arc Additive Manufacturing of Metals Using Image Processing and Reinforcement Learning

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Currently, metal additive manufacturing systems can melt metal materials using high-energy sources. The most common high-energy sources such as lasers and electron beams are considered the stable energy sources, but the biggest weakness of these sources is the costly and high energy consumption system. In this research, the wire and arc additive manufacturing (WAAM) is used which characterized by low cost. However, the imperfect energy control system makes this manufacturing technology have the following shortcomings: accuracy and surface irregularities. In this research, the monitoring vision system is set up to capture fused deposition images while the CNC platform is moving at speed 1.5 mm/s. About 1300 continuous images are synthesized by template matching, and then the full images under different feeding rates will be extracted contour information by using edge detection. The contour information will be used for training reinforcement learning model to obtain a good feeding rate strategy to improve the profile accuracy. Therefore, this research integrates computer vision, image processing, and reinforcement learning technologies to learn the best feeding rate parameter strategy. Then use this set of parameter strategy in the process to reduce the appearance change of the printed result. This research uses a parameter strategy decision-making method based on the Q-learning algorithm to efficiently find out the good feeding rate strategy that can reduce appearance change to 0.29 mm in few training episodes. This method does not need to spend a lot of experimental time to find good process parameters.

1. Introduction

Generally, traditional processing which so-called subtractive processing is to slowly cut and engrave a large piece of material. The subtractive processing method is the mainstream processing method in many manufacturing industries in the past, but it often requires several processes such as cutting, making the molds and testing whether the parts meet the tolerances requirement which takes a very long time.

Different from traditional processing, rapid prototyping (RP) manufacturing is an additive technology that can quickly make parts, so it has attracted more and more attention from academia and industry. First, uses computer-aided design (CAD) software to generate a 3-D solid model. Second, converts it into a triangular mesh STL file format, and then transfers the file to the manufacturing system for layered division processing. Finally, uses a liquid or powdered material to make the models on the printing table.

In contrast to traditional manufacturing processes such as CNC machining that parts are constructed by subtracting material from a piece of material, additive Manufacturing (AM) technology is a processing of stacking and depositing materials layer by layer to build parts. AM is suitable for many different materials such as plastic, rubber or metal that can be used to make parts. This processing technology provides a high-efficiency, low-cost manufacturing method, and it has several advantages: (1) There are no restrictions on the shape of printing, and complex shapes that cannot be made by subtractive processing are also easy to form. (2) There is no need to prepare tools such as molds and can be processed directly. (3) The overall processing is automated. Therefore, AM technology has attracted many research teams to invest and develop, and they create many different AM technologies. Common ones are: Fused Deposition Modeling (FDM), Selective Laser Sintering, SLS) and Stereo lithography Appearance (SLA). However, the processing parameters of AM are not easy to adjust, and often have a significant impact on the microstructure of parts and the performance of subsequent products.

In the research, we use plasma arc welding(PAW) technology. Pl asma arc welding is a type of wire and arc additive manufacturing (W AAM). The advantages of this method are fast deposition and stackin g speed, high effective use rate of materials, unlimited size and shape of printed parts and forming large-area metal parts.

2. Experiment process

2.1 Experimental framework

The target of the research to improve the process stability of the arc wire additive manufacturing process. The method is as follow: design a set of experimental parameter strategies, and use the set of parameter strategies in the process of manufacturing to reduce the surface topography change of the process results. Because high and low fluctuations make the surface uneven, and the final result will also be uneven. If you continue to stack up, it is easy to cause stacking failure.

In order to more efficiently improve the parameter strategy of the process, we will use reinforcement learning to update the parameter strategy. The initial parameters of this experiment are designed with reference to the process parameters from Liang, Jing-Wei, who is the graduate student of Tsao, Che-Chih, assistant professor of National Tsing Hua University. The changed action parameter is the feeding speed. The feeding speed is 11.4, 11.6, and 11.8 mm/s. The discrete feeding speed can effectively reduce the convergence time. The learning goal is to obtain the optimized feeding parameters for a single line with a length of 50 mm.

Figure 1 is the flow chart of this experiment. First, a set of initial parameter strategies will be designed, and this set will be burned into Arduino. After printing, use the NIR camera to capture continuous images of the experimental results while the platform is moving, and observe its profile. This recorded profile information will be used to describe the state of reinforcement learning. Then feed the profile information to Q learning, Q learning will learn the next set of required profile parameter strategies.

2.2 Image processing

There are four steps in image processing. The first is to stitching the images, because this experiment is to shoot the metal forming results while the platform is moving; the second step is to use a filter to filter out the noise. If you do not do this step and directly detect the edge, the noise will also be detected; the third step is contour detection, using the edge detection operator to detect the height change of the metal forming result; the fourth step is to store the height data as the information needed for reinforcement learning.

We take the photos while the platform moving at a speed of 1.5 mm/s(x-direction), the continuous images after printing are captured at a speed of 40 frame per second. The platform moves at a distance of 50 mm, and the camera captures images at a rate of 40 frames per second, so about 1,300 images are obtained at a time. Figure 2 is the flow chart of image stitching. Because there are nearly 1,300 images, before performing template matching, compare the differences between neighboring images. For example, the result of subtracting the images of number 000001 and number 000006 is greater than the threshold value, and subsequent processing will be performed. Then set two kinds of the region of interest (ROI), which will be used for template matching. Then use the matching results for image stitching to get the final stitching image. The template image will extract a smaller ROI, and the matched image will extract a larger ROI. The ROI image read first is used as a matching template to match the larger ROI image which is loaded later. After successfully matching ROIs of different sizes, a small section of ROI image will be cut. Then this small section will be merged with the previously completed stitched image. Then continue ROI extraction, ROI template matching and image stitching until all images have been read.

Therefore, after the image stitching is completed, the printing contour need to be detected. The detection method is to use the edge detection method to observe change in height. We use three kinds of edge detection method: Otsu, Canny and Scharr edge detection method. The edge detection flowchart is shown in figure 3. The first one uses the threshold of Otsu algorithm to segment the stitching image. The image pixels larger than the threshold are displayed with a pixel value of 255 (white), and the image pixels smaller than the threshold are displayed with a pixel value of 0 (black), so the result image will be displayed as binarized representation; the second one uses the Scharr operator to convolute the stitching image, this operator calculates the X-axis and Y-axis directions, and the result will be a binary edge detection image; The third uses Canny algorithm to detect the edges of the stitching image. Finally, the three results are combined, and the morphology filter is used to filter out the noise points. That is, the surface morphology of the metal forming result is successfully detected.

2.3 Reinforcement learning

The goal of this experiment is to design a set of feeding rate parameter strategies, and use this set of parameter strategies during the manufacturing process to reduce the amount of change in the profile of the printing sample to increase the manufacturing process stability. So that the reinforcement learning output of this experiment will be a set of feeding rate parameter strategies. The main parameters of the process are plasma power, pulse frequency, duty cycle, feeding speed and welding speed. The action to be learned in this experiment is the feeding speed, and the learning state (State) is time, each state is 1 second, and the next second represents a new state. The reward is based on the height data obtained through the edge detection image. Rewards and punishments are given according to the difference between actual and ideal heights.

In this experiment, a high-energy plasma arc beam is used as the heat source for melting the stainless steel wire. In order to make the printed single line reach the desired height, the feeding speed strategy of the middle section is learned first. When the height result printed in the middle part reaches the learning goal, then learning head and tail ends that training is more difficult to try to make the entire single line reach at the target height.

Figure 1 The flow chart of this experiment.

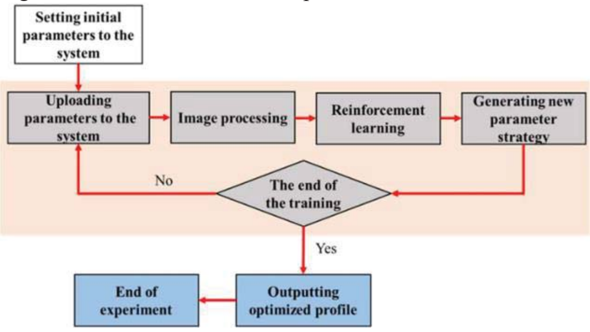


Figure 2 The flow chart of image stitching.

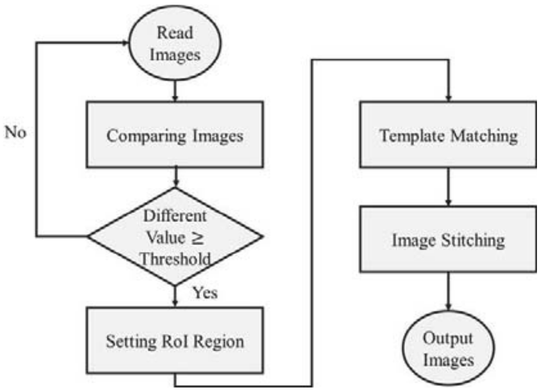
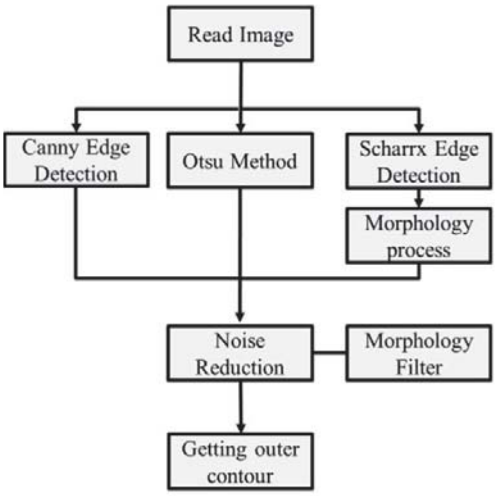


Figure 3 The flow chart of edge detection.



3. Conclusions

In this study, plasma arc welding was used to conduct the fused deposition additive manufacturing experiment of stainless steel wire. In terms of observing the results of stainless steel melt forming, we built a machine vision monitoring system and an image capture system. When the CNC platform moving speed is 1.5 mm/s, the camera can continuously shoot and store images at the same time, which is convenient for quickly recording the forming results of each experiment. With template matching, 1300 continuous images can be spliced quickly and accurately. Because the calculation of the stitching algorithm is not complicated, the correct stitching of a large number of images can be completed in 10 seconds. Then can obtain high-resolution stainless steel fused deposition images, a length and width of about 2640×300 pixels. Furthermore, the actual height information of the printed result can be extracted through the edge detection algorithm, which can be used for training of reinforcement learning model.

Successfully train the feeding parameters through the Q-learning algorithm, and update the reinforcement learning model with the actual printing height per second as the state. Therefore, there are only a few states in each learning episode, and the training can be completed quickly. The interaction between the printed result and the reinforcement learning model, coupled with the specially designed reward function, makes the learning result successfully converge. For example, the middle section of a single line only needs 45 training episodes to learn to reach convergence. The average height is about 2.49 mm, and the surface height difference is only 0.29 mm. The front part of the single line is learned under the condition of preheating for 3 seconds, and successfully reaches convergence in 12 episodes.

As for the stacking of the second layer, it is much easier because o f a very flat first layer forming result.

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