Scalable Semi-supervised Landmark Localization for X-ray Images using Few-shot Deep Adaptive Graph

Xiao-Yun Zhou1, Bolin Lai2, Weijian Li3, Yirui Wang1, Kang Zheng1, Fakai Wang4, Chihung Lin5, Le Lu1, Lingyun Huang2, Mei Han1, Guotong Xie2, Jing Xiao2, Kuo Chang-Fu5, Adam Harrison1, Shun Miao1

1 PAII Inc., Bethesda, MD, USA
2 Ping An Technology, Shenzhen, China
3 University of Rochester, Rochester, NY, USA
4 University of Maryland, College Park, MD, USA
5 Chang Gung Memorial Hospital, Linkou, Taiwan, ROC

Abstract. Landmark localization plays an important role in medical image analysis. Learning based methods, including convolutional neural network (CNN) and graph convolutional network (GCN), have demonstrated the state-of-the-art performance. However, most of these methods are fully-supervised and heavily rely on manual labeling of a large training dataset. In this paper, based on a fully-supervised graph-based method, deep adaptive graph (DAG), we proposed a semi-supervised extension of it, termed few-shot DAG, i.e., five-shot DAG. It first trains a DAG model on the labeled data and then fine-tunes the pre-trained model on the unlabeled data with a teacher-student semi-supervised learning (SSL) mechanism. In addition to the semi-supervised loss, we propose another loss using Jensen–Shannon (JS) divergence to regulate the consistency of the intermediate feature maps. We extensively evaluated our method on pelvis, hand and chest landmark detection tasks. Our experiment results demonstrate consistent and significant improvements over previous methods.

Keywords: Few-shot Learning · GCN · Landmark Localization · X-ray Images · Deep Adaptive Graph · Few-shot DAG.

1 Introduction

Landmark localization is a fundamental tool for a wide spectrum of medical image analysis applications, including image registration [4], developmental dysplasia diagnosis [10], and scoliosis assessment [25]. Although many recent improvements have been proposed [6,24], most of them are still based on fully-supervised learning and rely heavily on the manual labeling of a large amount of training data. Human labeling is prohibitively expensive and requires medical expertise. Thus, it is challenging to obtain large-scale labeled training data in practical applications and decreased scales of training data can impede achieving strong
performance. Yet, large-scale unlabeled X-ray images can be efficiently collected from picture archiving and communication systems (PACSs). Hence, a promising strategy is to adopt semi-supervised learning (SSL) scheme, which enables efficient learning from both labeled and unlabeled data.

State-of-the-art landmark detection methods are typically learning-based, i.e., graph convolutional network (GCN) [12,11,9], heatmap regression [23,28,17,21], and coordinate regression [13,26,27,20]. Among these, deep adaptive graph (DAG) [9] employs GCNs to exploit both the visual and structural information to localize landmarks. By incorporating a shape prior, DAG reaches a higher robustness compared to heatmap-based and coordinate regression-based methods [9]. While there are efforts towards SSL for landmark localization [5,18], they are based off of convolutional neural network (CNN)-only approaches, rather than the state-of-the-art GCN-based DAG. Some other prominent SSL successes in medical imaging have also been reported, such as for segmentation [2,15] and abnormality detection [22], but these are also CNN-based. Most other SSL methods are mainly developed for natural image classification tasks [7,8,1,19], which likewise do not address GCN-based landmark localization.

In this work, we propose few-shot DAG, an effective SSL approach for landmark detection. Few-shot DAG can achieve strong landmark localization performance with only a few training images (e.g., five). The framework of few-shot DAG is illustrated in Fig. 1. We first train a fully-supervised DAG model on the labeled data and then fine-tune the pre-trained DAG model using SSL on the unlabeled data. Inspired by [19], for SSL, dual models are used, i.e., a teacher and a student model. The output of the teacher model is used as the pseudo ground truth (GT) to supervise the training and back-propagation of the student model. The parameters of the teacher model are updated by the exponential moving average (EMA) of the parameters of the student model. In addition to the semi-supervised loss inspired by [19], we further add a Jensen–Shannon (JS) divergence loss on the intermediate feature map, to encourage similar feature distributions between the teacher and student models. The proposed few-shot DAG is validated on pelvis, hand and chest X-ray images with 10, 10, and 20 labeled samples and 5000, 3000, and 5000 unlabeled samples, showing consistent, notable and stable improvements compared with state-of-the-art fully-supervised methods [14] and other semi-supervised methods [16,7].

2 Method

Our work enhances prior efforts at using DAG for landmark detection [9]. We first briefly describe the network structure and training mechanism of DAG in Sec. 2.1 and then introduce the proposed SSL extension of DAG with the JS divergence loss in Sec. 2.2.

2.1 Deep Adaptive Graph

DAG [9] formulates landmark localization as a graph evolution task, where the vertices of the graph represent the landmarks to be localized. The evolution starts
from the mean shape generated from the training data, and the evolution policy is modeled by a CNN feature extractor followed by two GCNs. The CNN encodes the input image as a feature map, from which graph features are extracted via bi-linear interpolation at the vertex locations. The graph with features is further processed by cascading a global GCN and local GCNs to respectively estimate the affine transformation and vertex displacements toward the targets.

The DAG is trained via fully-supervised learning using a global GCN and local GCN loss. Specifically, the global GCN outputs an affine transformation that globally transforms the initial graph vertices (i.e., the mean shape). The average L1 distances between the affine transformed vertices and the GT locations are calculated as the global loss:

$$L_{\text{global}} = \mathbb{E} \left( |v_{\text{global}} - v_{\text{gt}}| - m \right)$$

where $[x]_+ := \text{max}(0, x)$, $v_{\text{global}}$ and $v_{\text{gt}}$ denote the affine transformed and GT vertices, respectively. $m$ is a hyper-parameter specifying the margin of allowable error. The local GCN iteratively displaces $v_{\text{global}}$ to refine their locations. The average L1 distances between the displaced vertices and the GT are calculated as the local loss:

$$L_{\text{local}} = \mathbb{E} \left( |v_{\text{local}} - v_{\text{gt}}| \right)$$

where $v_{\text{local}}$ denotes the vertices after displacement by the local GCN. The final loss for DAG is $L_{\text{global}} + w_1 \times L_{\text{local}}$, where $w_1$ is a weight used to adjust the ratio between the global and local loss.
2.2 Few-shot DAG

Inspired by [19], we adopt a mean teacher mechanism to exploit both the labeled and unlabeled data. In particular, we first train a DAG model using only the labeled dataset, referred to as the pre-trained model. In the mean teacher training, the teacher and student models share the same architecture and are both initialized using the pre-trained model. The same input images are fed into the teacher and student models. Gaussian noises are added to the input images of the student model as an additional augmentation. For unlabeled images, a consistency loss is enforced between the teacher and student models. In the proposed few-shot DAG, we apply two forms of unlabeled loss.

First, the landmarks detected by the teacher model are used as the pseudo GT to supervise the training of the student model. In particular, the output $v_{local}$ of the teacher model is used as the pseudo GT for the student model to calculate the global and local losses of Equ. (1) and (2), respectively. While this is helpful, it only applies a sparse consistency constraint on the GCN outputs. As a result, we apply a second loss in the form of JS divergence between the CNN feature maps of the teacher and student model, encouraging a similar distribution between the two. Specifically, the output feature maps of CNN are converted to pseudo-probabilities via a Softmax along the channel dimension. The JS divergence loss is then formulated as:

$$L_{js} = \frac{1}{2|\Omega|} \sum_{x \in \Omega} (D(a_S(x), m(x)) + D(a_T(x), m(x)))$$

where $D(.)$ is the Kullback–Leibler divergence, $a_S$ and $a_T$ are the student and teacher activation maps, respectively, $\Omega$ is their batch, spatial and channel domain, and $m$ is the mean of $a_S$ and $a_T$.

For the labeled data, we use the fully-supervised loss: $L_{global} + w_1 \times L_{local}$. For the unlabeled data, we calculate $L'_{global} + w_1 \times L'_{local} + w_2 \times L_{js}$, where $L'_{global} + w_1 \times L'_{local}$ use the pseudo GT produced by the teacher model and $w_2$ balances the contribution of the JS divergence loss. The labeled and unlabeled batches are fed with a ratio $1 : R$ (R is 100 in our experiments) to form the semi-supervised training iterations. Finally, the weights of the student model are updated through back-propagation of the loss. The weights of the teacher model are updated iteratively via the EMA of the student model’s weights [19]:

$$\theta_T^t = \alpha \theta_T^{t-1} + (1 - \alpha) \theta_S^t,$$

where $\theta_T$ and $\theta_S$ are the weights of the teacher and student models, respectively, $t$ is the training step, and $\alpha$ is a smoothing coefficient to control the pace of knowledge updates.

3 Results

Experimental setup The proposed few-shot DAG is validated on three X-ray data sets: pelvis (60 labeled images, 5000 unlabeled images, 6029 test images),
Table 1. The mean and std Euclidean error and the failure rate of the proposed method, with comparisons to Payer et al., pseudo label, II-model and temporal ensemble on the pelvis, hand and chest datasets. Best performance is in bold.

| Data    | Method                   | Mean error | Std error | Failure rate |
|---------|--------------------------|------------|-----------|--------------|
| Pelvis  | Payer et al. [14]        | 46.29      | 106.63    | 12.62%       |
|         | Pseudo label [16]        | 20.50      | 54.27     | 2.21%        |
|         | II-Model [7]              | 58.31      | 98.41     | 14.66%       |
|         | Temporal ensemble [7]    | 21.12      | 42.90     | 2.07%        |
|         | DAG [9]                  | 25.89      | 44.60     | 4.29%        |
|         | Few-shot DAG             | 19.63      | 34.29     | 1.27%        |
|         | Few-shot DAG + JS        | 18.45      | 30.69     | 1.31%        |
| Hand    | Payer et al. [14]        | 12.29      | 37.81     | 1.24%        |
|         | Pseudo label [16]        | 9.27       | 24.82     | 0.77%        |
|         | II-Model [7]              | 17.96      | 45.07     | 3.56%        |
|         | Temporal ensemble [7]    | 10.20      | 22.35     | 0.81%        |
|         | DAG [9]                  | 10.97      | 27.60     | 1.51%        |
|         | Few-shot DAG             | 9.07       | 21.76     | 0.50%        |
|         | Few-shot DAG + JS        | 9.07       | 19.67     | 0.47%        |
| Chest   | Payer et al. [14]        | 61.41      | 131.27    | 5.75%        |
|         | Pseudo label [16]        | 55.33      | 57.84     | 8.32%        |
|         | II-Model [7]              | 208.38     | 138.45    | 64.80%       |
|         | Temporal ensemble [7]    | 52.41      | 47.54     | 5.92%        |
|         | DAG [9]                  | 58.99      | 73.55     | 12.35%       |
|         | Few-shot DAG             | 54.94      | 55.00     | 9.37%        |
|         | Few-shot DAG + JS        | 43.46      | 47.22     | 5.28%        |

hand (36 labeled images, 3000 unlabeled images, 93 test images), and chest (60 labeled images, 5000 unlabeled images, 1092 test images). All datasets were collected from anonymous hospital after de-identification of the patient information. All experiments, except the ablation study, were conducted with 10/10, 10/6, and 20/10 training/validation examples for the pelvis, hand, and chest data respectively. For the ablation study, additional experiments with 1/5/50, 1/5/30, 1/5/10/50 training examples for the pelvis, hand and chest data are conducted to validate the scalability of the proposed few-shot DAG on different numbers of training examples. The Euclidean distance between the GT and the predicted landmarks is used as the main evaluation metric. In addition, the failure rate (defined as error larger than 5% of the image width) is supplied as a supplementary evaluation metric. As the failure rate may change along the chosen threshold, we view the Euclidean error as more important and objective.

To manage the GPU memory consumption, the batch size is set as 1, 4, and 8 for experiments with 1, 5, and >8 training examples. Adam is used as the optimizer [3], with learning rate set to $10^{-4}$, and is decayed by 0.96 after every 10 epochs. The weight decay is $10^{-4}$. $w_1$ and $w_2$ are both set as 1. The backbone used is HRNET [17]. $\alpha$ for updating the teacher model is set as:

$$
\alpha = \min \left( \max \left( 1 - \frac{1}{(\text{global step} + 1)}, 0.99 \right), 0.999 \right),
$$

(5)
### Table 2. The mean and std Euclidean error and the failure rate of DAG, few-shot DAG and few-shot DAG + JS on different numbers of training examples. Best performance is in bold. - indicates no convergence.

| Data    | Training samples | Method       | Mean error | Std error | Failure rate |
|---------|------------------|--------------|------------|-----------|--------------|
| Pelvis  | 1                | DAG [9]      | -          | -         | -            |
|         | 5                | DAG [9]      | 55.53      | 80.05     | 14.72%       |
|         |                  | Few-shot DAG | 34.48      | 44.17     | 3.22%        |
|         |                  | Few-shot DAG + JS | 27.31 | 39.14 | 3.19%        |
|         | 10               | DAG [9]      | 25.89      | 44.60     | 4.29%        |
|         |                  | Few-shot DAG | 19.63      | 34.29     | 1.27%        |
|         |                  | Few-shot DAG + JS | 18.45 | 30.69 | 1.31%        |
|         | 50               | DAG [9]      | 15.62      | 34.40     | 1.29%        |
|         |                  | Few-shot DAG | 13.44      | 30.03     | 0.55%        |
|         |                  | Few-shot DAG + JS | 13.37 | 28.26 | 0.58%        |
| Hand    | 1                | DAG [9]      | -          | -         | -            |
|         | 5                | DAG [9]      | 24.17      | 47.05     | 5.07%        |
|         |                  | Few-shot DAG | 23.30      | 36.13     | 2.52%        |
|         |                  | Few-shot DAG + JS | 15.41 | 31.99 | 1.78%        |
|         | 10               | DAG [9]      | 10.97      | 27.60     | 1.51%        |
|         |                  | Few-shot DAG | 9.07       | 21.76     | 0.50%        |
|         |                  | Few-shot DAG + JS | 9.07 | 19.67 | 0.47%        |
|         | 50               | DAG [9]      | 8.44       | 22.00     | 0.67%        |
|         |                  | Few-shot DAG | 8.09       | 17.51     | 0.40%        |
|         |                  | Few-shot DAG + JS | 7.74 | 17.55 | 0.43%        |
| Chest   | 1 & 5            | DAG [9]      | 133.09     | 121.57    | 38.49%       |
|         | 10               | DAG [9]      | 128.74     | 102.61    | 39.73%       |
|         |                  | Few-shot DAG | 76.11      | 78.01     | 14.80%       |
|         |                  | Few-shot DAG + JS | 43.46 | 47.22 | 5.28%        |
|         | 20               | DAG [9]      | 58.99      | 73.55     | 12.35%       |
|         |                  | Few-shot DAG | 54.94      | 55.00     | 9.37%        |
|         |                  | Few-shot DAG + JS | 27.31 | 28.64 | 1.07%        |
|         | 50               | DAG [9]      | 27.31      | 42.33     | 2.69%        |
|         |                  | Few-shot DAG | 23.32      | 28.64     | 1.07%        |
|         |                  | Few-shot DAG + JS | 22.49 | 27.29 | 0.85%        |

where $global_{step}$ is the global step of the training.

All input images are resized to $512 \times 512$ and normalized into an intensity range of $[0, 1]$. A rotation within the angle range of 30°, a scale within the range of $[0.8, 1.25]$, and a translation within the range of the landmark bounding box are applied as the data augmentation in the training. The noise added between the teacher and student model’s input follows a $\mathcal{N}(0, 0.1^2)$ distribution and the image intensity is clipped into $[0, 1]$ after adding the Gaussian noise.

**Comparison with other baselines** We compare against the fully-supervised DAG [9] and also Payer et al. [14], who introduced a heatmap based method focusing on leveraging the spatial information. Three semi-supervised methods
are used for the comparison: (1) pseudo label [16], which trains the SSL model with the pseudo GT generated by the pre-trained model in Sec. 2.1; (2) Π-Model [7], which maintains only a student model with the semi-supervised loss between the two input batches (one is with Gaussian noise and one is not); (3) temporal ensemble [7], which updates the pseudo GT after each epoch via the EMA of historically and currently generated pseudo GT. For the proposed method, performance in stages is offered, including few-shot DAG and few-shot DAG + JS. It is worth mentioning that temporal ensemble consumes much longer training time than other methods.

Detailed results of validating the seven methods on the pelvis, hand and chest data set are presented in Tab. 1. We can see that for the main evaluation metric, i.e., mean and std Euclidean error, out of the fully-supervised methods, DAG noticeably outperforms Payer et al. For the semi-supervised methods, few-shot DAG + JS outperforms Π-Model with large margins while also outperforms pseudo label and temporal ensemble with notable margins. Furthermore, the proposed method shows consistent performance gains from DAG to few-shot DAG, and to few-shot DAG + JS, demonstrating the value of the proposed SSL
scheme and JS divergence loss. For the supplementary evaluation metric - failure rate, similar trends can be observed. Even though few-shot DAG + JS does not achieve the lowest failure rate in one experiment, its failure rate is very close to the lowest value, i.e., 1.31% vs. 1.27% on the pelvis.

Ablation study on the scalability of few-shot DAG We show that the proposed few-shot DAG can work well for different scales of training data. To illustrate this, we conduct experiments on varied numbers of labeled data. The corresponding results are shown in Tab. 2. We can see that the fully-supervised DAG cannot converge on extremely few training examples, i.e., 1 for pelvis, 1 for hand, 1 and 5 for chest, resulting in non-converged few-shot DAG as well. On converged experiments with few training examples, for the main evaluation metric, the proposed SSL scheme (DAG vs. few-shot DAG) achieves notable performance improvements on all experiments. The proposed JS divergence loss (few-shot DAG vs. few-shot DAG + JS) performs best on most experiments, except one (hand-50) where the std error is comparable (17.55 vs. 17.51). For the supplementary evaluation metric, the proposed semi-supervised methods, including few-shot DAG and few-shot DAG + JS fail much less than the fully-supervised method. While in most experiments, few-shot DAG + JS fails less than few-shot DAG; only in three experiments (pelvis-10, pelvis -50, hand-50), comparable failure rates are achieved for semi-supervised DAG with or without the JS divergence loss.

Visual results We select two examples for each data set and show the landmark localization results in Fig. 2. We can see that, Payer et al. and Π-Model generally performs unstably while pseudo label and temporal ensemble can achieve reasonable landmark localization except for a few hard cases, i.e., the second hand image. The fully-supervised DAG can out-perform Payer et al., however, it under-performs strong semi-supervised methods, i.e., pseudo label and temporal ensemble. But, the proposed SSL scheme (few-shot DAG) and the JS divergence loss (few-shot DAG + JS) can correct the less-optimal localization generated in fully-supervised DAG and achieves the visually reasonable localization on all images including the hard cases.

4 Conclusion

In this paper, we introduced few-shot DAG, an SSL enhancement of DAG that significantly improves landmark localization. It first trains a DAG model on a few labeled training examples (e.g., five), and then fine-tunes the trained model on a large number of unlabeled training examples using consistency losses tailored for CNN and GCN outputs. Overall, our approach achieves strong landmark localization performances with only a few training examples. As shown in the validation on three datasets, the proposed few-shot DAG consistently out-performs both previous fully-supervised and semi-supervised methods with
notable margins, indicating its good performance, robustness and potentially wide application in the future.

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