ISSN: 2664-9640

Identification method of standard section of transperineal ultrasound measurement

Jianguo Qi[1, a], Mengqiang Zhou[1, b]

School of Information science and technology, Jinan University, Guangzhou 510632, China.

[a]qijianguo2004@126.com;

[b]zmq0911@stu2020.jnu.edu.cn.

Abstract

In order to ensure the accuracy of Angle of Descend (AOD) measurement, the most important thing is to choose the correct ultrasonic measurement surface. The selection of ultrasonic measurement surface often depends on the experience of the operator. Improper selection of measurement image and unclear presentation of relevant structures may easily lead to excessive measurement error. And it is a time-consuming and laborious work for the operator to select the standard section image for measurement. Therefore, it is necessary to add the automatic recognition method of measurement standard section in AOD automatic measurement algorithm. In this study, the identification method of AOD measurement standard section will be evaluated experimentally.

Keywords

Standard section; Angle of Descend; Automatic measurement; Algorithm.

1. Introduction

The selection of ultrasonic standard section is of great significance in clinical practice [1-2]. It is a challenging task to select the appropriate ultrasound image in the video of labor ultrasound for the measurement of labor parameters [3-4]. The quality of ultrasonic image has a great influence on the calculation of the parameters of the Angle of labor progression. The accuracy of the measurement of the Angle of labor progression depends on the correct selection of ultrasonic measurement section to a great extent. Improper selection of ultrasonic standard section is easy to lead to too much error in measuring the Angle of labor progression. However, manual selection of ultrasound standard sections often depends on the experience of the operator, which leads to a large difference between the doctor's observers. Therefore, adding automatic identification of standard measurement section into automatic measurement algorithm can not only reduce the workload of doctors, but also improve the consistency of measurement results [5]. Previous studies on the segmentation and key point recognition methods of ultrasonic images in production based on multi-task learning, this study added a classification branch on the basis of Unet model, and transferred the knowledge learned in the segmentation and key point recognition tasks of the model to the classification branch, so as to improve the generalization ability of the classification model. The model can be used for ultrasonic image segmentation and key point recognition while automatically selecting ultrasonic standard section [6-7].

2. The algorithm structure design

We transfer the knowledge learned in the target segmentation and key point recognition tasks to the ultrasonic measurement section automatic recognition task through transfer learning.

The network structure part of the classification module is independently trained. First, we pre-train the model on target segmentation and key point recognition tasks. For a given image, a shared encoder is used to extract multi-scale features, and then the extracted features are input into two independent decoders to generate predicted segmentation maps and regression locating Gaussian heat maps respectively. Because the two tasks have a certain correlation, the two tasks sharing a feature encoder can reduce feature redundancy to a certain extent, reduce the total number of parameters and operations, and promote feature learning in the training process. We use the trained model as a pre-training model and derive a branch at the end of the encoder for image classification. In this study, the classification branch module uses VGG or ResNet structure to stack convolutional blocks, and outputs classification results through the full connection layer. The training process includes the following steps: 1) freezing the parameters of the pre-training model. 2) Calculate the gradient of the parameters of the classification module through the back propagation algorithm. 3) Update classification module parameters. 4) Repeat steps 2) and 3) until the model converges. The trained model can make inferences about all three tasks simultaneously. In model inference, whether the input ultrasound image is the ultrasonic measurement plane is judged by classification branch first. If the inferred result is not the ultrasonic measurement plane, it indicates that the automatic calculation result of labor progress Angle is not reliable. If the inferred result is the ultrasonic measurement plane, it indicates that the automatic calculation result of labor progression Angle can be used as a reference, and the generated segmentation map and regression positioning Gaussian heat map can provide interpretation for the automatic calculation result. The practicability of the algorithm can be greatly improved by adding ultrasonic measurement plane task, so as to avoid seriously misleading measurement results in the case of non-ultrasonic measurement standard plane input.

3. AOD measurement standard section recognition algorithm

At present, several scholars have used VGG to design a recognition method for their good performance on the task. Among them, Van et al.[6] designed a standard section recognition algorithm for fetal head circumference measurement by simplifying VGG and adjusting parameters. Since the identification task in this paper is a binary task, which is relatively simple, the network structure with too many parameters may be difficult to train, under-fitting and low algorithm efficiency. Therefore, referring to Van et al. 's ideas, this paper proposes a standard section recognition method for AOD measurement by simplifying VGG adjustment. Its network structure is shown in. This model uses 9 convolutional layers and 3 fully connected layers in total. After every 2-3 convolutional layers, a pooling layer is added, followed by the fully connected layer. Since our task is binary, the model ends up with a numeric output and uses the Sigmoid activation function to map the values of the output nodes between 0 and 1. 3*3 size convolution kernel and 2*2 size pooling are all used in the network. In order to speed up the convergence of the network, Batch Normalization is used after the convolutional operation. In order to prevent overfitting, we add Dropout methods to the full connection layer. The Loss Function of the network model adopts the Cross Entropy Loss Function.

3.1. Loss function design

The loss function used in pre-training. We used Dice loss in segmentation task and MSE loss function in positioning task to train our network. Specifically, since our segmentation target had three categories, we adopted a multi-category Dice loss. Multi-scale monitoring is introduced in the location branch to calculate the MSE loss and final output of the middle layer. Therefore, positioning loss is the sum of MSE loss calculated at multiple scales.

3.2. Experimental results and analysis

To verify the performance of our method, we use two classical classification models trained on our data set as comparison models. It can be seen from Table 1 that the classification algorithm pretrained by transfer learning principle generally achieves better measurement section classification performance than the model with random initial parameters. At the same time, the multi-branch structure can simultaneously complete multiple sub-tasks during inference, and it does not need to re-read new network and load parameters, which not only improves the performance of the model, but also saves computing time and resources. In addition to the comparison with the traditional classification network, in order to study the optimal classification branch construction, we design Pretrain_0 (directly from the end of the encoder of the pre-training model to carry out global average pooling and then connect the whole connection layer for classification), Pretrain_1V (classification branch uses a VGG structure of the convolution module), Pretrain_2V (convolutional module with two VGG structure for classification branch), Pretrain_1R (coiling module with one ResNet structure for classification branch), Pretrain_2R (convolutional module with two ResNet structures stacked with classification branches) is used to compare five classification branches. It can be seen from the results that when two stacked ResNet convolution modules are used as classification branches, the recognition effect of labeled measured sections is better. The Experimental results is shown in Table 1 below:

Table 1 Experimental results of different standard measurement section recognition algorithm

	Accuracy	Precision	Recall	Specificity
VGG	87.55	86.64	92.38	89.90
ResNet	90.13	89.56	91.43	90.07
Pretrain_0	90.21	85.59	95.30	90.33
Pretrain_1R	94.28	91.26	91.07	93.28
Pretrain_2R	92.14	93.06	92.17	95.35
Pretrain_1V	91.55	91.26	93.87	90.28
Pretrain_2V	90.21	92.57	91.23	92.52

4. Conclusion

In this study, the identification method for AOD measurement standard section proposed in this paper is introduced in detail. The convolutional neural network is used to build an image classifier, and the images conforming to the measurement standards in ultrasonic images are sent to the measurement algorithm for measurement, and the images not conforming to the measurement standards are discarded, so as to avoid measurement error caused by the wrong selection of measurement section, reduce the operator's difficulty in using, and reduce the labor of doctors.

References

[1] Simonyan K, Zisserman A. VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION[C]. computer vision and pattern recognition, 2014.

[2] HE K, ZHANG X, REN S, et al. Deep residual learning for image recognition; proceedings of the Proceedings of the IEEE conference on computer vision and pattern recognition, F, 2016 [C].

[3] CHOLLET F. Xception: Deep learning with depthwise separable convolutions; proceedings of the Proceedings of the IEEE conference on computer vision and pattern recognition, F, 2017 [C].

[4] HEINRICH M P, STILLE M, BUZUG T M. Residual U-net convolutional neural network.

[5] LONG M, WANG J. Learning multiple tasks with deep relationship networks [J]. arXiv preprint arXiv:150602117, 2015, 2(1).

[6] BAXTER J. A Bayesian/information theoretic model of learning to learn via multiple task sampling [J]. Machine learning, 1997, 28(1): 7-39.

[7] YANG Y, HOSPEDALES T M. Trace norm regularised deep multi-task learning [J]. arXiv preprint arXiv:160604038, 2016.