Mechanisms and Machine Science

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Contents

Weld Surface Defect Detection Based on Improved YOLOv7

Tianyu Qi, Quancheng Dong, and Baizhen Li

Abstract Welding is the most economical and effective permanent metal connection method. However, the surface defects caused by various factors, is the quality of welding products cannot be fully guaranteed. In order to improve the efficiency and accuracy of defect detection, this paper proposes a new weld defect detection algorithm based on YOLOv7. Firstly, the DCGAN model is used to enhance the data set of welding defects collected in the industrial field. Secondly, the Repvgg model architecture is analyzed, and the residual branch and 1×1 convolution architecture are added between each module of the high-efficiency layer attention network, and the CBAM attention module is integrated. Finally, Focal-EIoU is used to replace CIoU in the original YOLOv7 network model to optimize the loss function, which accelerates convergence, improves regression accuracy and network robustness. The experimental results show that the improved YOLOv7 network model has the highest average detection accuracy and the lowest model convergence compared with the original network and the classical target detection network model.

Keywords Weld defect detection · YOLOv7 · Data augmentation · Attention mechanism

1 Background

Welding is an indispensable material forming technology in modern industrial manufacturing. It is widely used in aerospace, automobile industry, shipbuilding industry and other fields [1]. In the welding process, due to the limitation of welding conditions and welding technology, various welding defects are often formed such as welding tumors, pores, depressions and splashes. In order to ensure the safety of welding

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products, strict welding quality inspection must be carried out after welding which can find the type and location of welding defects and take targeted solutions [2].

2 Literature Review

The traditional detection method of weld surface defects is usually manual detection. The accuracy of the detection results depends on the experience and concentration of workers. Therefore, the efficiency of manual defect detection is low, and the accuracy is poor. With the increase of labor costs, it has been unable to meet the growing industrial needs [3].

In recent years, computer vision technology has developed rapidly, and defect detection methods using feature extraction have been widely used to distinguish different defects by extracting physical features of defect regions, such as shape, texture and gray distribution [4]. In 2016, Angelo et al. proposed a feature extraction algorithm based on CBIR, which uses multi-layer perceptron to experiment in defect samples of aerospace structures and meets the accuracy requirements of the experiment [5].

With the rapid development of artificial intelligence, deep learning technology has been widely used in industrial production and has achieved excellent performance. In 2017, Girshick et al. proposed the Faster R-CNN model based on the R-CNN and Fast R-CNN models, which solves the problem of repeated calculation when extracting eigenvalues and improves the accuracy and efficiency of target detection [6]. In 2016, Liu proposed a fast multi-class single target detector SSD, whose detection accuracy on PASCAL VOC and COCO datasets is better than Faster-R-CNN [7]. In 2022, Wang proposed a new real-time target detection architecture and corresponding model scaling method and developed a YOLOv7 network model based on this [8].

Although the above network model has high detection accuracy, it is usually used to detect common target objects. Therefore, in order to apply the deep learning to the defect detection of industrial welds, the algorithm model needs to be optimized [9]. In 2023, Zhao et al. proposed a steel surface defect detection RDD-YOLO network based on YOLOv5, which achieved high accuracy on both NEU-DET and GC75-DET datasets [10]. In 2021, Kou et al. developed an end-to-end defect detection model based on YOLOv3 by using the anchor-free feature selection mechanism, and achieved high detection accuracy and speed [11]. In 2022, Based on YOLOv4, Li et al. proposed a new automatic defect detection scheme based on deep learning, and achieved high-precision detection results on the online arc additive manufacturing defect dataset [12].

Deep learning technology requires sufficient samples for training, but it is difficult to collect weld defect samples. Data augmentation technology can be used to expand the number of defect samples [13]. In 2014, Goodfellow et al. proposed a new network to estimate the generative model through the adversarial process, that is, the generative adversarial network (GAN), which is used to generate images close to real samples [14]. In this paper, the deep convolutional generative adversarial network

(DCGAN) proposed by A Radford is used. Compared with the original network, the convolutional layer is used instead of the fully connected layer, which greatly improves the stability of network training and the quality of generated picture samples [15]. Through the above analysis, this paper proposes a weld surface defect detection method based on improved YOLOv7, and solves the problem of insufficient number of weld surface defect samples.

3 Methodology

This paper mainly studies the detection of weld surface defects and realizes the high-precision detection of weld surface defects through deep learning algorithms. Firstly, the data set used for training needs to be created. Secondly, the collected defective data should be expanded to improve the quality of the data set. Finally, an appropriate network model is selected for training. In this paper, the YOLOv7 network model is selected, and by improving its backbone network, and integrating the attention mechanism and changing the loss function, the accuracy of the model is further improved, which make it is more suitable for detecting weld defects.

3.1 Image Acquisition

The collection of images containing defects is the basis for the detection of weld surface defects. The types of defects collected in this study mainly include four types: pores, welds, depressions and splashes. The images are shown in Fig. 1.

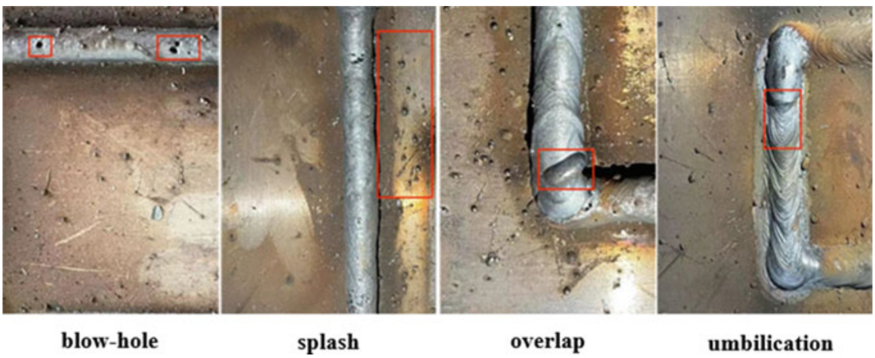


Fig. 1 Image of weld surface defects

3.2 Data Augmentation

Traditional data augmentation. Before that, people usually use traditional image processing techniques to complete the expansion and optimization of data sets. These techniques are simple and easy to implement, but they easily affect the performance of the algorithm.

Generative adversarial networks. The GAN model consists of two parts: the generative network and the discriminative network. The generative network inputs random noise z, while the discriminative network inputs real data x and the samples generated by the generator. Therefore, the essence of GAN can be regarded as a confrontation process between generator and discriminator.

Deep Convolutional Generative Adversarial Network (DCGAN) is a deep learning model derived from convolutional neural network (CNN) based on GAN. The structure of DCGAN is shown in Fig. 2.

Poisson image fusion. The samples generated by DCGAN must be fused with the background image to be used. However, the samples generated by the traditional image fusion method will have the phenomenon that the excessive edges of the defect target and the weld background are abrupt. Therefore, this paper uses the Poisson image fusion method [16]. This method can make the fusion edge transition smooth and optimize the defect target to adapt to the background image of the weld, The optimization process is shown in Fig. 3.

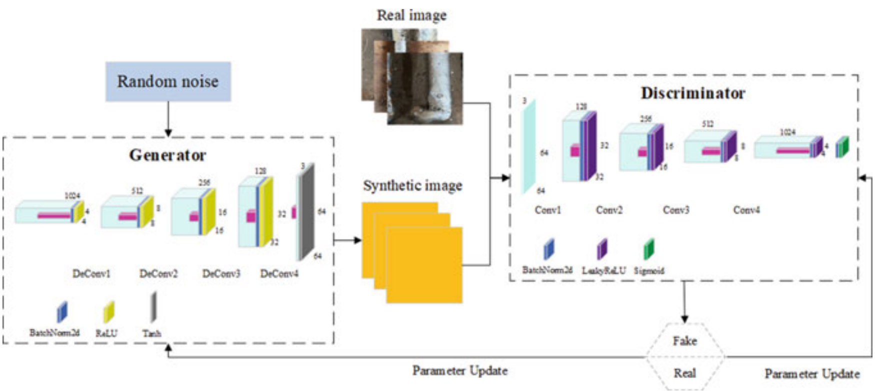


Fig. 2 DCGAN network structure

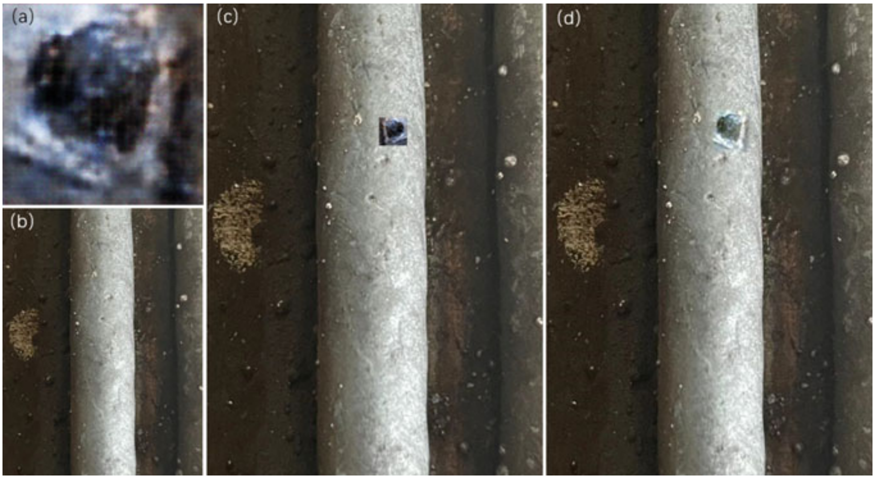


Fig. 3 Poisson fusion optimization process. **a** Defect image generated by GAN; **b** background image; **c** fused defect image by traditional method; **d** fused defect image by Poisson Fusion

3.3 Improvement of YOLOv7 Target Detection Model

YOLOv7 is a synthesizer of the development of YOLO series models. It is one of the more advanced algorithms at present. It integrates a variety of technologies and methods in the field of target detection, which effectively improves the accuracy of target detection and the speed of reasoning and makes the two achieve a good balance.

Improve the ELAN module. The original YOLOv7 algorithm has excellent performance in the detection of common target scenes, which is attributed to its core module-ELAN module. As an efficient network structure, it enables the network to learn more features by controlling the shortest and longest gradient paths. However, when it is directly used for the detection of weld defects, the feature extraction ability will decrease. Therefore: in this paper, the residual structure in the Rep VGG network is introduced. A 1×1 convolution branch and a skip connection branch are added between each convolution module, so that the network can simultaneously utilize the multi-branch model feature extraction ability and the single-channel model inference speed during the training process. The network structure is shown in Fig. 4.

Fusion convolution attention mechanism module. Attention mechanism has been widely used in natural language processing, computer vision and other tasks in recent years, which is an effective means to improve the performance of the model. The collected weld defect samples exhibit phenomena such as small target scale, increased noise, and background interference. The Convolutional Attention Mechanism Module (CBAM) provides a feature attention method that takes into account both channel and spatial dimension weights. The network structure is shown in Fig. 5.

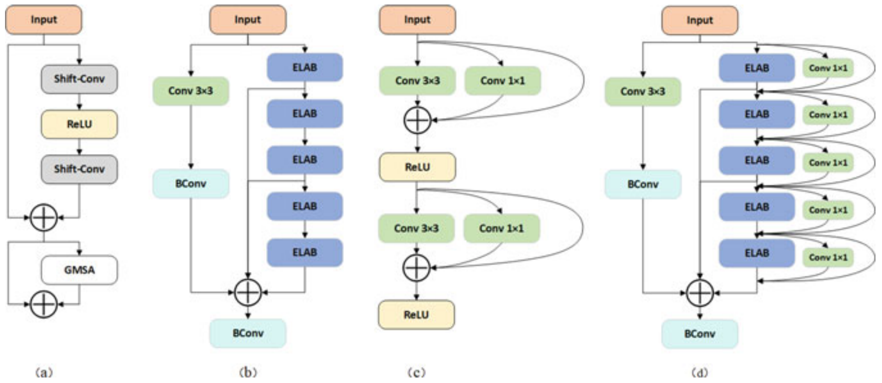


Fig. 4 Improved ELAN structure diagram. **a** ELAB; **b** ELAN; **c** Rep VGG Block; **d** Improved ELAN

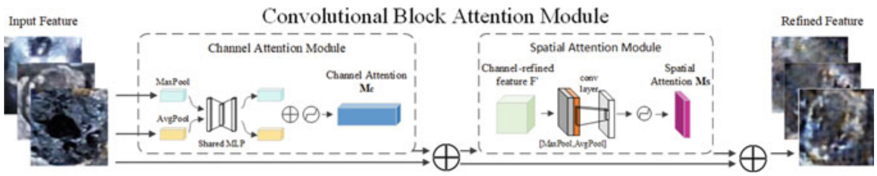


Fig. 5 CBAM network structure

Its function is to make the training model selectively ignore irrelevant information, and improve the recognition accuracy [17].

Loss function replacement. The coordinate regression loss in the YOLOv7 network model is calculated using the CIoU loss function. However, the CIoU loss function has the problem that the width and height cannot increase or decrease at the same time, so the CIoU loss function cannot be stably expressed.In this paper, we use the Focal-EIoU loss function obtained by integrating the EIoU and FocalL1 loss functions, and replace the CIoU loss function in the YOLOv7 network model. The Focal-EIoU loss function theoretically solves the problem that the width and height of the CIoU loss function cannot increase or decrease at the same time and can reduce the negative impact of low-quality data samples on the gradient.

4 Experiments and Results Analysis

4.1 Experimental Platform

The experiment was carried out on the Dell® 5820 T workstation of Windows 10 operating system with a camera of Rindo E3517. The NVIDIA GeForce RTX 3080 GPU processor was used. PyCharm integrated development environment and PyTorch deep learning framework based on Python 3.7.

4.2 Data Set Preparation

Firstly, a total of 999 defect images were obtained through shooting. Secondly, the data augmentation method is used to expand the amount of defect samples to 2816, and the distribution of defect types is shown in Table 1. Figure 6 illustrates that as the number of epochs increases, the image samples generated by the network become more closely resemble the real samples.

Table 1 Amount of weld surface defect

Defect name	Number of original defects	After traditional data augmentation	After DCGAN data augmentation
Blow-hole	316	349	823
Overlap	231	265	671
Umbilication	167	201	557
Splash	285	319	765
All	999	1134	2816

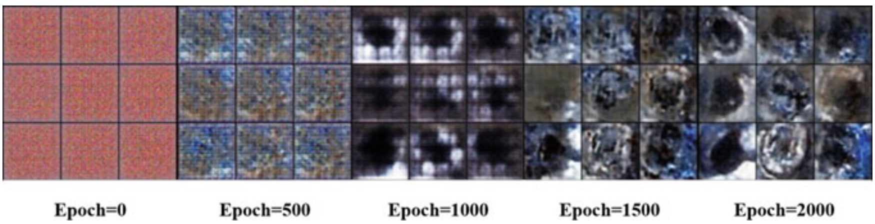


Fig. 6 Defect sample generation process

4.3 Algorithm Comparison and Evaluating Indicator

In addition to the YOLOv7 model, this paper also introduces classical target detection algorithms such as SSD, which are utilized in training the weld surface defect data set for comparison. The main evaluation criteria are the average precision (AP) and the convergence of the loss function.

4.4 Experimental Results and Analysis

The convergence of the loss function before and after the modification of YOLOv7 is verified. As shown in Fig. 7, with the increase in the number of training iterations, both the Focal-EIoU and CIoU loss functions eventually converge to an equilibrium state. However, the Focal-EIoU loss value is smaller and exhibits greater stability compared to the CIoU loss value.

To further validate the superiority of the optimized network model in weld defect detection over other classical algorithms, training and testing were conducted in the same experimental environment. The results are presented in Table 2 and Fig. 8. It can be observed that the improved YOLOv7 network model exhibits better classification performance compared to other classical network models. In fact, the mAP value of

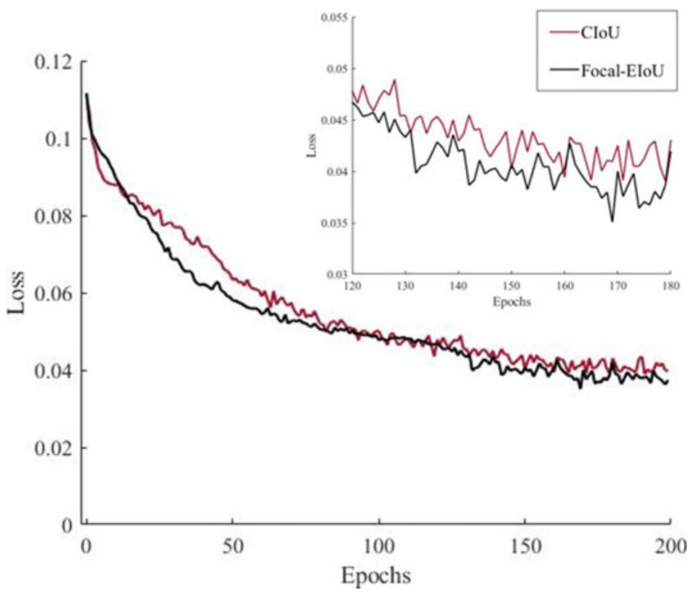
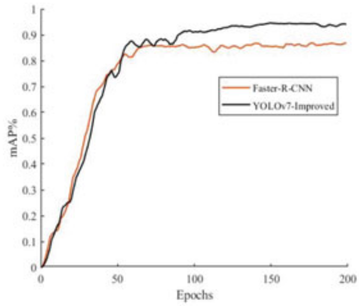


Fig. 7 Comparison of loss function iteration

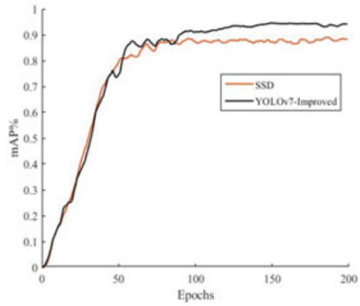
the improved model reached 94.3%, representing a 1.9% increase compared to the original network.

Table 2 Comparison of detection accuracy on different target detection algorithms

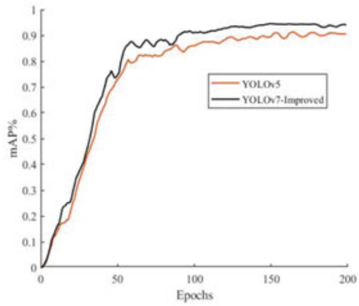
Methods	AP@ 0.5(%)				mAP@ 0.5 (%)
	Blow-hole	Splash	Overlap	Umilication	
Faster R-CNN	89.0	88.4	85.0	84.1	86.6
SSD	90.9	90.3	86.3	85.3	88.2
YOLOv5	93.0	92.2	89.2	88.4	90.7
YOLOv7	94.2	93.1	91.8	90.5	92.4
Improved- YOLOv7	96.7	95.5	93.0	91.9	94.3



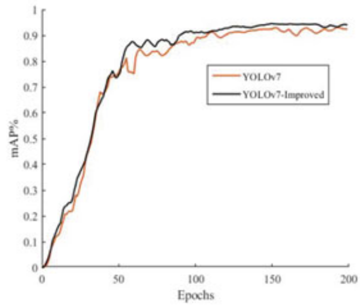
(a). The proposed algorithm is compared with Faster-R-CNN



(b). The proposed algorithm is compared with SSD



(c). The proposed algorithm is compared with YOLOv5



(d). The proposed algorithm is compared with YOLOv7

Fig. 8 The mAP values of the improved model and the classical model

5 Conclusion

In order to achieve high-precision detection of weld surface defects, this paper has carried out a series of research and optimization on the deep learning network model. Firstly, a limited amount of defect sample images is obtained by using the camera. Secondly, the traditional data enhancement method and DCGAN model are used to expand the defect sample data set, which enhances the quality of model training. Finally, by comparing other classical target detection algorithms, the YOLOv7 network model is finally selected, and the jump connection and 1×1 convolution structure are added between each module of the high-efficiency layer aggregation network, so that the model can obtain richer feature information. The convolution attention mechanism module is integrated to make the model ignore irrelevant information. The Focal-EIoU loss function is introduced to improve network detection accuracy. The experimental results show that the detection accuracy of the improved YOLOv7 network model reaches 94.3%, which is better than the original network model and other target detection network models.

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High-Frequency Electrically-Assisted Turning: Application to Aluminium

Ahmad Abdul Kadir, Konstantinos P. Baxevanakis, and Anish Roy

Abstract The manufacturing of engineering alloys has been developing over the years to meet the increasing demand for more efficient techniques and high-quality products. The electrically and ultrasonically-assisted manufacturing processes have been gaining attention due to their potential in reducing energy consumption and improving machined surface qualities. This research explores the capability of the combination of these techniques using continuous and pulsed currents at high frequencies to improve the machinability of metals. Electric current is applied to the workpiece through the cutting tool to harness the electroplastic effect with local softening due to high current density at the cutting zone. The electric current was delivered into the workpiece in continuous and in pulses at different peak current values, with low cutting speed and feed rate. Ultrasonic vibrations were added to amplify the current frequency and reduce the cutting force. Results showed a reduction in cutting force and surface roughness when electric current was applied in pulses at a high peak current. The study showed that electrically-assisted turning has great potential to help improve the machinability of materials.

Keywords Electroplasticity · Electrically-assisted machining · Cutting force · Surface roughness · Ultrasonic vibrations

1 Introduction

Electroplasticity is the enhanced plastic deformation of a metallic material under the influence of a flowing electric current. This effect was discovered in the 1960s [1] and gained resurgence in recent years as a potential alternative towards more efficient and

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effective manufacturing. It can be utilised in many metal forming processes such as forming [2, 3], drawing [4], rolling [5], and also machining such as milling, drilling [6], and turning [7]. Electrically-assisted manufacturing can replace the traditional assisted manufacturing processes that were mostly using heat to help modify the mechanical properties of materials in order to improve their workability [8]. It has been reported that flow stress in electroplastic deformation was reduced when electric current was delivered in continuous form [9, 10]. On the other hand, several studies also showed that current delivered in short pulses exhibited better improvement in materials formability [11]. It was also reported that electropulsed current used in drilling aluminium 7075 and 1045 carbon steel has improved the material machinability [6]. However, to the authors' knowledge, the electrical frequency used in previous studies has been limited to the range available through the respective electrical generators, which were typically well below 2 kHz [12]. The amount of current density applied to the workpiece at the cutting area during electrically-assisted turning processes was also obscured due to the application of electric current on the workpiece while having an isolated cutting tool [12–14]. This paper presents the study of the hybrid manufacturing process of electrically-assisted turning with local softening at the cutting zone which is achieved by applying current to the workpiece directly through the cutting tool. At the same time, an alternative way of delivering pulsed current with a very high frequency (ultrasonic) was made possible by using the setup of a hybrid manufacturing process of ultrasonically-assisted turning. Through the combination of these two hybrid manufacturing processes, the cutting force data and surface quality analyses were carried out to investigate the effectiveness of this new approach in the turning process.

2 Experimental Procedure

2.1 Experimental Setup and Material

The experimental setup for the electrically-assisted turning operation is shown in Fig. 1. The experiment was conducted using a Harrison M300 lathe. The workpiece was covered by cured epoxy resin at both ends so as to be insulated from the lathe machine at the chuck and the tailstock. In addition, any surfaces that were potentially exposed to the chip removed from the workpiece during the turning operation were covered with a rubber mat and electrical gaffer tape to insulate the experimental setup from the rest of the lathe machine components. The electric current was supplied to the setup flowing from the cutting tool into the workpiece (cathode) while a carbon brush clamp (anode) was attached to one end of the rotating workpiece. The electric current was supplied using a Dynatronix (DP20-50-200 XR) power generator which can deliver the highest continuous current of 50 A and a highest peak current of 200 A in pulsed current mode. The turning operation was done in dry conditions without coolants or lubricants.

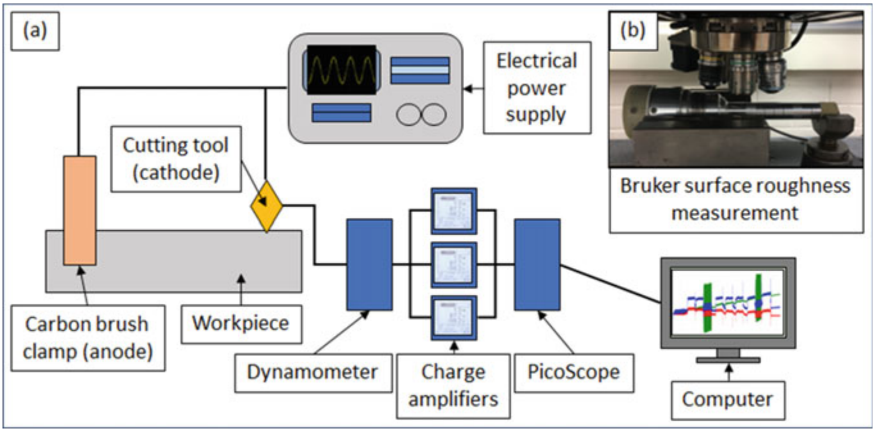

Fig. 1 **a** Experimental setup for electrically and ultrasonically-assisted turning and the data collection for cutting force. **b** Surface roughness measurement

The workpiece used in the experiments was a cylinder of pure aluminium ingot with a diameter of 18 mm. The cutting tool used to machine the workpiece surface was a tungsten carbide insert coated with TiAlN (SECO DNMG150608-MF1 CP500) which had a nose radius of 0.8 mm and a chip breaker groove on the rake face. The cutting tool is suitable for machining with superalloys and is a good electrical conductor.

2.2 *Experimental Parameters*

The electric current was supplied in two forms, i.e., continuously and in pulses. Five machining conditions were investigated during the experiment: (i) conventional turning (CT), (ii) electrically-assisted turning with continuous current (EAT), (iii) electrically-assisted turning with pulsed current (PEAT), (iv) ultrasonically-assisted turning (UAT), and (v) electrically-ultrasonically assisted turning (VEAT). The highest electrical capacity was used in continuous current with 50 A for EAT and VEAT, while in pulsed current mode (PEAT), the same average current of 50 A was used but with varying peak currents of 75, 100, 150 and 200 A. The current densities achieved from the applied electrical parameters were measured by dividing the supplied current by the contact area between the cutting tool tip and the workpiece being cut. At a depth of cut of 0.25 mm, the current densities used were as shown in Table 1. The ultrasonic vibration frequency and amplitude were 20.3 kHz and 4 μm respectively. The frequency value was obtained as resonance at which the transducer that holds the cutting tool vibrates at its natural frequency while the amplitude of vibration was achieved by optimizing the amount of power applied to the piezoelectric component of the transducer. The spindle speed was consistent at 40 rpm and

Table 1 Electrical parameters used in the electrically-assisted turning experiments

Cutting operation	Peak current (A)	Average current (A)	Current density (A/mm^2)
EAT 50 A	50	50	369.60
VEAT 50 A	50	50	369.60
PEAT 75 A	75	50	554.41
PEAT 100 A	100	50	739.21
PEAT 150 A	150	50	1108.81
PEAT 200 A	200	50	1478.42

the feed rate was 0.1 mm/rev for low cutting speed to ensure tool separation from the workpiece during ultrasonic vibration. The cutting length in the feed direction for each machining condition was 10 mm and each turning condition was covered by the cutting tool in approximately 2.5 min.

2.3 Measurement of Cutting Force and Surface Roughness

As shown in Fig. 1a, the cutting force was measured using a force-measuring dynamometer (Kistler 9257B) which converted the force data into charges and was amplified using charge amplifiers (Kistler 5015) in each of the orthogonal cutting directions of tangential, radial, and feed. The data was then visualised using PicoLog software with the help of a data acquisition oscilloscope (PicoScope 4424). The surface roughness of the machined surfaces was measured using a Bruker (NPFlex Elite) optical measurement system as shown in Fig. 1b.

3 Results and Discussion

3.1 Cutting Force

The average real-time cutting force results in the main cutting direction are shown in Fig. 2. The cutting force obtained after conducting EAT was lower than that of CT, which was assisted by the local softening induced by the electric current at the cutting zone. Interestingly, the tangential cutting forces after applying pulsed current in PEAT steadily decreased with increasing peak current, signifying the importance of high energy transmitted intermittently in a short period of time. Moreover, the lowest cutting force was achieved when electric current was delivered with very high frequency aided by the ultrasonic vibration in VEAT, which was even slightly lower than the well-documented low cutting force of UAT.