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The Computer Vision-based Tolerancing Callout Detection Model

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Abstract

Tolerancing symbols play an important role in mechanical product drawings, and they directly determine the functions, mating properties, interchangeability and working life of geometrical products. A symbolic tolerancing callout containing a set of symbols represents a set of pre-ordered operations with attributes. It includes an amount of knowledge from the drawing and standard documents, which is often reconstructed manually by engineers. Thus, at the same time, a symbolic tolerancing callout makes it difficult for the end-user to understand and interpret these callouts manually. To this end, this study puts forward a tolerancing callout detection model via the use of off-the-shelf costumer-grade cameras on current mobile devices for extracting and recognizing tolerancing callout blocks and symbols in them intelligently. This model has four core components: image preprocessing, callout location and extraction, symbol and character segmentation, and deep learning-based symbol recognition. The image preprocessing component is developed to remove the interferences on the target technical drawings through the corresponding morphological methods. This study proposes a novel solution on callout block locations and extractions in callout intensive scenarios since the callout locations and extractions can directly affect the accuracy of symbol and character recognitions. Then, Huff Transform and improved projection methods have been devised to symbol and character segmentations. Finally, this study constructed a convolutional neural network (CNN) to train a symbol recognition model. The experimental results show that the proposed model gains applicability on intelligent callout extractions and the corresponding symbol recognitions.

Keywords: Tolerancing symbols;Callout location and extraction;Symbol and character segmentation;CNN

1. Introduction

Symbols – meaningful graphic entities, are often used as design aids with semantic information in the main pictures in fields of architectural, electronic and mechanical engineering[1]. However, different domains have different symbol sets holding different domain knowledge respectively, which leads to the differences in symbol drawings, the corresponding semantic meanings, and the constraints among them. Thus, recognitions and usages the semantics inherent in specific symbols extracted from various drawings precisely and intelligently become research hotspots in CAx, such as computer-aided design, computer-aided tolerance and computer-aided manufacturing.

In mechanical product drawings, tolerancing symbols can visually express the balance between the production cost and the quality of a mechanical part[2-3], so tolerancing symbols are particularly important in mechanical engineering. A tolerancing callout is a group of tolerancing symbols with predefined attributes and combined semantic information, which are often manually constructed by engineers. Thus, only ISO GPS (Geometrical Product Specification and Verification Standards) experts can read and interpret these symbolic callout blocks unambiguously. To assist the engineers to interpret and understand these callouts, this research devises a novel tolerancing callout detection model by using the off-the-shelf costumer-grade cameras on current mobile devices for

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extracting and recognising tolerancing symbols in callout blocks on technical drawing intelligently.

The organization of the paper is as follows. Section 2 gives a brief review of the previous related works, which leads to further clarify the contributions of this research. Section 3 presents the proposed tolerancing callout detection model in detail. Experiments are demonstrated and evaluated in Section 4. Finally, Section 5 concludes this paper and summarizes the future works.

2. Related work

In 2006, Feng et al. proposed a tolerancing symbol recognition algorithm based on the combination of key graphic features and marked characters[4]. This method starts with a key symbol element search, and then it keeps looking for other elements in its surrounding area according to the construction grammar rules defined by human experiences. At last, this algorithm applies pre-defined symbol and character information to determine whether these elements form a tolerancing callout. The major weakness of this algorithm is that key elements need to be identified in accordance with human experiences, such that it still relies largely on expert knowledge, and has certain level of uncertainty. Furthermore, it also lacks interaction facility for users when the algorithm occurs recognition errors. Later, in 2009, Xie devised a path recognition method based on the constraints of the internal elements of the predefined symbols[5]. It establishes a directed graph for each symbol, and records all the constraint relationships among these graphs, such that a predefined symbol can be matched automatically by searching constraint relationships on the paths of directed graphs. However, the constraint relationships may become too complex to be modelled and searched when the target symbol sets become relatively big. Moreover, these manually defined directed graphs still fail to stand for the efficiency and intelligence requirements in current intelligent manufacturing applications. In 2017, Qi et al. applied the indicator of the aspect ratio of connected areas of characters in the drawings. They devised an optimized connected domain algorithm to locate characters, and then applied a high-level convolutional neural network (CNN) to identify symbols and characters on technical drawings[6]. However, in practices, it is extremely difficult to locate the target areas accurately only based on the structural features of the connected domains on technical drawings due to various symbol and character distortions, such as skew and sticking. Moreover, it hasn't considered the interferences of callout lines and characters during the recognition stage.

Till now, there are few researches on intelligent detections and recognitions of tolerancing callouts on technical drawings.

3. Tolerancing callout detection model

This section presents the proposed tolerancing callout detection model, and it has four major components, i.e., image preprocessing, callout location and extraction, symbol and character segmentation, and deep learning-based symbol recognition. The overall workflow of the tolerancing callout detection model is illustrated in Fig. 1. These four components are discussed in detail in subsections 3.1-3.4.

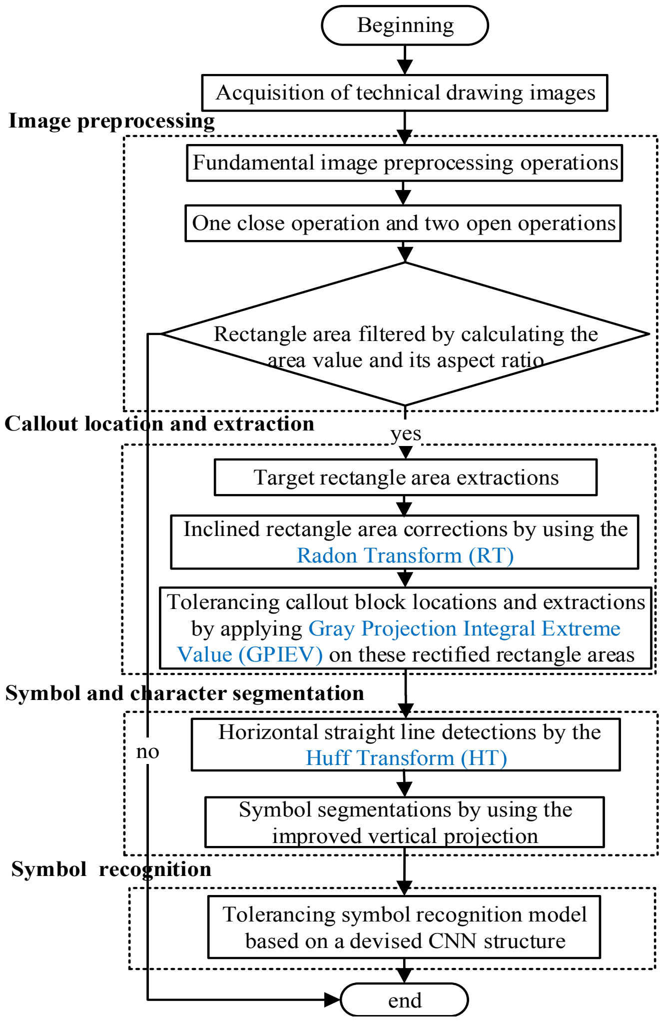

Fig. 1. The overall workflow of the tolerancing callout detection model.

3.1. Image preprocessing

In order to ensure the accuracy of the final tolerancing callout recognition, the original images should be pre-processed before locations, extractions, segmentations and recognitions. The pre-processing of technical drawings is very different from the classic image pre-processing since it contains more interferences, such as part graphics, assist indicators, indicating arrows, and callout lines, etc., see Fig. 2. Thus, this model devised a pre-processing workflow in accordance with the features of technical drawings. It starts with performing fundamental image pre-processing operations, such as grayscale and binarization, edge detection, etc., to simplify the original drawings, and highlight the outlines of the target interests. Then, the morphological processing is applied here to remove the interferences on technical drawings[7-8], such that the rectangle areas of tolerancing callout blocks can be located and extracted more precisely on technical drawing. In this stage, two fundamental operations (i.e., the open operation and close operation) of morphology had been applied on original technical drawings[9]. The open operation, i.e., applying erosion at first and then the dilation, to eliminate small

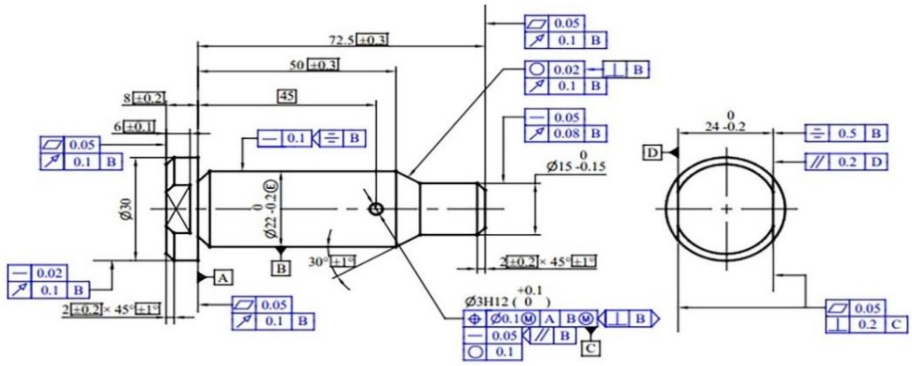

Fig. 2. A technical drawing.

Fig. 3. The rectangle area extractions in the image pre-processing.

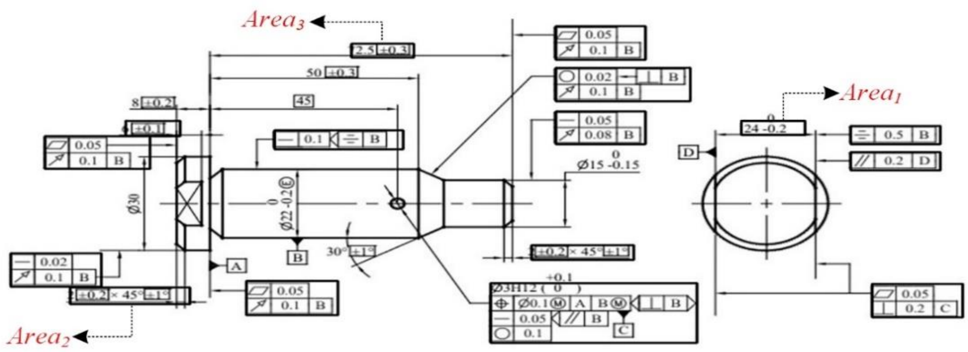

Fig. 4. The outlined black boxes for suspected tolerancing callout blocks on the technical drawing in pre-processing stage.

objects, separate objects at tiny points, and smooth the boundaries of large objects. On the contrary, the close operation, i.e., applying dilation at first and then the erosion, to eliminate small holes, and connect small discontinuities and contour lines. The erosion and dilation can be defined as the following equation (1) and (2) respectively.

$$X \odot Y = \left\{ z \mid (Y)_z \subseteq X \right\} \tag{1}$$

$$X \oplus Y = \left\{ z \mid (Y)_z \cap X \neq \varnothing \right\} \tag{2}$$

In equation (1) and (2), X is the original image and Y is a structural element. The size and shape of the structural element have a great impact on the result of the original image processing. After extensive experiments, we found the optimum parameter setting for the morphological processing: 1) one close operation with the 8 × 12 size of structural element; 2) two open operations with the 1 × 20 and 15 × 20 size of structural element respectively; 3) the shape of the structural element is rectangle area. Fig. 3 demonstrates that all rectangle areas on the target technical drawing can be clearly identified based on the optimum parameter setting (the white areas). Furthermore, other areas that are obviously not part of the tolerancing callout blocks are removed by calculating the rectangle area values and corresponding aspect ratio of the remaining areas. Finally, all rectangle areas that are suspected tolerancing callout blocks are outlined in black boxes in Fig. 4.

3.2. Callout location and extraction

Most of the interferences have been removed during the image pre-processing stage, but some rectangle areas (e.g. $Area_1$ in Fig. 4) that are not tolerancing callout blocks might be identified by using the proposed morphological methods. Thus, this stage focuses on filtering out all these areas, and locating the real areas of tolerance callout blocks. It starts with cutting all suspected areas into a single picture. And then, Radon Transform(RT)[10-11] is applied to rectify the positions of inclined rectangles. Finally, Gray Projection Integral Extreme Value(GPIEV)[12] is used to locate and extract the exact rectangle areas of tolerancing callout blocks.

RT defines that the projection of function $f(x, y)$ is a line integral in a certain direction, and it can be expressed as the following:

$$R(\rho,\theta)=\iint_D f(x,y)\delta(\rho-x\cos\theta-y\sin\theta)dxdy \tag{3}$$

$$\delta(t)=\begin{cases}1 & t=0\\ 0 & t\neq 0\end{cases} \tag{4}$$

In equation (3) and (4), eigenfunction δ is Dirac delta function, ρ is the distance from the projection line to the original point in the (x, y) plane, θ is the angle between the normal of the projection line and the x-axis. The RT method can obtain the slope and offset of the straight line with strong anti-noise capability and fast detection speed. However, RT cannot locate the position of a straight line due to that lines with different starting points have similar peaks for same mapping parameters [13]. For instance, the inclined rectangle in Fig.5 can be rectified by using RT. Firstly, we horizontally project it from angles 0 to π, and combine the horizontal projection histograms obtained from each angle into a matrix. The angle having the maximum value of addition on absolute value of first derivative is selected as the horizontal tilt angle. Similarly, a rectangle is vertically projected to obtain the tilt angle in the vertical direction. Fig.6 demonstrates the rectified position of Fig.5.

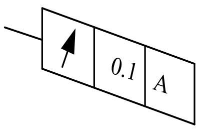

Fig. 5. Inclined tolerancing callout.

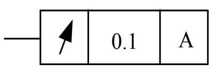

Fig. 6. Rectified tolerancing callout.

If the line is perpendicular to the projection plane, all points on the line are projected into a point on the projection plane, however, if the line is not perpendicular to the projection plane, the projection of all points on the line is still a straight line on the projection plane. Based on this capability, GPIEV in this study can be used to form the outer contour rectangles for a suspected tolerancing callout block area on the corresponding cutting picture by finding two parallel straight lines that have the farthest distances. In this way, suspect areas that do not have any outer contour rectangle or have multiple ones (e.g. $Area_1$ and $Area_2$ in Fig. 4) all are filtered. However, areas having only one outer contour rectangle but without any tolerancing symbol (e.g. $Area_3$ in Fig. 4) are also considered as tolerancing callout blocks in this step.

3.3. Symbol and character segmentation

At this stage, we still don't know how many and what kinds of tolerance symbols and characters and their relative positions are in an extracted tolerancing callout. In order to improve the accuracy of symbol recognition, symbol segmentation is a core step in the proposed model. Huff Transform(HT)[14] and an improved projection method are applied here.

The core idea of HT is the duality of point-line. It converts the two-dimensional plane x-y coordinate into polar coordinate, transforms a straight line in the original image into a point in space, and forms a peak point in the polar coordinate. Thus, this study applies HT to detect the horizontal straight line, and then divide a tolerancing callout block having multiple lines into several single-line tolerancing callouts, see Fig.7. HT also removes the upper and lower white straight lines for each single-line tolerancing callout, see Fig. 8.

Fig. 7. (a) A multi-line tolerancing callout block;

(b) two single-line tolerancing callout.

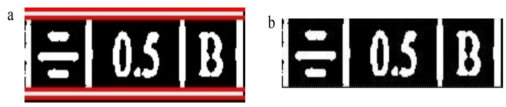

Fig. 8. (a) A callout with two white straight lines;

(b) A tolerancing callout removing the white straight lines.

The classic vertical projection[15] is enough for symbol segmentation on a processed single-line tolerancing callout. This model transfers a tolerancing callout image into a vertical projection histogram that can determine the left and right boundaries of a symbol, see Fig.9. However, there are numeric tolerancing values in a tolerancing callout, and they are often decimals, this will cause the excessive division. Therefore, this model needs to improve the vertical projection method.

This model sets the minimum length of a character to T (after extensive experiments, the T value is set to 30 px). Assuming that the left and right cutting point pixels obtained by projecting and dividing each character are A and B, then it must satisfy the following equation (5).

$$B - A \geq T \tag{5}$$

This model discards the pixel of a point and makes a judgement loop until equation (5) is satisfied when the excessive segmentation happened on the corresponding point (i.e., the equation (5) is unsatisfied on this point). At last, this model performs the vertical projection again to remove the white vertical lines between two segmented callout elements, see Fig.10, and provides a unique number for each segmented symbol or character in a tolerancing callout to record their relative positions.

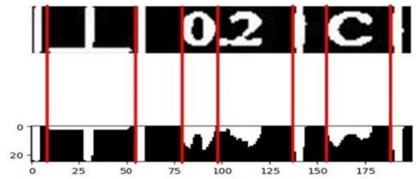

Fig. 9. A vertical projection picture.

Fig. 10. Three segmented callout elements.

More importantly, the symbol and character segmentation can obtain at least two segmented callout elements, so these suspected callout block areas that failed to be filtered out in the callout location and extraction stage can be removed here depending on whether a suspected callout can only get one element (e.g. $Area_3$).

3.4. Deep learning-based symbol recognition

In order to train the CNN, this study found 4200 pictures of tolerancing callout blocks, and Fig.11 demonstrates the constructed CNN structure[16]. Firstly, the image features are automatically extracted from 32 convolution kernels with a size of 3 × 3 and a step size of 1. A max pooling layer chooses the 2 × 2 kernel with a step size of 2. The effect of max pooling layer is to reduce parameters and aggregate features[17-18]. And then, C2 chooses 64 convolutional kernels with a size of 3 × 3 and a step size of 1, and a same max pooling layer. C3 chooses 128 convolutional kernels with a size of 3 × 3. Finally, a fully connected layer is applied to combine features, and output the classification categories.

4. Experiment results and evaluation

4.1. Hardware and Testbed

The experiments of this study are implemented by using Python 3.5 and OpenCV 4.1.2. Table 1 presents the hardware specification. The datasets used in this study had been collected from about 1500 actual technical drawings. The tolerancing symbol datasets for training the CNN contain a total of 14 kinds of tolerancing symbols and a total of about 4,200 extracted symbol pictures. Characters, such as numeric tolerancing values and capital letters are identified by the open source OCR recognition engine − Tesseract[19]. The 14 tolerancing symbols and their predetermined numbers are listed in Table 2.

Table 1. Experimental hardware specification.

Device	Type
CPU	Inter Core i5-9300H
Memory	8GB
Graphics card	NVIDIA GeForce GTX 1650
Operating system	Windows 10

Table 2. Tolerancing symbols and their meanings

Tolerancing symbols	Meaning	Predetermined numbers
—	Straightness	1
▱	Flatness	2
○	Circularity	3
⌭	Cylindricity	4
⌒	Profile of a line	5
⌓	Profile of a surface	6
//	Parallelism	7
⊥	Perpendicularity	8
∠	Angularity	9
⌖	Position	10
◎	Concentricity	11
⌯	Symmetry	12
↗	Circular runout	13
⌰	Total runout	14

4.2. Analysis of experimental results

In 2006, Feng et al. proposed a tolerancing symbol recognition algorithm based on the combination of key graphic features and marked characters. However, this method does not really complete, and it only achieves the location of the tolerancing callout blocks, and it is the second step of the proposed model. Moreover, the extracted tolerancing blocks still have the labeling lines, see Fig.12.

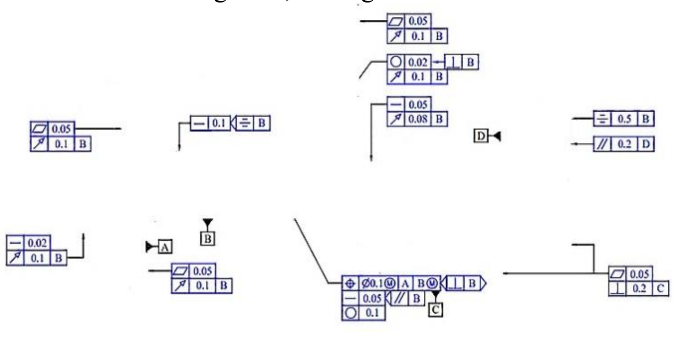

Fig. 12. Feng's results.

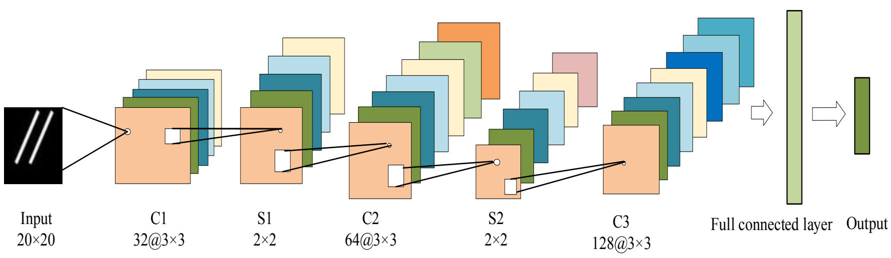

Fig. 11. The devised CNN structure.

This study proposes a tolerancing symbol location and extraction algorithm by combining RT and GPIEV, and the experimental results are shown in Fig. 13.

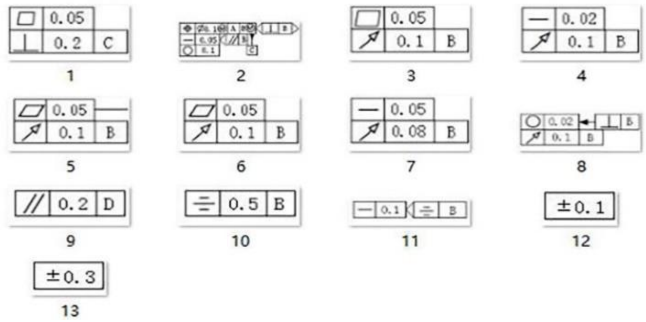

Fig. 13. Experimental results of this study.

In comparison, the proposed method can have better location and extraction results of tolerancing callout blocks. However, areas having only one outer contour rectangle but without any tolerancing symbol are still identified incorrectly in the callout location and extraction stage (e.g. 12 and 13 in Fig.13). This problem can be solved in the segmentation stage by using HT and the improved projection method. In this stage, a unique number is provided for each segmented symbol or character to record their relative positions, see Fig.14.

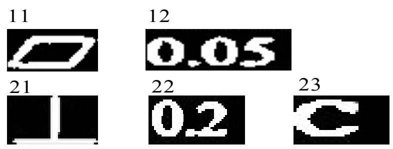

Fig. 14. Number pictures.

The proposed CNN applied 80% of the symbol pictures for training and 20% of the pictures for testing. The accuracy rate of the symbol recognition is about 92%.

5. Conclusions and future work

This paper presents a tolerancing callout detection model, and it has four core components: image preprocessing, callout location and extraction, symbol and character segmentation, and deep learning-based symbol recognition. Experimental results show that the devised model has good applicability and recognition rate on actual technical drawings, so it can serve as a foundation for non-professionals to interpret tolerancing symbols, and support the subsequent realization of the intelligent tolerance specification and verification platform.

One avenue opened up during the study for future exploration is to test this model with other kinds of tolerancing symbols to improve its universality. In addition, this detection model only can recognize the semantics of tolerancing symbols rather than explanations of tolerancing callouts. Future research on explanations of tolerancing callouts will be great value for practitioners.

Acknowledgements

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