Relative distance matters for one-shot landmark detection

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Abstract. Contrastive learning based methods such as cascade comparing to detect (CC2D) have shown great potential for one-shot medical landmark detection. However, the important cue of relative distance between landmarks is ignored in CC2D. In this paper, we upgrade CC2D to version II by incorporating a simple-yet-effective relative distance bias in the training stage, which is theoretically proved to encourage the encoder to project the relatively distant landmarks to the embeddings with low similarities. As consequence, CC2Dv2 is less possible to detect a wrong point far from the correct landmark. Furthermore, we present an open-source, landmark-labeled dataset for the measurement of biomechanical parameters of the lower extremity to alleviate the burden of orthopedic surgeons. The effectiveness of CC2Dv2 is evaluated on the public dataset from the ISBI 2015 Grand-Challenge of cephalometric radiographs and our new dataset, which greatly outperforms the state-of-the-art one-shot landmark detection approaches.

Keywords: Medical Landmark Detection · One-shot Learning

1 Introduction

As a fundamental first step in therapy planning and intervention, precise and reliable anatomical landmark detection has attracted great interest from academia and industry [22,15,27,28]. Moreover, it serves as an important step in medical image analysis [14,18], e.g., initialization of segmentation or registration algorithms. Recently, deep learning based methods have great success in efficiently localizing anatomical landmarks in radiological images [2,10,18,15]. Chen et al. [4] regress the heatmap and offset maps simultaneously. Zhong et al. [25] use cascade U-Net to perform a two-stage heatmap regression. Li et al. [12] adapt multiple deep adaptive graphs to capture relationships among landmarks.
A common wisdom is that more training data enhance the supervised methods’ better performance and generalization. However, for medical image analysis, the annotation of datasets needs well-trained, highly-engaged radiologists, which is especially challenging as experts are costly and busy. To break this limitation, an array of self-supervised learning attempts have been explored in classification and segmentation tasks, including image restoration [32,31], patch ordering [34], superpixel-wise [16] and patch-wise [3] contrastive learning [26].

For medical landmark detection, two previous approaches have challenged the hardest scenario: Only one annotated data is available. RPR-Net [11] embeds the patches with similar anatomical contexts into close relative positions. Cascade comparing to detect (CC2D) [24] learns to project the pixels with the same anatomical structures into embeddings with high cosine similarities, by solving a self-supervised “patch matching” proxy task in a coarse-to-fine fashion.

Delving into CC2D, despite the great performance with one labeled data available, we find that the important cue of relative distance between landmarks [30,29,5] is ignored. Therefore, we add a novel relative distance bias (RDB) in the training stage of CC2D. Theoretical analysis proves that RDB multiplies the gradient of the negative points by a relative distance aware factor, which encourages low similarities for relatively distant points. This add-on term brings two benefits: 1) It makes the framework less possible to detect a wrong point far from the correct landmark; 2) It prevents the encoders from wasting too much effort on decreasing the similarities of the relatively close points with similar anatomical contexts. Here, we name our upgraded version of “relative distance aware cascade comparing to detect” as CC2Dv2.

The effectiveness of CC2Dv2 is evaluated by extensive experiments on the public ISBI 2015 Grand-Challenge dataset [8]. Our CC2Dv2 outperforms the state-of-the-art medical one-shot landmark detection methods with a significant accuracy improvement. Furthermore, we contribute an open-source dataset for the measurement of BioMechanical Parameters of the Lower Extremity (BMPEL) arising from orthopedic surgery, which is suitable to evaluate the effectiveness of both one-shot and fully-supervised landmark detection methods.

2 Method

The overall framework of CC2Dv2 is build on top of CC2D [24], consisting of two stages: self-supervised learning (SSL) and training from pseudo-labels (TPL). CC2Dv2 differs from CC2D in the SSL stage: It incorporates a relative distance bias to encourage low similarities between the relatively distant landmarks. TPL stays the same, that is, using the pseudo-labels generated from SSL stage, a multi-task U-Net [23] is trained to generate heatmap and offset-maps simultaneously, which effectively improves the performance and inference speed [1].

Cascade cosine similarities: The computation flow in CC2Dv2-SSL is the same as in CC2D-SSL [24]. As shown in Fig. 1, let $X_r$ denote an input image resized to $H \times W$, we arbitrarily select a target point $P_r = (x_r, y_r)$. First, we randomly crop a patch $X_p$ containing $P_r$ with size $H_p \times W_p$, and augment the
Fig. 1. The training strategy of the proposed relative distance aware cascade comparing (CC2Dv2-SSL). For each layer of the cascade features, CC2Dv2-SSL penalizes the cosine similarities drastically between the selected ground-truth point and the relatively distant points, by adding a novel relative distance bias (RDB) before applying softmax function. As consequence, the feature extractors are encouraged to embed the distant landmarks to the embeddings with low similarities.

content of $X_p$ by rotation and color jittering, which moves the anchor point $P_r$ to $P_p = (x_p, y_p)$. Then, the input $X_r$ and the patch $X_p$ are projected into cascade of multi-scale feature embeddings $F_r = E_r(X_r)$ and $F_p = E_p(X_p)$, by two feature extractors $E_r$ and $E_p$, respectively. Here, the embedding of $i^{th}$ layer is marked as $F^i$ with size $H^i_p \times W^i_p$. Next, for each layer, we extract the anchor feature $f^i_a$ of the anchor point $P_p$ from $F^i_p$, guided by its corresponding coordinates $P^i_a = (x_p/2^i, y_p/2^i)$ which are down-sampled for $i$ times. Finally, the cosine similarity map $s^i$ for each layer between input feature $F^i_r$ and anchor feature $f^i_a$ is computed:

$$S^i = \frac{\langle f^i_a \cdot F^i_r \rangle}{\|f^i_a\|_2 \cdot \|F^i_r\|_2},$$  \hspace{0.5cm} (1)

Then, following CC2D [24], we crop the matrix of interest $S^i_\Delta = \{s^i_m\}_{M \times N}$ from the similarity map $S^i = \{s^i_{xy}\}_{H^i \times W^i}$ with a size of $M \times N$ for each layer. The selected point $P^i_r = (x_r/2^i, y_r/2^i)$ now has a new coordinate $P^i_t = (m^i_t, n^i_t)$ in the matrix $S^i_\Delta$.

**Relative distance bias (RDB):** Next, we compute the relative Euclidean distance $d^i_{mn}$ for each pixel $P^i_{mn}$ in $S^i_\Delta$ with coordinate $(m, n)$ to the selected point $P^i_t = (m^i_t, n^i_t)$ as follow:

$$d^i_{mn} = \sqrt{(m - m^i_t)^2 + (n - n^i_t)^2},$$  \hspace{0.5cm} (2)

Then the relative distance is clipped to $[0, \beta]$ and added to the cropped cosine similarity matrix $S^i_\Delta$, resulting in relative distance aware similarity matrix $W^i_{mn}$.
whose element $w_{mn}^i$ is given as:

$$\{w_{mn}^i\}_{M \times N} = (s_{mn}^i + b_{mn}^i)_{M \times N},$$

(3)

where $\alpha$ controls the slope of the relative distance.

**Cascade comparing to detect:** Here, we mark $P_{lt}^i$ as the ground-truth point and denote other non-ground-truth points in matrix $W^i$ (or matrix $S^i$) as $P_{mn}^i$. The ground truth matrix $GT^i$ is computed as $GT_{mn}^i = 1, GT_{mn}^i = 0$. After applying softmax function to normalize $W^i$ to probability matrix $Q^i$ with a temperature $\tau$: $q_{mn}^i = \text{softmax}(w_{mn}^i \star \tau)$, we use cross-entropy loss $L_{CE}^i$ to increase the probability $q_{mn}^i$ of the selected ground-truth point $P_{lt}^i = (m_t^i, n_t^i)$ while decreasing the probabilities $q_{mn}^i$ of other non-ground-truth points $P_{mn}^i$ for multi-scale layers:

$$L_{CE}^i(Q^i, GT^i) = - \sum_m \sum_n GT_{mn}^i \log(q_{mn}^i) = - \log(q_{m_t^i, n_t^i}^i),$$

(4)

Then, we compute $L_{CE}^i(q^i, GT^i)$ for all layers as final loss $L_{SSL}$:

$$L_{SSL} = \sum_i L_{CE}^i(Q^i, GT^i),$$

(5)

**Theoretical analysis:** To better understand the effectiveness of the relative distance bias, we compute the partial derivative of $L_{CE}^i$ with respect to the cosine similarities $s_{mn}^i$ of the negative points $P_{mn}^i$ in $W^i$ on the layer $i$:

$$\nabla_{s_{mn}^i} L_{CE}^i = \sum_{m,n} \left[ \nabla q_{mn}^i L_{CE}^i(q_{mn}^i, GT^i) \times \nabla s_{mn}^i w_{mn}^i \right]$$

$$\nabla_{s_{mn}^i} L_{CE}^i = -\nabla q_{mn}^i \log(q_{mn}^i) \times \sum_{m,n} \left( \nabla w_{mn}^i q_{mn}^i \times \nabla s_{mn}^i w_{mn}^i \right)$$

$$\nabla_{s_{mn}^i} L_{CE}^i = -\nabla q_{mn}^i \log(q_{mn}^i) \times \nabla w_{mn}^i q_{mn}^i$$

$$\nabla_{s_{mn}^i} L_{CE}^i = \tau \times \exp(w_{mn}^i \star \tau) \times \exp(b_{mn}^i \star \tau) \times \exp(s_{mn}^i \star \tau),$$

(6)

The derivative results show that the relative distance bias $d^i$ directly multiplies the gradient of the cosine similarities $s_{mn}^i$ of the negative points by $\exp(b_{mn}^i \star \tau)$. Accordingly, the negative points farther from the selected GT (positive) point (with greater relative distance $b_{mn}^i$) are penalized more harshly to have low cosine similarities in the embedding space, which is exactly what we need.

**Inference steps of SSL stage:** Consistent with CC2D [24], the template anchor features $f_a$ are embedded by $E_p$ from the content of the labeled landmark in the template image. Next, we compute cascade cosine similarities $s^i$ between $f_a$ and $F_q^i$, where $F_q$ is the query features extracted from the query image by $E_q$. At last, we multiply the cascade similarities $s^i$, which are clipped to range $[0, 1]$. The final prediction is returned by $\text{argmax}$ operator in the coarse-to-fine fashion [24]. We infer the landmark locations for the unlabelled images in the training set as pseudo-labels needed for the TPL stage.
Table 1. Comparison of the state-of-the-art landmark detection methods under fully-supervised and one-shot setting on the cephalometric testset. * represents the performances copied from their original manuscripts, while # represents the performances we re-implement according to the their official code.

| Model          | Labeled images | MRE (↓) (mm) | SDR (↑) (%)  |
|----------------|----------------|--------------|--------------|
| Human experts  | -              | 1.07         | 85.60 90.48 93.64 96.92 99.51 99.83 |
| Ibragimov et al. [7]* | 150            | -            | 68.13 74.63 79.77 86.87 - - |
| Lindner et al. [13]* | 150            | 1.77         | 70.65 76.93 82.17 89.85 - - |
| Payer et al. [19]* | 150            | -            | 73.33 78.76 83.24 89.75 - - |
| GU^2-Net[33]#   | 150            | 1.69         | 76.95 81.98 88.82 94.24 98.23 99.14 |
| GU^2-Net[33]#   | 25             | 2.41         | 66.88 76.29 82.40 90.02 95.71 97.45 |
| GU^2-Net[33]#   | 10             | 9.79         | 48.77 58.74 65.07 74.23 80.65 82.61 |
| GU^2-Net[33]#   | 5              | 18.88        | 38.06 46.86 52.93 62.40 70.15 73.52 |
| RPR_Net[11]#    | 1              | 4.45         | 19.45 26.4 36.06 52.74 76.48 88.97 |
| CC2D-SSL [24]* | 1              | 4.67         | 40.42 47.68 55.54 68.38 - - |
| CC2D [24]*     | 1              | 2.72         | 49.81 58.73 68.18 81.01 - - |
| CC2Dv2SSL      | 1              | 2.23         | 53.75 64.93 76.48 89.14 97.43 99.16 |

3 Experiments

3.1 Settings

Dataset: A widely-used public dataset released for cephalometric landmark detection in IEEE ISBI 2015 grand Challenge [21,8] is used, which contains 400 radiographs. 19 landmarks of clinical anatomical significance are labeled by two expert doctors for each radiograph. We take the average annotations as the ground truth. The image size is 1935 × 2400 and the pixel spacing is 0.1mm. The dataset is split into training and test subsets with 150 and 250 radiographs according to the official website, respectively.

Metrics: Following the challenge [21], we use mean radial error (MRE) and successful detection rate (SDR) as metrics. We set four radii (2mm, 2.5mm, 3mm, and 4mm) for the cephalometric dataset.

Implementation details: The models are implemented in PyTorch [17], accelerated by an NVIDIA TITAN RTX GPU. We resize the images in cephalometric and BMPLE dataset to 384 × 384 and 384 × 768, respectively. For SSL stage, the two feature extractors are optimized by Adam [9] optimizer for 5000 epochs with a learning rate of 0.001 decayed by 0.5 every 500 epochs, with a batch size of 8. The size of cropped patch $X_p$ is set to 192 × 192, while the shape of matrix $T$ is 19 × 19. The $\beta$ and $\alpha$ in Eq. 3 are 0.7 and 0.1. For the template image, we choose the 125# training image in cephalometric dataset, and 120# training data in BMPLE dataset. For TPL stage, the multi-task U-Net is optimized by Adam optimizer for 900 epochs with a learning rate of 0.0003 decayed by 0.1 every 300 epochs, with a batch size of 8. We set $\tau = 10$.

3.2 The effectiveness of RDB

We visualize the cosine similarities in Fig. 2(a). Compared with CC2D, the candidate pixels (pixels with similarity $s^t_{xy} > 0$) are more close to the correct
landmark, and the cosine similarities are more contrastive, which validate that relative distance bias successfully helps the encoders in CC2Dv2 project the relatively distant landmarks to the embeddings with low similarities. The quantitative performances in Table 1 and the visualizations in Fig. 2(b,c) demonstrate that CC2Dv2 greatly outperforms other one-shot stat-of-the-art methods in the two medical landmark detection datasets, and is even competitive to the fully-supervised methods (the first [13] and second [7] place in the ISBI Challenge [21]) in terms of SDR-4mm.

**Limitation:** Despite that CC2Dv2 effectively decreases MRE by reducing the huge errors (e.g., 4mm SDR for cephalometric dataset is improved from 81.01% to 89.14%), there is still a considerable performance gap compared with fully-supervised methods to precisely detect landmarks with error less than 2mm.

### 3.3 Hyper-parameter analysis

We study the influence of different settings of the slope $\alpha$ and the maximum value of the RDB $\beta$ in Eq. 3. According to Table 2, the performances are stable when $\alpha$ lies in $0.7 \sim 1.3$. For $\beta$, a small $\beta$ decreases the effectiveness of RDB. As the maximum value of similarity is 1.0, a too large $\beta$ makes trouble in the convergence of $L_{SSL}$. Setting $\beta$ to 0.7 leads to the best performance.
Table 2. The performances of CC2Dv2-SSL under different settings of the slope $\alpha$ and the maximum value of the RDB $\beta$ in Eq. 3.

| Para. | Value | MRE (↓) (mm) | SDR (↑) (%) |
|-------|-------|---------------|-------------|
| $\beta$ | 0.9   | 2.87          | 39.12       |
|   | 0.8   | 2.82          | 40.09       |
|   | 0.7   | 2.70          | 44.15       |
|   | 0.6   | 2.98          | 40.55       |
|   | 0.5   | 3.14          | 41.85       |
| $\alpha$ | 0.04  | 3.32          | 43.32       |
|   | 0.07  | 2.73          | 44.95       |
|   | 0.10  | 2.70          | 44.15       |
|   | 0.13  | 2.71          | 44.86       |
|   | 0.16  | 3.07          | 39.38       |

Table 3. Comparison of the state-of-the-art landmark detection methods under fully-supervised and one-shot setting on the BMPLE testset.

| Model                  | Labeled images | Test Dataset 1 | Test Dataset 2 |
|------------------------|----------------|----------------|----------------|
|                        |                | MRE (↓) (mm) | SDR (↑) (%) | MRE (↓) (mm) | SDR (↑) (%) |
| Human experts          |                | 1.66          | 90.50        | 97.50        | 98.25        |
| Payer et al. [18]      | 120            | 5.61          | 34.00        | 81.50        | 95.50        |
| Chen et al. [4]        | 120            | 3.08          | 85.25        | 95.50        | 95.50        |
| RPR-Net [11]           | 1              | 129.2         | 0.50         | 1.00         | 2.00         |
| CC2D-SSL [24]          | 1              | 27.86         | 17.50        | 35.00        | 43.00        |
| CC2D [24]              | 1              | 21.55         | 14.75        | 37.25        | 53.75        |
| CC2Dv2                 | 1              | 12.28         | 18.25        | 53.25        | 77.50        |

4 BMPLE Dataset

Clinical significance: Biomechanical parameters are essential for orthopedic refined procedures, e.g., measuring the degree of varus/valgus of the knee, planning osteotomy angle, evaluating the improvement of lower limb force lines, and predicting the risk of abnormal wear and loosening of artificial joints [6]. However, BMPLE measurement is time-consuming and laborious for orthopedic surgeons. It takes up to 10 minutes to carefully annotate and connect the bone markers [20].

Data acquisition: The dataset consists of 190 radiographs collected from two collaborated hospitals. The study has been approved by the Hospitals Committee and carried out in accordance with the Declaration of Helsinki. All of the radiographs have been desensitized. The radiographs sizes are distributed from 2396 × 4950 to 3200 × 8500, while the pixel spacing lies in 0.13 mm ∼ 0.16 mm.

Annotation: The dataset is split into three subsets (Training, Test1, and Test2) with 120, 20, and 50 radiographs, respectively. The radiographs in the training and Test2 subsets are annotated by one senior orthopedic surgeon, while the Test1 subset is labeled by three experts, we compute the average annotations as the ground-truth and report the error of human experts in Table 3.

Measurement of biomechanical parameters of lower extremity relies on accurate anatomical landmark localization. As illustrated in Fig. 3, for each lower limb, 10 landmarks are defined and labeled, 6 axes are generated by connecting
Fig. 3. (a) The illustration of the 20 annotated landmarks in the lower extremity radiography in BMPLE dataset, 1-10 landmarks are on the right (R) lower limb, while the left 11-20 landmarks are on the left (L) lower limb. (b) The biomechanical angle (“Right FTA” in figure b) is calculated between two axes, each axis is connected by two landmarks. (c) The detailed definitions of axis and biomechanical angles.

The corresponding landmarks, and 7 biomechanical angles are computed according to the corresponding two axes [20], the illustrations of other biomechanical angles can be found in the supplemental materials.

**Fully supervised performances** We establish a preliminary automatic BMPLE measurement framework, which localizes landmarks using the well-trained SOTA method (Chen et al. [4]) and computes BMPLE according the definitions in Fig. 3(b,c). The errors are $3.90° ± 5.17°$ and $4.25° ± 7.09°$ on Test1 and Test2 subset, respectively, while the error of human experts on Test1 is $0.69° ± 2.38°$. The inference speed is 1.55s per image. We hope that this dataset can help the community develop an accurate and fast BMPLE measurement framework, which is valuable to orthopedic surgeons.

**One-shot performances** Table 3 shows the landmark detection performances of varying competing methods. It is evident that CC2Dv2 clearly outperforms other one-shot approaches by a large margin. However, there is a large performance gap between CC2Dv2 and fully supervised methods and Human experts, which motivates us to improve the accuracy in the future work.

5 Conclusion

In this paper, we upgrade cascade comparing to detect (CC2D) to CC2Dv2, by adding a simple-yet-effective relative distance bias (RDB) in the training stage. The theoretical analysis proves that RDB encourages the encoder to project the
distant landmarks into the embeddings with low cosine similarities. Extensive experiments on two medical landmark detection datasets validate that CC2Dv2 greatly surpasses other state-of-the-art one-shot landmark detection methods. Future work includes developing faster and more accurate methods for the BM-PLE dataset to benefit the orthopedic surgery community.
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