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Improved Semi-Supervised Learning Method for Fetal Heart Echo-cardiogram Image Segmentation

Weibin Chen, Yan Han
College of Computer Science and Artificial Intelligence Engineering
Wenzhou University, Wenzhou 325035, P.R. China.

Abstract—*Fetal heart disease is the most common and serious congenital anomaly in newborns, and the incidence rate is about 0.4%~1.3% of newborns. In recent years, the incidence rate of shows a significant increasing trend.It is one of the leading causes of death in newborns and in childhood.Traditional manual delineation of cardiac occupation is not only time-consuming, but also not accurate enough.However, current deep learning algorithms rely mainly on training data and require large amounts of manually labeled data for training.Due to the large amount of medical image data, manual labeling is very time-consuming and laborious, and subjective errors may occur, which limits the application of deep learning methods in the field of medical image segmentation.Therefore, this paper presents an automatic segmentation method of echo-cardiogram images of the fetal heart based on a semi-supervised machine learning method.Compared to state-of-theart, our method shows cardiac space segmentation can be processed quickly, so as to evaluate cardiac function and provide an important guarantee for eugenics.*
Keywords— *Fetal heart, Echo-cardiogram, image segmentation, semi-supervised machine learning*

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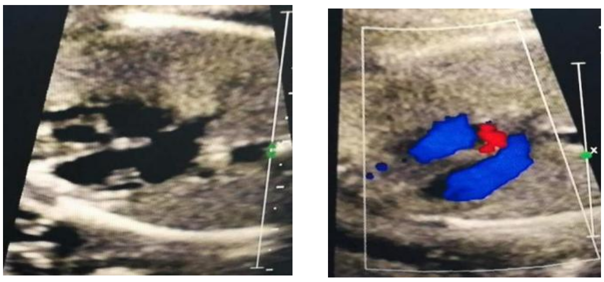
I. Introduction

Fetal heart disease is characterized not only by structural abnormalities, but also by functional abnormalities.Fetal cardiac dysfunction is closely related to congenital heart disease[1], intrauterine growth retardation and other diseases.Many changes in measures of fetal disease reflect some aspects of the status of fetal heart function.Therefore, accurate evaluation of fetal heart function and early intervention and treatment are important for eugenics and eugenics.

With the continuous development of ultrasound medicine and ultrasound imaging technology, the ultrasound screening mode of fetal heart disease has undergone a series of changes from two-dimensional plane, real-time three dimensions cardiograms can assess the condition of the fetal heart, so the evolution from two to three dimensions is a huge step forward, ventricular size, atrioventricular and large vascular connections and activity from different angles[2-4]. Rapid and accurate fetal heart assessment can effectively reduce the time of fetal heart ultrasound radiation, early detection of fetal unhealthy conditions can effectively reduce the birth rate of fetal malformation. At the same time, real-time three dimensions cardiography can quantitatively analyze fetal cardiac parameters.



(a) (b)

Figure1. Echocardiography examination of the fetus. (a)Four-chamber view of the actual fetal echocardiography. (b)The segmentation results of the standard four-compartment view

The multidimensional information of the heart can help doctors to comprehensively evaluate the development of the fetal heart, but its high-dimensional and complex data characteristics make it difficult for traditional image processing methods to adapt to the needs, and encounter huge bottlenecks.When dealing with real-time 3D echocardiography, existing methods will produce a large number of high-dimensional complex redundant features, such as the shape, texture, edge and dynamic features of the heart, occupy storage space, processing algorithms is very time consuming, especially in the clinical application of 3D echocardiography noise reduction and fetal left ventricular modeling and segmentation.

In recent years, the rise of sparse representation technology has undergone a new revolution in many fields of information technology, and many difficult to solve problems have discovered a breakthrough [5].By constructing a hypercomplete dictionary, the sparse representation uses the least possible non-zero coefficients to represent the main information and internal properties of the image, thus greatly reducing the data dimension.Currently, sparse representations have been successfully applied to image denoising [6], image recovery [7], compression sensing [8], and face recognition [9].The application of sparse representation in medical image processing also achieves good results.In particular, [10][11] has been proposed since 2010.By grouping the sparse decomposition coefficients and considering the sparsity of each group, the trained dictionary can better adapt the data, so the data representation with high accuracy.Group sparse representation (GSR) utilizes the group structure in the data and works well in many problems.However, the group structure must be provided manually in advance.In many practical cases, such as classification, the samples are grouped according to their labels.In this case, building a consistent group structure is really not easy.The reasons are as follows: 1) samples may be mislabeled; 2) tagging is a very time consuming and expensive task.Therefore, Gao proposed the idea of semisupervised sparse in 2016.Semi-supervised group sparse representation (ss-gsr) is used to support group sparse representation in both labeled and unlabeled data.Also, learn a more powerful group structure, which can be further used to more efficiently represent other unlabeled data.For multi-dimensional medical images, sparse representation theory has high research value.Applicants' previous study found that although multidimensional medical images have a large amount of data, their distribution had high sparsity.When using appropriate sparse representation techniques, the amount of data can be significantly reduced, thus extracting effective features and improving the efficiency of the algorithm.Therefore, how to extract sparse characteristic parameters from complex medical information can fully describe the left ventricle and establish a 3 D universal model of the fetal left ventricle to evaluate the level of fetal heart development, which is of theoretical value and application prospect.

II. Materials

2.1 Datasets

We selected a variety of fetal B-cardiac images, mainly including five fetal b-cardiac images of 5-28 weeks.These included four cases of ventricular heart, cardiac malformation, fetal heart B ultrasound atrioventricular defect, fetal heart B ultrasound ventricular defect and normal B ultrasound images of fetal heart.Each set contained 100 images, and a total of 500 images were selected for analysis.

2.2 Fundamental theory

Unsupervised learning can use unmarked samples to train and learn, and improve the learning ability of samples through reasonable training.At the same time, due to the uncertainty of unlabeled samples, we must use reasonable and effective methods to label the subordination and category of the original unlabeled samples.The nature of the hypothesis is that “similar samples have similar outputs”.

Semi-supervised learning can be divided into pure semi-supervised learning and direct learning. Unlabeled samples are not used as test samples in semi-supervised learning, while the latter assumes that the unlabeled samples during learning are only the data to be predicted.The learning aims to obtain the optimal generalization performance on these unlabeled samples.

2.3 No label data initializes the network

The accuracy of sample markers directly affects the diagnostic accuracy of the results, and efficient and accurate sample markers can reduce the number of iterations of the network, thus improving the robustness of the network. Therefore, the semi-supervised approach can use unlabeled sample networks with good initial generalization capability.

2.4 Semi-supervision method

We mentioned these two initialization methods, unsupervised and semi-supervised training: all training data is used to train the autoencoder, then the parameters of the self-encoded network as initial parameters, and labeled data to fine-tune the network (validation set).

Semi-supervised pre-training: attach pseudo-label information to the unlabeled data through a semi-supervised algorithm or clustering algorithm.The network is first pre-trained with pseudo-label information.Then, the validation set is used to test and local adjustment of the relevant network parameters is made.

III. Methods

3.1The algorithm flow of proposed method

Semi-supervised learning of extracting features from labeled data.

1) Use partially calibrated data to train the network (in this case, repeated labor process can be avoided);

2) Use features in hidden layer combined with deep learning combination algorithm, and use some classification algorithms to classify unlabeled data;

3) Select the unlabeled data that is considered correct and add it to the training set;

Repeat the above procedure.

3.2 Description of algorithm

Through the above algorithm flow we established a semi-supervised image segmentation model, a deep learning network in the hidden layer to classify the labels of labeled data without classification, and then a fully connected (dense) combined algorithm to synthesize predictions while preserving image edges.In this paper, we present semi-supervised labeled pre-training data, in order to simply use methods to train combined parameters from weak labels, using deep learning combination algorithms in the hidden layer.Good results are obtained by integrating end-to-end training of parameter with a deep learning method.

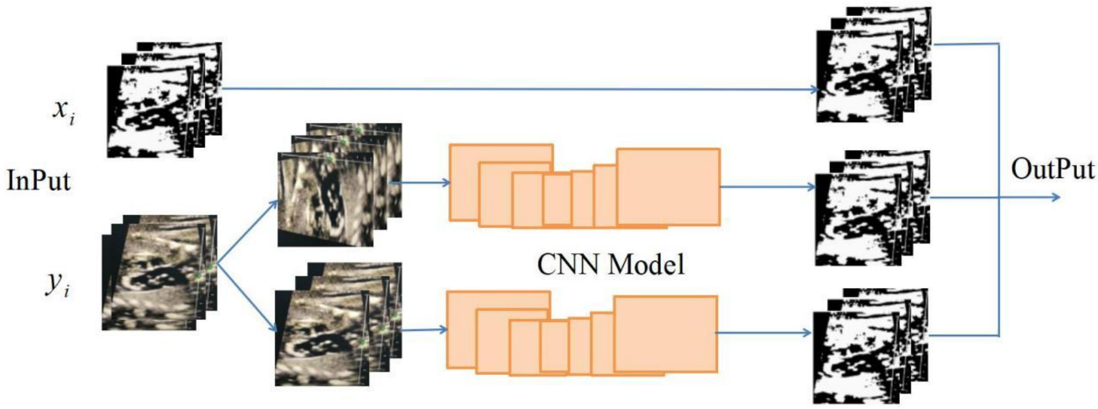


Figure 2. The details of the Semi-supervised learning. Use features in hidden layer combined with deep learning combination algorithm.The orange part is the CNN model for learning refined lesion maps.

IV. Experiments Comparative Analysis

4.1 Training set

In experiments, we can usually access a large number of semi-supervised labeled images, and can only obtain detailed pixel-level annotations for a small fraction of these images.We process the image of this mixed training scene with the real image process and are able to get better results from the hidden layer.The segmentation estimated from the bounding box annotation.

4.2 Comparative Analysis

We explore three alternative approaches to train our segmentation model from the labeled bounding boxes.

The first semi-supervised approach is equivalent to simply taking each pixel in the bounding box as a positive example of the respective object class.The ambiguities were resolved by assigning pixels belonging to multiple bounding boxes to the pixels with the smallest area.Each image contains both foreground and background images, but the false positive examples of the object contaminate the training set.

To thoroughly filter out these interfering background pixels, we also explore a second training approach, in which we perform automated foreground/background segmentation.When performing this segmentation, we use the deep learning method for automatic annotation.More specifically, we restrict the central region of the bounding box to the front ground, while we restrict the pixels outside the bounding box to the background.We do this by appropriately setting the unary term of the deep learning approach.We can then infer somewhere in between for labeled and unlabeled pixel labels.We cross-validated the combined parameters to maximize the segmentation accuracy in a small fully annotated image.The method is similar to graben method.Examples of the estimated segmentation using both methods are shown in Figure 3.

The above two methods, as shown in Figure 3, estimate the segmentation map from the bounding box annotation as a pre-processing step, followed by a semi-supervised training process.3.1, treating the labels of these estimates as basic facts.

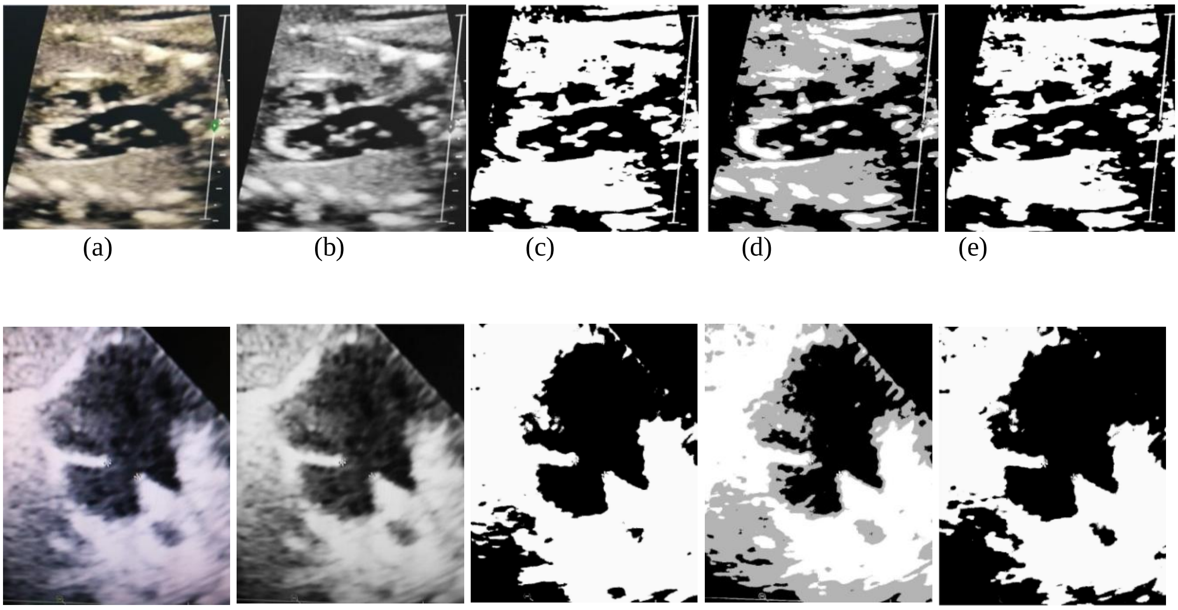


Figure 3. Segmentation results of the two methods. Sub-Figures(a)-(e) adopt the semi-supervised method, and Sub-figures(f)-(j) adopt the semi-supervised fusion deep learning method.

Our third fixed method, based on the semi-supervised and deep learning joint, is an intelligent algorithm that allows us to refine the estimated segmentation graph throughout the training process.The method is a variant of the simplex semi-supervised method, where we improve the scores of current foreground objects only within the bounding box region.

Table 1. Evaluation the effectiveness of the two methods in segmenting lesions was evaluated on the self-built data set.

Datasets	No.1		No.2	
Methods	Acc.	Kappa	Acc.	Kappa
Method1(Pretrained)	0.7614	0.7816	0.7968	0.8231
Method2(Semi)	0.8923	**0.9011**	0.8912	0.8981
Method3(Semi+CNN)	**0.9201**	0.8998	**0.9125**	**0.9002**

Table 1 shows two important indicators for the classification of different methods. Based on the pixel level reliable pre training model, the segmentation accuracy is improved by 3.61% and the kappa score is improved by 3.9%. By using the method of semi supervised learning and deep learning of image level annotation data, more significant improvement can be achieved.

V. Conclusion

This paper explores the application of semi-or partial supervision in training an existing model for fetal ultrasound image segmentation.A number of experiments on challenging hospital-based realistically collected datasets show that: (1) using purely semi-supervised image-level annotations seems insufficient to train a high-quality segmentation model.(2) Using semi-supervised or deep learning methods, combined with careful segmentation of images in the training set can improve the accuracy, but bring labeling difficulties.(3) Under the semi-supervised setting, combining a small number of pixel-level annotated images and a large number of remaining weakly annotated images with deep learning methods, can achieve excellent performance. The results are far better than only semi-supervised method or only deep learning method.(4) Using semisupervised combined with deep learning training and annotation methods to greatly improve the segmentation results.The proposed method achieves a good balance between the segmentation accuracy and efficiency of the image algorithm, and has a good promotion significance in 3d fetal ultrasound images with high real-time requirements.

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