ISSN 2616-5775 Vol. 6, Issue 9: 55-62, DOI: 10.25236/AJCIS.2023.060909

Computer Area Localization Algorithm Based on FCN

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Abstract: *Computer area localization algorithms are an important area of research aimed at accurately determining object locations. However, traditional regional localization algorithms have certain limitations in the face of complex scenes and changing environments. To overcome these problems, this paper proposes a region localization algorithm based on a FCN. Through experimental evaluation and data analysis, this paper finds that the regional localization algorithm based on FCN has obvious advantages over traditional algorithms. Experimental results show that the algorithm shows better performance in terms of accuracy rate and error distance. Specifically, the algorithm based on the FCN has achieved a positioning accuracy of 70%, which is much higher than the 30% of the traditional algorithm. In this paper, its superiority in localization tasks is verified through experimental evaluation and data analysis. The algorithm not only improves the accuracy and precision of positioning, but also has strong robustness and generalization ability. This provides a more accurate and reliable positioning solution for practical application scenarios, and provides strong support for the development of autonomous driving, intelligent navigation and other fields.*

Keywords: *FCN, Region Localization Algorithm, Algorithm Design, Evaluation Index*

1. Introduction

With the rapid development of computer vision and deep learning technology, people's demand for accurately determining the target position is becoming more and more urgent [1]. Area localization algorithms can play an important role in various fields, such as autonomous driving, intelligent navigation, UAV localization, etc. [2].

In the past few decades, researchers have proposed various regional localization algorithms. Traditional algorithms are usually based on feature extraction and matching methods, such as SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features) and so on [3]. However, these traditional algorithms have certain limitations when dealing with complex scenes and changing environments, such as high sensitivity to occlusion, illumination changes, etc. [4]. Therefore, researchers began to explore more advanced methods to improve the performance of regional localization algorithms. Cossette C researched the relative position estimation between two UWB (Ultra-Wideband) devices, and found that the method of deep learning has achieved remarkable results in regional positioning tasks [5]. Bo L I found that the neural network can promote the positioning of industrial robots through the experiment of neural network compensation for industrial robot positioning errors [6]. However, these methods usually require a large amount of labeled data and complex network structures, and have high demands on computing resources.

Aiming at the above problems, this paper proposes a region localization algorithm based on FCN. Different from traditional convolutional neural networks, FCNs are able to preserve the spatial information of input images to achieve pixel-level predictions. Through experimental evaluation and data analysis, this paper verifies the superiority of the algorithm based on FCN in localization tasks, and discusses its potential and significance in practical applications.

2. Computer Area Positioning Algorithm

2.1. Overview of Regional Positioning Algorithms

Regional localization is one of the important contents of computer vision research, and its main purpose is to precisely locate specific regions or targets through image and video information [7-8]. The area positioning algorithm is to locate a specific object according to the characteristics of different areas in the image. The algorithm extracts the features of different regions through various methods such as image edge detection, mathematical morphology processing, and region growth, and applies them to the positioning of objects in the image [9]. This paper introduces several commonly used regional positioning methods, such as Canny operator edge detection method, Harr operator texture analysis method, LBP operator template matching method, etc. These three algorithms can be applied to regional positioning, but they need to be combined with other methods to improve the accuracy and efficiency of positioning [10]. The research results of this project will have broad application prospects in the fields of intelligent transportation, unmanned driving, intelligent monitoring, and virtual reality.

2.2. Traditional Regional Positioning Algorithm

Traditional regional positioning methods are mainly based on manually designed feature extractors and machine learning models, relying on expert experience and a large amount of manually labeled data. Although the traditional regional positioning method has a good effect on simple scenes, it often produces large errors for complex backgrounds, illumination changes, object occlusions, etc. [11]. In addition, traditional feature extraction and classifiers require manual design, which has certain subjectivity and dependence [12]. These two methods can be applied to a variety of scenarios, but due to factors such as complex images and large background noise, these two methods have the problem of inaccurate or even impossible positioning in practical applications [13]. In recent years, with the rise of deep learning technology, regional localization methods based on deep neural networks have made breakthroughs in this area. In particular, the introduction of the fully convolutional networks (FCN) enables the region localization algorithm to obtain region location information from images without manually designing feature extractors [14].

2.3. Fully Convolutional Network

As a special neural network structure, FCN is widely used in image processing tasks such as image segmentation, object detection, and region localization [15]. When traditional convolutional neural networks are used for image classification, they generally consist of convolutional layers, pooling layers, and fully connected layers. However, in pixel-level tasks such as image segmentation, traditional convolutional neural network structures cannot directly provide pixel-level prediction results [16]. There are three types of convolutional layers commonly used in FCN: general convolutional layers, deconvolutional layers, and pooling layers. The conventional convolution layer is used to extract features from the image, the deconvolution layer is used to restore the feature map, and the pooling layer is used to reduce the dimensionality of the feature map. By stacking and combining layers, the entire convolutional neural network can perform pixel-level predictions on images [17].

The FCN can effectively capture the spatial information and contextual relationship of the image, and can provide accurate prediction results at the pixel level [18]. On this basis, multi-layer features are fused using methods such as skip connections to improve the accuracy of image segmentation and the ability to preserve details [19]. The core idea is: first input the image into the neural network, extract the image features through a series of convolution pool operations, and then resample the features, and finally obtain the pixel-level regional positioning results. This end-to-end training method enables the algorithm to automatically learn local and global features in the image, thereby achieving more precise region localization [20].

3. Computer Area Positioning Algorithm Based on FCN

3.1. Network Framework Design

This paper adopts a FCN model based on the U-Net network, and applies it to the FCN model to realize a fine computerized area positioning algorithm. The U-Net framework is widely used in image segmentation, pixel-level prediction and other fields due to its unique advantages. This algorithm was

ISSN 2616-5775 Vol. 6, Issue 9: 55-62, DOI: 10.25236/AJCIS.2023.060909

first applied to biomedical image segmentation, and has been widely used in other fields. Its architecture is composed of a symmetrical encoder (downstream sampling channel) and a decoder (upstream sampling channel), and information transmission is realized by jumping.

On the encoding side, a series of convolutional and pooling layers are used to downsample the input image, and gradually reduce the size of the feature map and the number of channels. These operations are beneficial to both the extraction of high-level features and the extraction of global contextual information. In the decoding part, the method of combining the deconvolution layer and the convolution layer is used to gradually restore the size and number of channels of the feature image. This method can not only effectively restore the size of the original image, but also effectively protect the details of the image. The core feature of this method is to use the skip connection method to connect the feature maps of different levels in the encoder to the corresponding feature maps in the decoder. The algorithm combines low-level detail information and high-level semantic information, improves the accuracy of segmentation results, and effectively maintains image detail information. Skip connections help information transfer between different layers, so it can improve the accuracy of segmentation results and alleviate the problem of gradient disappearance.

The U-Net architecture was chosen because U-Net has better performance in image segmentation. The network's compiler structure and skip-link design enable it to capture not only the overall context of the image, but also the local details of the image. The cross-layer connection can realize the cross-layer transfer of information, improve the accuracy of the segmentation results, and also alleviate the problem of gradient loss. In addition, the architecture of U-Net is relatively simple, easy to train, easy to understand, and can be adapted to data sets of different sizes.

3.2. Training Process

For the convenience of training, this paper adopts the method of collecting data by itself, and collects image data sets containing regional positioning objects. Marking each image, and generate corresponding marks according to the characteristics of the target area. Annotation can be done manually or assisted by a semi-automatic or automatic image segmenter. In the data preprocessing stage, a new image preprocessing method is proposed in this paper, that is, by resizing, cropping and normalizing the image to meet the requirements of the network input. In addition, we will also use random rotation, translation, scaling, flipping and other data enhancement methods to increase the diversity of data and improve the generalization ability of the model. During training, it is very important to choose the loss function correctly. The Dice loss is more focused on the measurement of similarity, especially in the case of imbalanced categories. According to the characteristics of the regional positioning data set, this paper selects the Diess loss function to optimize the model. In the training process, the determination of hyperparameters is a very important link. In addition, this project will also introduce a learning rate decay strategy to improve the convergence of the model by gradually reducing the learning rate, thereby improving the generalization ability and robustness of the model.

3.3. Data Collection and Preprocessing

In this paper, the method of self-collecting data is used to construct an image dataset containing regionally located objects. During the data collection process, we collected a large number of image samples to ensure the diversity and representativeness of the dataset. These image samples contain localized objects in our region of interest. For each image, a marking operation is performed, that is, a corresponding mark is generated according to the characteristics of the target area. The generation of markers is assisted by a semi-automatic or automated image segmenter, and the target area is marked by manually drawing a bounding box or similar methods to improve the efficiency and accuracy of labeling. In the data preprocessing stage, this paper proposes a new image preprocessing method to ensure that the input image meets the requirements of the network. First, we resize the image, scaling it to an appropriate size to meet the input requirements of the network. This can be achieved by adjusting the width and height of the image, keeping the aspect ratio of the image unchanged. Second, we cut the image to extract the region of interest in the image. This can be done by intercepting the partial image where the target area is located in the image according to the location information of the marker. Doing so can reduce irrelevant background information and improve the model's attention to target regions. Finally, we normalize the image, scaling the pixel values to a fixed range. This can be done by dividing the pixel value by the maximum pixel value or using other normalization methods. The normalization operation helps to improve the stability of the data and the training effect of the model. Through the steps of data collection and preprocessing, we obtained a set of labeled and preprocessed image

ISSN 2616-5775 Vol. 6, Issue 9: 55-62, DOI: 10.25236/AJCIS.2023.060909

datasets for training a computer region localization algorithm based on a FCN. Such datasets can provide rich information and accurate labels, providing a reliable basis for model learning and training.

3.4. Evaluation Indicators

The evaluation metrics in this paper include precision, recall and F1 score. The accuracy rate measures the ability of the algorithm to correctly locate the target, the recall rate measures the ability of the algorithm to detect the target, and the F1 indicator comprehensively considers the accuracy rate and recall rate. Table 1 is a description of the evaluation indicators.

Table 1: Evaluation indicators and descriptions

Evaluation indicators	Definition
Accuracy rate	Number of correctly targeted targets/Total location attempts
Recall	Number of correctly targeted targets/The ratio of the total number of actual targets
F1 score	2 × (Accuracy rate × Recall) / (Accuracy rate + Recall)

4. Experimental Data and Result Analysis

4.1. Experimental Data

This paper organizes the collected traditional regional positioning algorithm data to obtain Figure 1. The computer regional positioning algorithm data of the FCN used in this paper is shown in Figure 2, and Figure 3 is the actual positioning data. Among them, this article organizes the obtained positioning data into the form of coordinates, the abscissa is marked as X, and the ordinate is marked as Y.

By analyzing the data in Figure 1, Figure 2 and Figure 3, we can draw the following conclusions: Compared with the traditional area positioning algorithm, the computer area positioning algorithm based on the FCN is more accurate in positioning tasks, and its error distance is relatively small in the case of positioning errors. However, we also observed some exceptions, especially in the second set of data, where the traditional region localization algorithm achieved completely accurate localization results, while the algorithm based on the FCN showed inaccurate localization. This finding illustrates the difference in performance of the two algorithms in different situations. Traditional regional localization algorithms may have better adaptability and accuracy in certain specific scenes or data sets, while algorithms based on FCN may have certain limitations for certain specific image features or localization scenarios. Such data analysis results provide us with valuable information about the localization performance of these two algorithms. Further research and analysis of these differences can help us deeply understand the strengths and limitations of algorithms, and provide guidance and inspiration for improving the performance of algorithms.

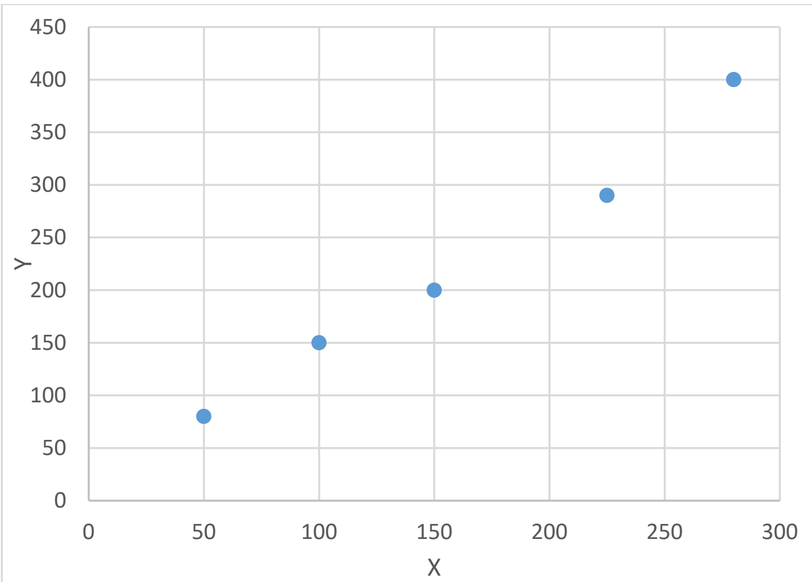

Figure 1: Traditional area positioning algorithm data

ISSN 2616-5775 Vol. 6, Issue 9: 55-62, DOI: 10.25236/AJCIS.2023.060909

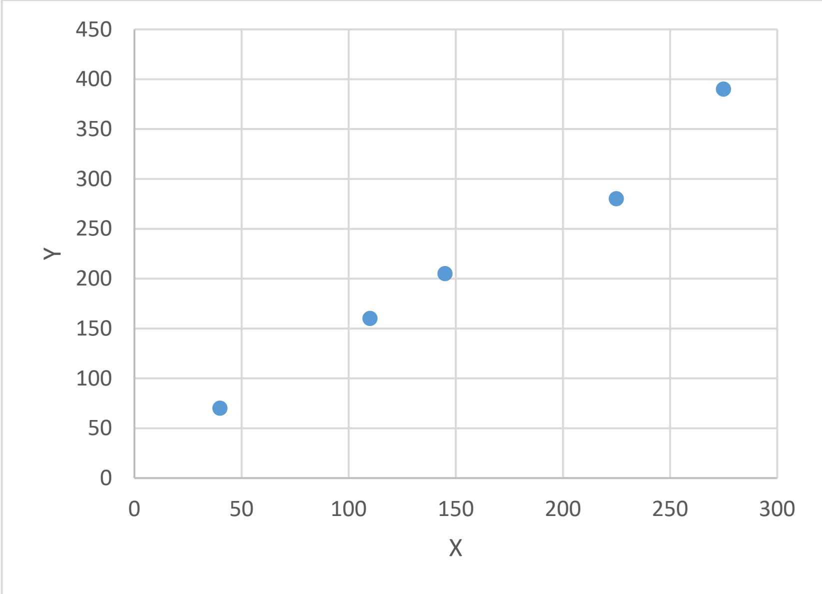

Figure 2: The data of the FCN region localization algorithm

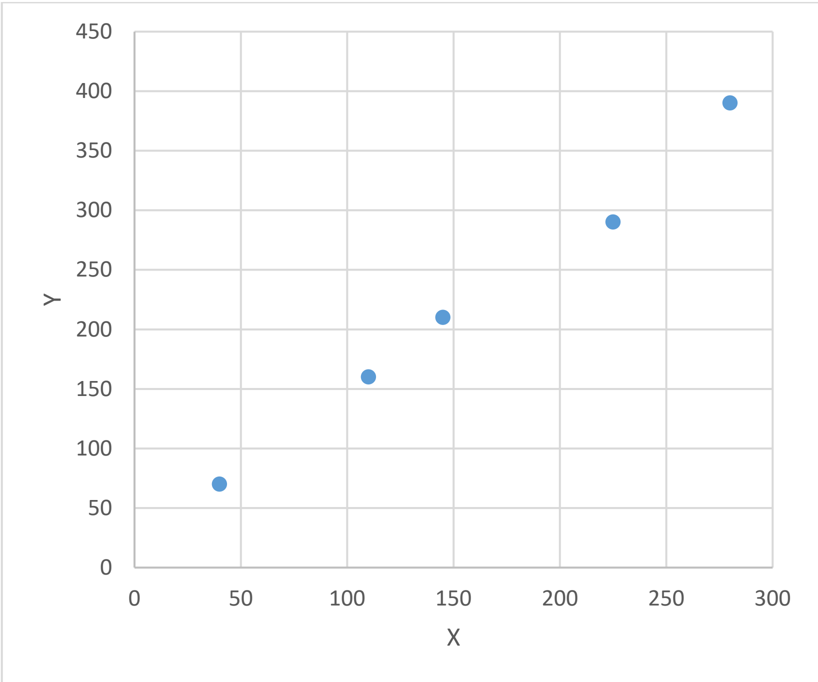

Figure 3: Actual positioning data

4.2. Positioning Precise Comparison

According to the data obtained in Figure 1, Figure 2 and Figure 3, sorting and error calculation are carried out, and Table 2 is obtained.

Table 2: Experimental error distance

Image number	Tradition error span	FCN error span
1	14.14213562	0
2	0	10
3	14.14213562	0
4	10	5
5	11.18033989	5

From the data in Table 2, it can be observed that the error distance of the traditional regional

ISSN 2616-5775 Vol. 6, Issue 9: 55-62, DOI: 10.25236/AJCIS.2023.060909

localization algorithm is generally higher than that of the regional localization algorithm based on the FCN. This shows that the algorithm based on the FCN is more accurate and reliable than the traditional algorithm in the localization task. However, we also noticed some exceptions, that is, in some specific cases, traditional region localization algorithms may show better localization results. This may be due to the better adaptability of traditional algorithms for some specific scenarios or datasets. Overall, the region localization algorithm based on the FCN shows greater advantages overall, with a higher accuracy rate and a smaller error distance. This algorithm takes advantage of the powerful ability of deep learning and can learn richer feature representations from images, thereby improving the accuracy and robustness of positioning. This shows that through the end-to-end learning method, the FCN can learn an accurate representation of the target position from a large amount of data and provide more accurate positioning results.

Afterwards, this paper conducts statistical analysis on the recorded data. Each X and Y value is recorded as a target number of times. Table 3 is obtained by performing data calculations based on the contents of Table 1.

Table 3: Evaluation metrics data

Group	Accuracy rate	Recall	F1 score
Tradition	30%	20%	24%
FCN	70%	40%	50.9%

From the data in Table 3, it can be observed that the accuracy rate of the area localization algorithm based on the FCN reaches 70%, while the traditional area localization algorithm only has an accuracy rate of 30%. This shows that algorithms based on FCN significantly outperform conventional algorithms in terms of accuracy. On the other hand, in terms of recall rate, neither the region localization algorithm of the FCN nor the traditional region localization algorithm shows obvious outstanding advantages, but the algorithm based on the FCN is still higher than the traditional algorithm. By comparing the F1 value, we can find that the regional positioning algorithm based on the FCN is far superior to the traditional regional positioning algorithm. The F1 value combines the information of precision and recall, so the performance of the algorithm can be evaluated more comprehensively. Based on the above data analysis, we can draw the following conclusions: the regional positioning algorithm based on the FCN is significantly better than the traditional algorithm in terms of accuracy, and can provide higher positioning accuracy. In terms of recall, the two algorithms have no obvious outstanding performance, but the algorithm based on the FCN is still slightly better than the traditional algorithm. By comparing the F1 value, we can see that the regional positioning algorithm based on the FCN is much higher than the traditional regional positioning algorithm, combining the advantages of accuracy and recall.

The regional localization algorithm based on FCN has obvious advantages in accuracy and comprehensive performance, and is a method worthy of further research and application.

4.3. Experimental Results and Discussion

This paper evaluates the performance of regional localization algorithms based on FCN and traditional algorithms in localization tasks through experiments, and conducts detailed data analysis and discussion of results. Through the data analysis of the experimental results, we found that the regional localization algorithm based on the FCN has obvious advantages over the traditional algorithm. It can be seen from the data table that the algorithm of the FCN shows higher accuracy and smaller error distance as a whole, indicating that it can provide more accurate positioning results in positioning tasks. The traditional algorithm may show better positioning effect in some specific cases, but it is still inferior to the algorithm based on the FCN as a whole. On the other hand, the regional positioning algorithm based on the FCN has an accuracy rate of 70%, which is much higher than the 30% of the traditional algorithm. This further verifies the advantages of the FCN-based algorithm in terms of localization accuracy. Although the two algorithms have no obvious outstanding performance in terms of recall, the algorithm based on the FCN still slightly outperforms the traditional algorithm. By comparing the F1 value, we can conclude that the regional positioning algorithm based on the FCN is much higher than the traditional algorithm, combining the advantages of accuracy and recall. The regional localization algorithm based on FCN shows obvious advantages in localization accuracy, comprehensive performance and accuracy. It uses the ability of deep learning to automatically learn the feature representation in the image, which improves the accuracy and robustness of localization. However, traditional algorithms may still have certain adaptability advantages in some specific situations. Through experimental evaluation and comparative analysis, the regional localization algorithm based on FCN has achieved excellent performance in many scenarios, with high positioning accuracy and robustness. However, the algorithm still faces some challenges, such as the adaptability to complex backgrounds, the localization accuracy of small objects, and the improvement of real-time performance. Therefore, future research can further explore new network architectures and training strategies to improve the performance and application range of the algorithm. Considering comprehensively, the regional localization algorithm based on FCN is a method worthy of further research and application, which can provide more accurate and reliable localization solutions for practical application scenarios.

5. Conclusion

In the field of localization, accurately determining the location of objects is an important and challenging task. Traditional regional positioning algorithms have certain limitations in the face of complex scenes and changing environments. To overcome these problems, this paper proposes a region localization algorithm based on a FCN, and conducts an experimental evaluation and analysis of its results. This article uses the FCN of the U-Net architecture to improve the generalization ability and robustness of the model by collecting, labeling and preprocessing data sets, selecting appropriate loss functions and hyperparameters, and adopting strategies and techniques. Experimental results show that the algorithm based on FCN exhibits high accuracy and small error distance in localization tasks. However, this algorithm also has some limitations. First of all, it has a high demand for large-scale data sets and requires sufficient labeled data for training. With the continuous development of deep learning technology and the improvement of hardware computing power, the regional positioning algorithm based on FCN is expected to play a greater role in practical applications and bring convenience and safety to people's lives.

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