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Research paper

Adaptive building engineering component extraction model based on DSOD

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Abstract: With the purpose to bring up the extraction efficiency and accuracy of building construction image component information, the dense block structure and loss function were proposed to optimize the deep supervised object detection algorithm, and an adaptive building construction component extraction model based on this algorithm was constructed. The improved depth-supervised target detection algorithm constructed by the study is validated and found to have an accuracy of 87.4% and a precision of 0.84, which is better than other comparative algorithms. The effectiveness of the adaptive extraction model of building components constructed by the research is verified, and it is found that the extraction error of the model is 9.8%, the value of the loss function is 0.2, and the satisfaction score of the experts is 8.8, and its extraction accuracy and efficiency are better than that of the other models, and it can satisfy the demand for the extraction of components of the construction project. In summary, it can be seen that the adaptive extraction model of building components constructed by the research has excellent information extraction performance, not only can it improve the efficiency of extracting engineering components, but it can also significantly enhance the decision support ability in construction management, optimize resource allocation, reduce risks, and improve the management efficiency of engineering projects. It has a positive contribution to the theory and practice of construction management discipline.

Keywords: adaptive, build extraction, construction engineering, deeply supervised target detection

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1. Introduction

Rapid development of construction engineering has occurred, and the continuous promotion of intelligence, the extraction of adaptive construction engineering components has become significant study direction. The research of adaptive construction engineering component extraction model has significant meaning for making the efficiency higher, reducing the cost and ensure the quality of construction engineering [1, 2]. The traditional component extraction method mainly relies on manual work, but this method has problems such as high labor cost, low efficiency and error-prone [3]. Deeply Supervised Object Detection (DSOD), as a deep learning-based target detection algorithm, has strong feature expression capability and detection accuracy [4]. Compared with traditional target detection algorithms, DSOD can better cope with the target extraction problem in various complex scenes. By introducing the DSOD algorithm, it can be effectively applied to adaptive construction engineering component extraction to improve the automation and accuracy of component extraction [5]. Although various algorithms have been proposed in recent years to improve the efficiency of component information extraction in construction images, these algorithms still face the challenges of low accuracy and efficiency in processing large-scale and complex scenes. In response to this challenge, the study proposes to construct an adaptive construction engineering component extraction model based on DSOD algorithm to improve the efficiency and accuracy of component extraction. Innovatively optimize dense block structures and loss functions, and apply the improved DSOD algorithm to the construction field to improve recognition accuracy and processing speed. The contribution of the study is that it can provide a new solution for automation and intelligence in the field of construction engineering, further make the efficiency of engineering component extraction greater and accuracy, while providing technical support for the construction management field, and assist the construction engineering to save human resources and time costs, improve the management level of engineering projects. The first section of this study introduces the current development status of DSOD algorithm and building engineering component extraction methods. The second section describes the optimization process of DSOD algorithm and constructs an adaptive extraction model for building engineering components based on the improved DSOD algorithm. The third section conducted performance tests on the optimized DSOD algorithm and building component extraction model constructed, evaluating their performance in terms of accuracy, efficiency, and stability. The fourth part is the conclusion and future research directions.

2. Literature review

With the rapid development of science and technology, DSOD algorithms have more and more extensive applications in various fields. In order to highlight target detection, Ji et al. proposed to construct a DSOD feature enhancement network based on branches by combining the global environment perception information in contextual relations, which utilizes self-attention to propagate the global environment information, and empirical experiments on this network found that it achieved better results than other methods on multiple benchmark datasets [6]. To realize adaptive reconstruction of masked images, Ma et al. proposed a DSOD two-stage self-supervised pre-training method, which was validated for effectiveness and found to perform better than traditional methods, and it showed good performance in domain-specific tasks [7]. In order to accurately identify human body movements and postures, Konier et al. proposed to construct a DSOD supported evaluation model for technical evaluation of old buildings. The effectiveness of the model was ultimately verified, and it was found that the action recognition performance of the model was superior to traditional methods [8]. Aiming at the problem of difficulty in correlating historical data with the latest data in multi-task object tracking task, Mishra and Aswathy proposed to construct a target detection model based on DSOD technique, validated the effectiveness of the model, and found that the model has better tracking, and detection performance compared to the traditional multi-task target [9].

The progress of computer technology has also led to the rapid development of other fields, and many technologies have been applied to building components. In order to further improve the detection and localization accuracy of building components, Kumar et al. proposed to construct a framework for the detection of building components based on the silo monitoring technology, and validated the effectiveness of the framework, which was found to be more convenient than the traditional method [10]. In order to analyze the influence of building orientation and process induction on component defects, Stern et al. proposed to validate the performance of engineering components based on fatigue testing, and found that the void distribution and fatigue behavior of components are related to component orientation [11]. To ensure the visual quality of motor vehicle drivers, Esmaeeli et al. proposed to construct a driving route planning model based on digital elevation model and urban road network, and validated the effectiveness of the model, and found that the model can be used to formulate a safety strategy for drivers by combining the geometric features of the building and the road [12]. In order to improve the strength of building components, Szymon et al. analyzed the defect factors related to building components from the perspective of additional load reinforcement of damaged load-bearing frame structures in coal-fired power plants, found that improper installation and environmental conditions were the main influencing factors, and proposed effective solutions. The experimental results verified the effectiveness of the proposed scheme [13].

To summarize, the research on DSOD algorithm is more and more mature, but the research on applying the algorithm in adaptive extraction of building components is still less. Therefore, the research constructs the adaptive component extraction model of construction engineering based on DSOD detection algorithm to the efficiency and accuracy of engineering component extraction.

3. DSOD-based adaptive construction engineering component extraction model construction

In order to improve the efficiency and accuracy of construction engineering components extraction, the study improved the DSOD algorithm and constructed an adaptive building engineering component extraction model based on this algorithm, aiming to solve the challenge of automatic recognition and extraction of components in building engineering images. The study first introduces the improvement of the dense block structure and loss function of the algorithm, and then constructs an adaptive building engineering component extraction model based on the improved DSOD algorithm. The model dynamically adjusts the detection parameters according to the characteristics of the input image. Among them, the adaptive mechanism of this model can ensure that the recognition of components still maintains high accuracy and low error in the ever-changing construction engineering environment, in order to provide an effective technical path for image analysis of construction engineering.

3.1. Improved DSOD building automatic detection algorithm construction

DSOD is a deep learning-based algorithm for automatic building detection, which can realize automatic detection and localization of building components by using a deep convolutional neural network The DSOD algorithm employs multi-scale feature fusion, which can effectively detect buildings of different scales and sizes [14, 15]. In addition, the DSOD algorithm can enable the network to better learn and understand the features of buildings by adding supervised signals at different layers of the network [16]. Therefore, the DSOD algorithm has good application in the field of automatic detection of building components, which can quickly and accurately detect the location and bounding box of the building, and provide the basis for the subsequent identification and classification of building components. The overall structure of the DSOD algorithm is shown in Fig. 1.

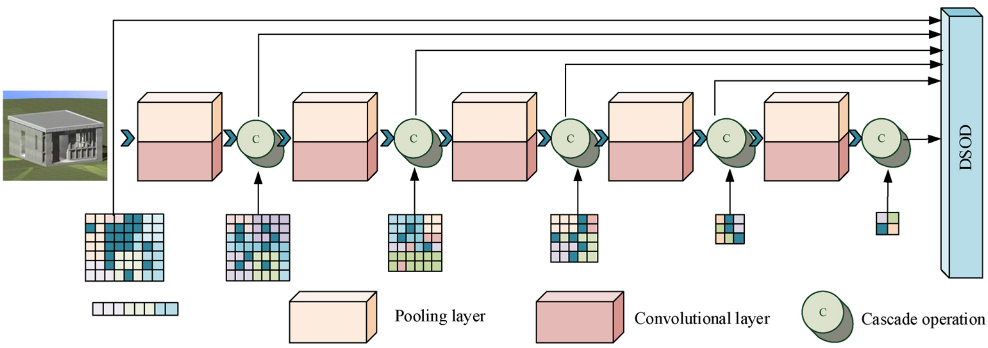


Fig. 1. Overall structure of the DSOD algorithm

As shown in Fig. 1, DSOD consists of two parts, mainly including the feature extraction backbone subnetwork and the prediction multiscale response front segment subnetwork. The main function of the former is image feature extraction and the latter is mainly multi-scale feature layer prediction. Among them, the feature extraction sub-network mainly utilizes the dense connected network (DenseNet) to facilitate the flow of information and the reuse of features. Compared with the traditional convolutional neural network, DenseNet is more compact and has better gradient propagation and feature representation. The DenseNet structure consists of multiple dense blocks, transition layers, unpooled transition layers, convolutional layers, and maximally pooled layers. In the feature extraction subnetwork, the formula for extracting features is shown in Eq. (3.1).

$$x_i = H_i\left([x_0, x_1, \ldots, x_{i-1}]\right) \tag{3.1}$$

In Eq. (3.1), x_0, x_1 and x_1 denote the inputs of the layers before the i th layer; $[x_0, x_1, \ldots, x_{i-1}]$ denotes the cascade of feature mapping. It can be seen that the traditional DSOD algorithm mainly relies on multi-layer supervised learning to improve the learning ability and generalization ability of the algorithm. However, multilayer supervised learning may have problems such as unstable training and vanishing gradient, which in turn leads to the reduction of the convergence speed and accuracy of the algorithm. Therefore, in order to optimize the training strategy of multilevel supervised learning, the study proposes to improve the dense block structure and loss function of DSOD algorithm. The improved dense block structure of DSOD is shown in Fig. 2.

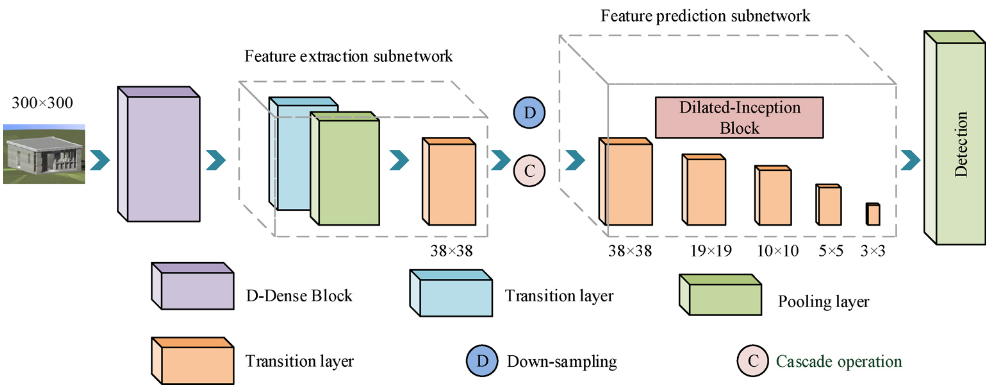


Fig. 2. Improved DSOD structure

As Fig. 2, in the improved feature extraction subnetwork, the input 300×300 image acquires a 38×38 feature layer when it passes through the second dense module. Subsequently, this feature layer passes through the transition pool layer into the inflated convolutional Inception module, which can simultaneously extract features at different scales and facilitate the flow of information and the fusion of feature information through dense connections. In the improved feature prediction sub-network, it is investigated to achieve automatic detection and localization of buildings through multi-scale feature fusion and multi-layer supervised learning. The feature prediction subnetwork fuses the 38×38 feature layer with the 19×19, 10×10, 5×5 and 3×3 feature layers to obtain feature information at different scales. In addition to this, the study also utilizes the depth-separated convolution and channel attention mechanism to improve the dense block structure. The modified dense block structure constructed by the study is shown in Fig. 3.

As shown in Fig. 3, the study improves the dense block structure using normalization, linear activation function and depth separable convolution. In this case, the dense blocks are connected in a densely connected manner. The formula for data normalization is shown in Eq. (3.2).

$$x' = \frac{x - E\,|x|}{\sqrt{Var\,[x]}} \tag{3.2}$$

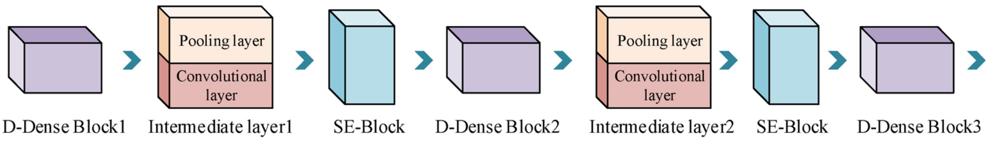


Fig. 3. Improved dense block structure

In Eq. (3.2), x represents the input data; $E\,|x|$ represents the mean operation of the input data; $\sqrt{Var\,[x]}$ represents the standard deviation of the input data. Since data normalization requires transform reconstruction of the input data, this operation may lead to changes in data distribution differences. For the purpose to ensure the robustness of the input data, the study proposes to add the transformation reconstruction parameter to correct it. The correction calculation formula for transform reconstruction is shown in Eq. (3.3).

$$y = \gamma x' + \beta \tag{3.3}$$

In Eq. (3.3), γ and β denote the transform reconstruction correction parameters. Among the linear activation parameters, the activation function used in the study is the Relu function, which is calculated as shown in Eq. (3.4).

$$\mathrm{Relu}(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \tag{3.4}$$

In the dense block information fusion method, the fusion method used in the study is the Concat connection method, which is calculated as shown in Eq. (3.5).

$$Z_{\text{concat}} = \sum_{i=1}^{m} x_i \otimes K_i + \sum_{i=1}^{m} y_i \otimes K_{i+c} \tag{3.5}$$

In Eq. (3.5), x_i and y_i denote the channel inputs of different paths, respectively; m denotes the number of feature layers; K denotes the fusion coefficient; c denotes the number of existing channels; and $\otimes$ denotes the fusion algorithm. In addition, the study also utilizes the attention mechanism module to improve the dense module in order to enhance the feature extraction and discrimination ability of the algorithm. Among them, the attention mechanism module includes three parts: Compression, reward and attention. Among them, the formula of compression is shown in Eq. (3.6).

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i, j) \tag{3.6}$$

In Eq. (3.6), W denotes the mapping; H denotes the output sequence; H denotes the output value vector. The formula of the excitation function is shown in Eq. (3.7).

$$s_c = s\sigma(g(z, W)) = \sigma(\omega_2 \delta(\omega_1 z)) \tag{3.7}$$

In Eq. (3.7), δ denotes the Relu activation function; σ denotes the Sigmoid function; W_1 and W_2 denote the weights of the two full connections; and g denotes the reward coefficient. The incentive module can enhance the attention of the key channel, and its final output is calculated as shown in Eq. (3.8).

$$\overline{x} = F_{\text{scale}}(u_c, s_c) = s_c u_c \tag{3.8}$$

The study improves the feature extraction sub-network and feature prediction sub-network along with the loss function of DSOD to achieve better results in the building detection task. The loss function of DSOD consists of the edge regression loss and the category confidence loss. The weighted sum of its total loss is calculated as shown in Eq. (3.9).

$$L(x, c, l, g) = \frac{1}{N}(L_{\text{conf}}(x, c)) + \alpha L_{\text{loc}}(x, l, g) \tag{3.9}$$

In Eq. (3.9), N denotes the number of positive samples in the default frame; L_{conf} denotes the category confidence loss; α denotes the weights; L_{loc} denotes the border regression loss. The formula of category confidence loss is shown in Eq. (3.10).

$$\begin{cases} L_{\text{conf}}(x, c) = -\sum\limits_{i\in\text{Pos}}^{N} x_{ij}^{p} \log(\hat{c}_i^p) - \sum\limits_{i\in\text{Neg}} \log(\hat{c}_i^0) \\ \hat{c}_i^p = \dfrac{\exp(c_i^p)}{\sum_p (c_i^p)} \end{cases} \tag{3.10}$$

In Eq. (3.10), i and j denote the i-th and j-th default box, respectively; p denotes the type of category. The formula for the border regression loss is shown in Eq. (3.11).

$$L_{\text{loc}}(x, l, g) = -\sum_{i\in\text{Pos}}^{N} \sum_{m\in\{cx,cy,w,h\}} x_{ij}^{k} \text{ smooth } L1(l_i^m - \hat{g}_j^m) \tag{3.11}$$

In Eq. (3.11), (x, y, w, h) denotes the real frame; l_i^m denotes the positional offset between the predicted frame and the default frame; $\hat{g}_j^m$ denotes the positional offset between the real frame and the default frame. The SmoothL1 loss calculation formula for border regression is shown in Eq. (3.12).

$$\text{Smooth}_{L1}(x) = \begin{cases} 0.5x^2, & |x| < 1 \\ |x| - 0.5, & \text{otherwise} \end{cases} \tag{3.12}$$

3.2. Adaptive construction engineering component extraction model construction based on improved DSOD

Traditional methods for component extraction in construction engineering mainly rely on building construction drawings and graphical understanding, or are based on rules and experience for component extraction. These methods often have the problems of strong dependence on rules and experience and the inability to recognize occlusion and fuzzy graphics [17, 18]. For the identification of structural elements, although simple building engineering component extraction models are easy to implement, their accuracy and robustness often cannot meet the requirements of engineering projects for high precision and efficiency. Therefore, a self-adaptive building engineering component extraction model based on the improved DSOD algorithm was constructed and applied to the extraction of building components in building engineering, in order to improve the model's generalization ability and adaptability to complex environments. There are many types of construction engineering components, and the number of their types is directly affected by the classification standard [19]. The research adopts the engineering data exchange standards and civil building design standards of international construction industry entities to ensure that the model can accurately identify and classify the main components of the building [20, 21]. These standards provide a standardized description of the main components of a building, defining building engineering components as beams, columns, slab walls, and stairs. Research is conducted on learning these different component categories through the DSOD algorithm, in order to accurately identify and classify the main building components in practical applications. The schematic diagram and geometric characteristics of each component are shown in Table 1.

Table 1. Schematic diagram and geometric characteristics of the building components

Engineering components	**Conception**	**Geometrical characteristics and their classification**
Beam	Beams are components placed horizontally or inclined to carry the gravity load of the superstructure such as floors and walls.	Rectangular beam, variable section beam, T-shaped beam, channel beam and box girder
Column	Columns are vertically placed components used to withstand the gravity and lateral loads of the structure and to transfer them to the foundation.	Rectangular column, round column, regular triangular column, regular pentagonal column, regular hexagonal column, regular octagonal column and regular dodecagonal column
Plank	The plate is used to cover the horizontal components between the floors, mainly bearing the floor weight and live floor load.	Rectangular, T, trough plates
Wall	Walls are vertically placed structural members used to withstand the gravity and lateral loads of the structure and to provide the stability and stiffness of the building. stiffness of the building.	Rectangular wall, square wall, X wall, L wall, T wall
Stairway	Stairs are a vertical channel connecting the different floors of a building for people to move up and down.	double run stairs, multi-run stairs, double parallel stairs, double corner stairs, cross stairs, double three run stairs, scissors stairs, triangular staircase and corner staircase staircase and corner staircase

As shown in Table 1, there is a wide variety of building foundation components, and the shapes of components in the same category are different. This makes it difficult to accurately and quickly identify and classify building components. Therefore, the study proposes to utilize the improved DSOD detection algorithm to construct the DSOD adaptive building engineering component extraction model to realize the accurate extraction of building foundation components. The adaptive component extraction model based on optimized DSOD algorithm is shown in Fig. 4.

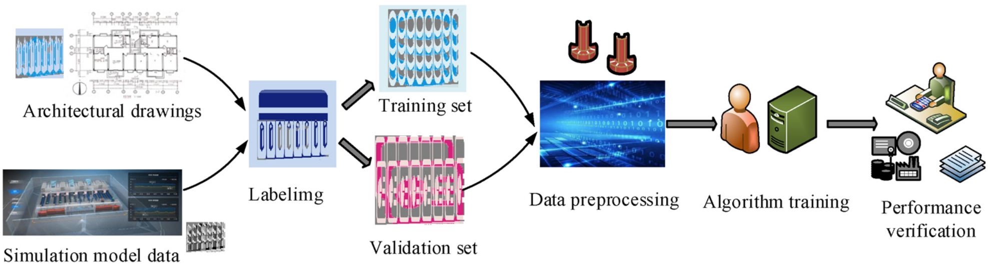


Fig. 4. Adaptive component extraction model based on optimized DSOD algorithm

As shown in Fig. 4, since there is a lack of ready-made construction project build images, the study proposes to utilize construction project drawings and simulation model data to construct a complete component library. After completing the construction of the dataset, the study utilizes Labelimg to label the location and category of the target images, and divides the dataset into a training set and a validation set. Subsequently, the data preprocessing stage was entered. The data preprocessing operations used by the study include dimensional unification of the images, data enhancement, etc., to improve the algorithm's ability to recognize building blocks of different scales and angles. Next, the study uses the constructed dataset to train the improved DSOD algorithm, and optimizes the model parameters and loss function through several iterations. During the training process, the study also utilizes operations such as learning rate decay and regularization to prevent the occurrence of overfitting phenomenon. After completing the training of the algorithm, the study inputs the validation set into the DSOD building component extraction model, and according to the actual needs of construction projects, the study labels the categories of components and evaluates their performance based on the labeling results. The evaluation metrics used in the study include accuracy, recall and F1 value. Subsequently, the study tunes the model according to the evaluation results, such as adjusting the model parameters and increasing the training data, in order to improve the performance of the model. Finally, the model is applied to actual construction projects for component prediction. The image data of the construction project is input, and the automatic detection and extraction of the components is carried out by the model, which outputs the location and category information of the components. The subsequent engineering analysis and design can be further carried out to improve the efficiency and quality of the construction project. The function of the adaptive extraction system for building project components constructed by the research is shown in Fig. 5.

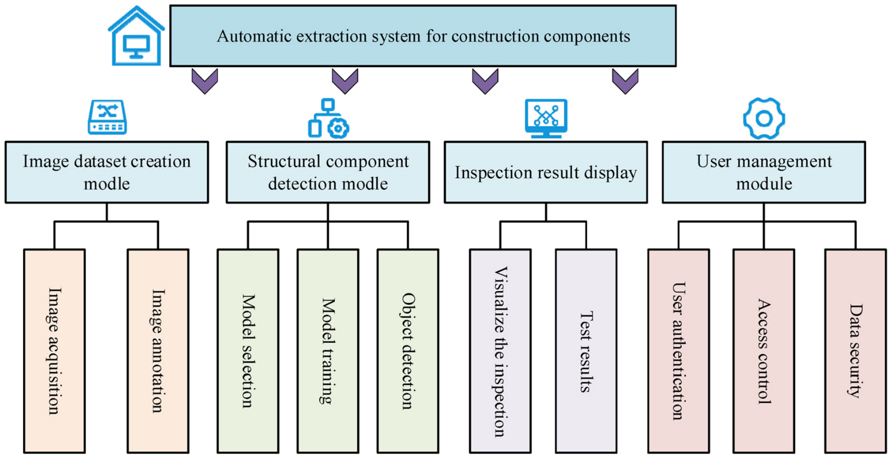


Fig. 5. Functional module of adaptive extraction system for construction engineering components

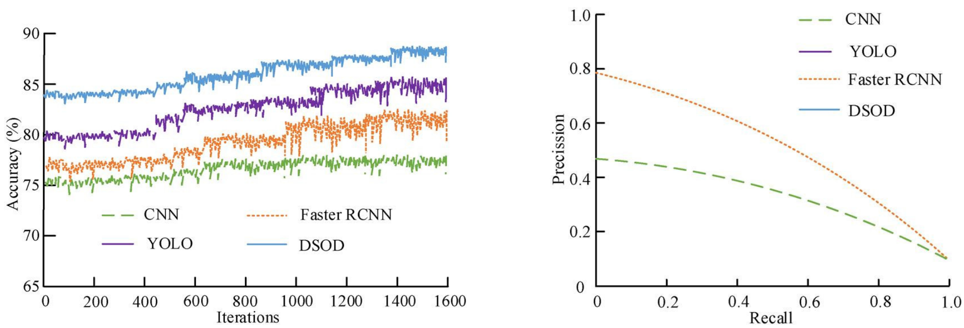
As can be seen from Fig. 5, the proposed adaptive extraction system for building engineering components includes an image dataset creation module, a structural component detection module, a detection result display module and a user management module. The image dataset creation module is mainly used to create image datasets of building engineering components for training and testing, including model generation, scaling, combining, transforming viewpoints and angles of components, etc., in order to obtain diversified image data. And the function of structural component detection module is to use DSOD algorithm to detect and recognize the components of the input construction engineering images, including image preprocessing, feature extraction, target detection and classification and other steps in order to achieve accurate component detection. Detection results display module can visualize the results of component detection to the user, the detection results are mainly in the form of images showing the detected component location, category and confidence and other information, which is convenient for the user to view and analyze. The user management module is used to manage the users of the system, including user registration, login, rights management and other functions, which will involve user authentication, access control, data security and other aspects of the work to ensure the security and reliability of the system. Through the adaptive extraction system of building engineering components constructed by the research, users can easily create image data sets, conduct component detection, and view the detection results.

4. Validation of the effectiveness of DSOD-based adaptive construction engineering component extraction model

To verify the effectiveness of the DSOD detection algorithm and the DSOD construction engineering component extraction model proposed in the study, the study conducts performance comparison experiments and empirical analyses on them respectively.

4.1. Validation of the effectiveness of DSOD construction detection algorithm

To validate the effectiveness of the improved DSOD-based component detection algorithm proposed in the study, performance comparison experiments are conducted using images of building structural components captured in the study as a validation set. The comparison algorithms are YOLO (You Only Look Once), Faster Region-based Convolutional Neural Network (Faster RCNN) and Convolutional Neural Network (CNN) based component detection algorithms. Network (CNN) based component detection algorithms. The performance comparison metrics are accuracy, Precision Recall (PR) curve, F1 value, precision, error and runtime. The experimental environment is Matlab. The comparison results of accuracy and PR curve between DSOD algorithm and other algorithms are shown in the Fig. 6.



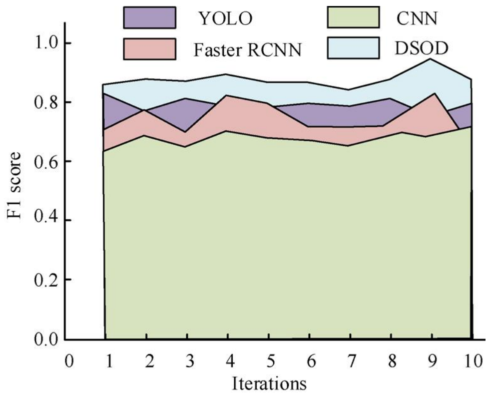
(a) Accuracy results of DSOD algorithm compared to other algorithms

(b) PR curves of DSOD algorithm and other algorithms

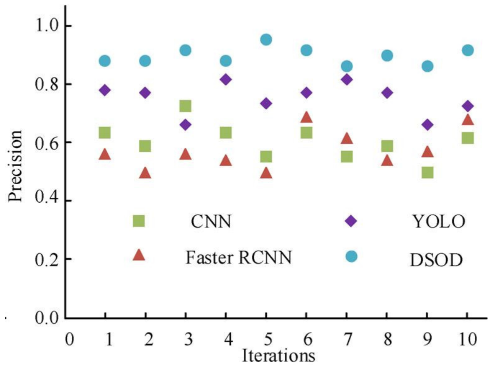
Fig. 6. Comparison of accuracy and PR curve between DSOD algorithm and other algorithms

In Fig. 6(a), as the number of iterations increases, the accuracy value of the selected algorithm also increases. Among them, the accuracy curve of DSOD algorithm is generally higher than YOLO, Faster RCNN, and CNN algorithms. The highest accuracy of the DSOD algorithm is 89.3%, the lowest accuracy is 84.31%, and the average accuracy is 87.4%. In Fig. 6(b), the PR curve of the DSOD algorithm has the largest offline area, with an offline area of 0.78, which is superior to other algorithms. It can be seen that the DSOD algorithm proposed by the research institute has good accuracy and precision performance. The comparison results of F1 values and accuracy between DSOD algorithm and other algorithms are shown in Fig. 7.

In Fig. 7(a), the F1 values of the DSOD algorithm proposed in the study are generally higher than those of YOLO, Faster RCNN, and CNN algorithms. Among them, the F1 value of DSOD algorithm is the highest, with a value of 0.86, which is 0.08 higher than the F1 value of YOLO algorithm. In Fig. 7(b), the DSOD algorithm has the highest accuracy, with a value of 0.84, which is 0.04 higher than the YOLO algorithm. It can be seen that the detection performance of the DSOD algorithm proposed by the research institute is superior to other detection algorithms, and has certain practical application value. The comparison results of error and running time between DSOD algorithm and other algorithms are shown in Fig. 8.



(a) F1 results of DSOD algorithm and other algorithms



(b) Accuracy results of DSOD algorithm compared to other algorithms

Fig. 7. Comparison results of F1 value and accuracy between DSOD algorithm and other algorithms

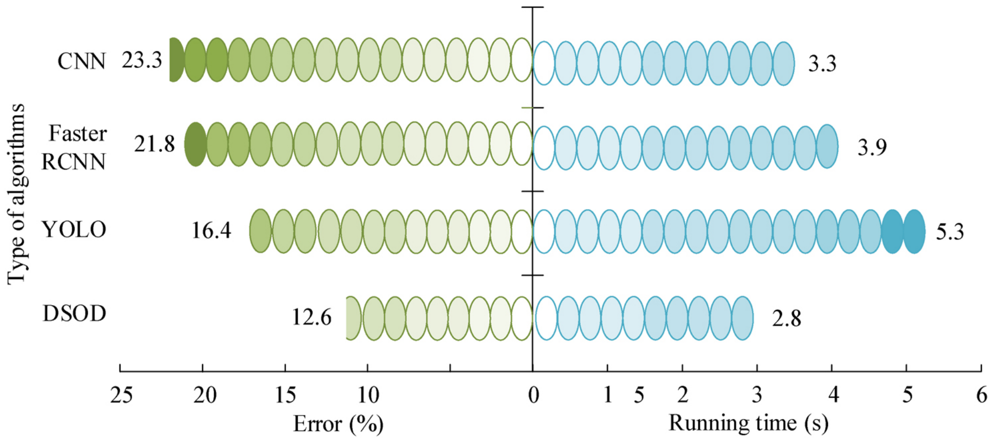
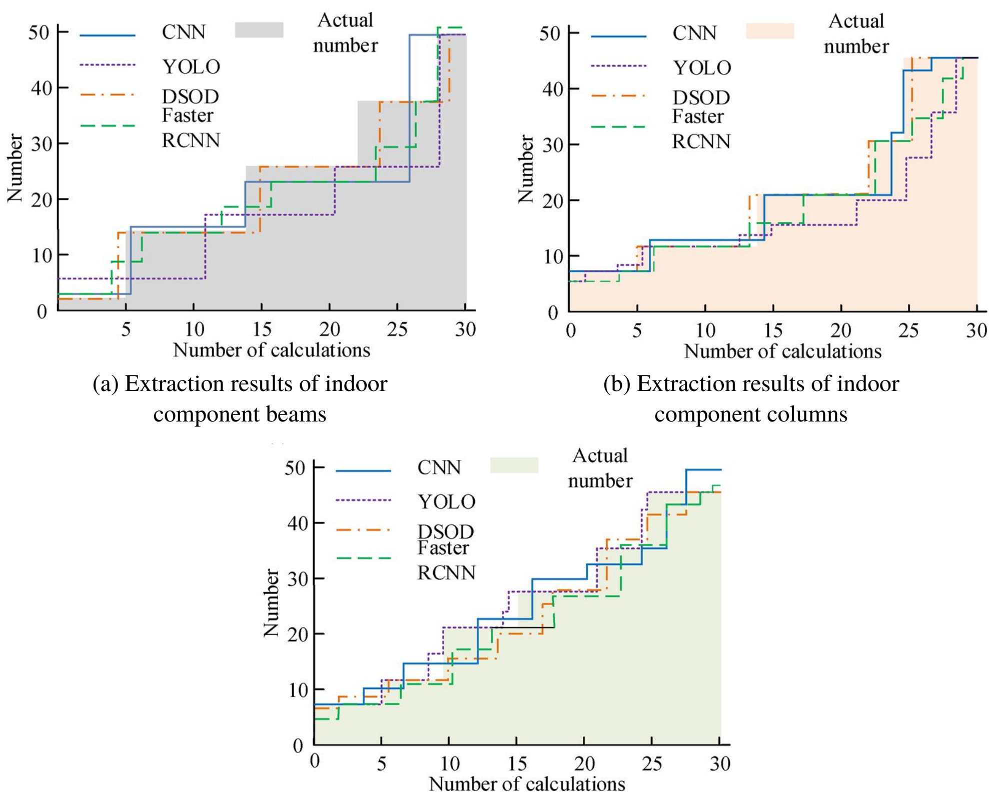


Fig. 8. Comparison results of error and running time between DSOD algorithm and other algorithms

As shown in Fig. 8, the error value of the proposed DSOD algorithm is 12.6%, while the error values of YOLO, Faster RCNN, and CNN algorithms are 16.4%, 21.8%, and 23.3%, respectively, which are lower than the error values of other detection algorithms. In addition, in the speed performance testing experiment, the running time of the DSOD algorithm was 2.8 seconds, while the running times of other detection algorithms were 5.3 seconds, 3.9 seconds, and 3.3 seconds, which was 0.5 seconds shorter than the CNN algorithm. It can be seen that the detection error and detection efficiency performance of DSOD algorithm are higher than other comparative algorithms, which is very helpful for the detection of building components.

4.2. Performance testing of adaptive construction engineering component extraction model for DSOD

After completing the validation of the effectiveness of the DSOD target detection algorithm, the study empirically analyzes the building component extraction model based on the DSOD target detection algorithm. The dataset used for this empirical analysis experiment is the building components dataset collected by the study. The comparison models are the building extraction models based on CNN target detection algorithm, Faster RCNN target detection algorithm, Faster RCNN target detection algorithm and YOLO target detection algorithm. The performance comparison metrics are construct extraction accuracy, error, and loss function value. In addition, in order to explore the practical application effect of the model, the study also conducts a satisfaction score. The experimental environment is a server with CPU (Intel®Core™i7-9700 CPU @ 3.00 GHz ×8) and Matlab simulation platform. The results of the comparison of the accuracy of extraction of member beams, columns and slabs for each comparison model are shown in Fig. 9.



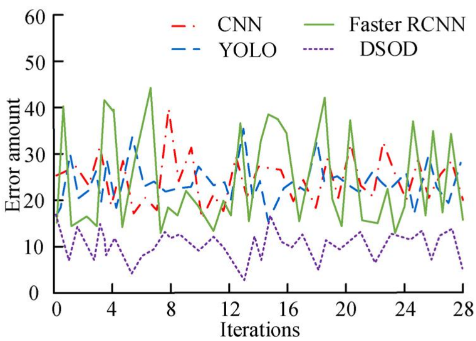
(a) Extraction results of indoor component beams

(b) Extraction results of indoor component columns

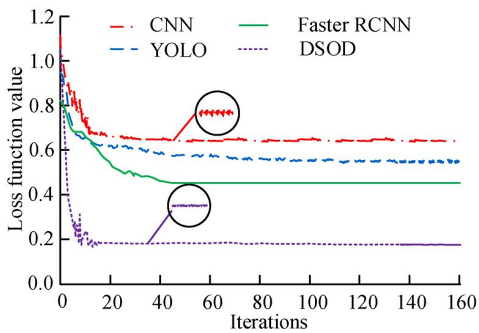
(c) Extraction results of indoor component boards

Fig. 9. Comparison results of the component extraction accuracy of each model

Fig. 9(a) shows the results of the comparison of the extraction accuracy of each model for building component beams, as shown in Fig. 9(a), the proposed DSOD building component extraction model of the study is better than the other models in building component beams, and its target extraction curves are better fitted to the actual values, with an accuracy of up to 90.1%. Fig. 9(b) gives the information about the extraction accuracy of each model for building component columns, as shown in Fig. 9(b) The DSOD building component extraction model proposed in the study is better than other models in building component beams, with an accuracy of up to 91.4%. Fig. 9(c) shows the results of the comparison of the extraction accuracy of each model for the building component plate, as shown in Fig. 9(c), the proposed DSOD building component extraction model of the research is better than the other models in the building component plate, with an accuracy of up to 89.4%. Summarizing the results, it can be seen that the accuracy performance of the research-proposed building component extraction model based on DSOD target detection algorithm is better than other models. The comparison results of the target extraction error values and loss function values of each comparison model are shown in Fig. 10.



(a) Comparison results of the target extraction error value of each comparison model



(b) Comparison results of the loss function value of each comparison model

Fig. 10. Comparison results of the target extraction error value and the loss function value of each comparison model

Fig. 10(a) shows the results of the error value comparison of each comparison model. As shown in Fig. 10(a), the error value curve of the proposed DSOD building component target extraction model is overall lower than that of other comparison models, and its average error is 9.8%, which is lower than that of other target extraction models. And the fluctuation amplitude of the error curve of this model is smaller than other comparative models, with better stability. Fig. 10(b) shows the results of the comparison of the loss function values of the comparison models, as shown in Fig. 10(b), the loss function value of each model decreases with the increase of the number of iterations until it stabilizes. However, the loss function value of the proposed DSOD building component target extraction model is overall lower than that of the other comparative models, which is 0.2. Summarizing the above results, it can be seen that the stability and reliability performance of the proposed DSOD building component target extraction model is better than that of the other models. The study also conducted a satisfaction survey using expert ratings. The results of the satisfaction survey for each model are shown in Fig. 11.

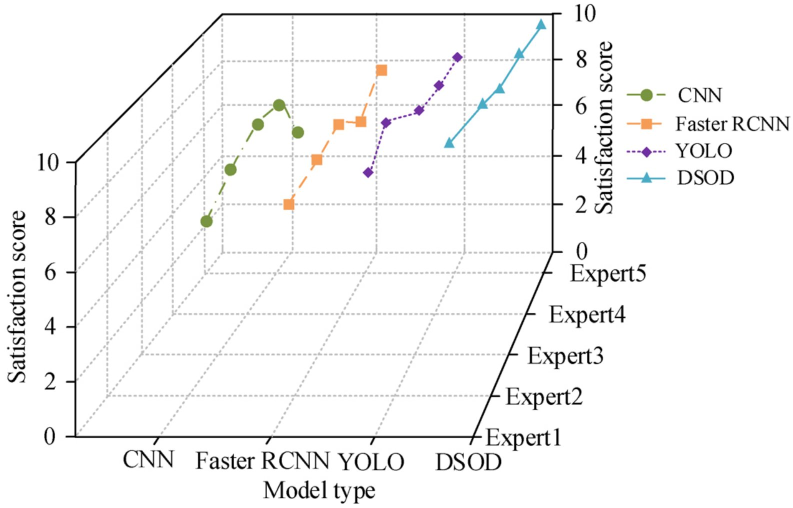


Fig. 11. Satisfaction evaluation results of each comparison model

As shown in Fig. 11, in the satisfaction evaluation, the proposed DSOD target detection algorithm gives an outcome of the highest satisfaction, with an average satisfaction score of 8.8, and all expert users' ratings are above 8, which indicates that the design results of the model can meet the actual needs of building component extraction, and further proves the validity of the automatic building component extraction model based on the DSOD target detection algorithm.

5. Conclusions

With the rapid development of computer technology, in order to realize the automatic recognition and extraction of building components in construction engineering images, the study proposes to improve the dense block structure and the loss function of DSOD algorithm, to construct the improved DSOD detection algorithm, and to construct the adaptive construction engineering component extraction model based on this algorithm. The effectiveness of the DSOD detection algorithm and the adaptive extraction model of building components constructed by the research is verified, and it is found that the accuracy of DSOD algorithm is 87.4%, the area under the line of the PR curve is 0.78, the F1 value is 0.86, the precision is 0.84, the error value is 12.6%, and the running time is 2.8s, which is better than other algorithms. The effectiveness of the DSOD adaptive extraction model for building components was verified and found to have an accuracy of up to 91.4% in building components with an average error of 9.8% and a loss function value of 0.2, which is better than other models. In addition, the study also conducted a satisfaction survey of the model and found that it had an average satisfaction score of 8.8, which is a higher satisfaction score than the other compared models. In summary of the results, the adaptive extraction model of building components based on DSOD algorithm constructed by the study shows excellent performance in building component recognition, the accuracy of risk prediction and resource allocation has been improved, as well as the overall quality and efficiency of construction project management. The application of this model helps with rapid decision-making in construction management. However, there are still some limitations in the study, and the number of samples and types of construction image datasets constructed in the study are limited, which affects the generalization ability and robustness of the model to a certain extent. In the future, more construction engineering image data can be added to construct the dataset.

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