# Hybrid Cascade Point Search Network for High Precision Chart Component Detection 

Junyu Luo
Sichuan University
Chengdu, China
asbljy@outlook.com

Jinpeng Wang
Microsoft Research
Beijing, china
jinpwa@microsoft.com

Chin-Yew Lin
Microcnftracoawh

## Background

- Chart images are commonly used for data visualization.
- However, during the process they are generally stored in forms of images, bring problems to the automatic data analysis



## Task



Fig. 4: An example image from ChartDet val set.

- Giving a chart image, we want to mark out each component.


## Challenges

EAOe

## 60\%

- Chart are relatively simplommmommen mmmen
- Yet contains diversity
- Rule-based method is in suffieient
- End2End Methods miss the important middle results for further analysis
- General object detection methods contains accuracy problems
- Region-based method may get the wrong border
(c) CornerNet
- Key-point-based method maxemiss group the key points


## Model

- Key Point Proposal
- Dynamically search the object
- Point Pairing Module


Fig. 3: A diagram of the hybrid cascade pairing network. Point Proposal Network (PPN), Object Search Network (OSN Point Pairing Module (PPM) work in a cascade order.


Step 1


Step 2


Step 3

$$
\begin{aligned}
& L_{\text {heat }}= \\
& \qquad \frac{-1}{N} \sum_{c=1}^{C} \sum_{i=1}^{H} \sum_{j=1}^{W}\left\{\begin{array}{l}
\left(1-\hat{y}_{c i j}\right)^{\alpha} \log \left(\hat{y}_{c i j}\right), \\
\left(1-y_{c i j}\right)^{\beta}\left(\hat{y}_{c i j}\right)^{\alpha} \log (1-
\end{array}\right.
\end{aligned}
$$

## Dynamically search the object - ISM



Step 1

* Estimated Bottom-Right Point


Iterative Search Module (ISM): ISM searches the main region of the current object in a few iterations.

$$
\begin{gather*}
\left(f_{w}, f_{h}\right)=\operatorname{ISM}\left(\text { RoI }_{t}^{\text {ISM }}, p_{t l} \cdot l a b e l, \text { Scale } e_{t}\right)  \tag{3}\\
p_{t l} \cdot w_{t+1}=p_{t l} \cdot w_{t} \times f_{w}, \quad p_{t l} \cdot h_{t+1}=p_{t l} \cdot h_{t} \times f_{h} \tag{4}
\end{gather*}
$$

## Dynamically search the object - FTM

$$
\left.\begin{array}{rl}
\left(d_{w}, d_{h}\right) & =\operatorname{FTM}\left(\text { RoI }^{\mathrm{FTM}}, p_{t l} \cdot l \text { abel },\right. \text { Scale }
\end{array}\right)
$$

2) Fine Truing Module (FTM): We add the FTM to further refine the predictions using linear di ISM. It is different from ISM.

## Point Pairing Module

```
Algorithm 1 Point Pairing Algorithm
Input: top-left point }\mp@subsup{p}{tl}{}\mathrm{ , top-k bottom-right points {p
    size of predicted region ( }\mp@subsup{p}{tl}{}\cdotw,\mp@subsup{p}{tl}{}\cdoth)\mathrm{ , threshold of IoU
    TIoU}\mathrm{ , threshold of the score }\mp@subsup{T}{\mathrm{ score }}{}\mathrm{ , ratio of candidate
    region }
Output: the paired bottom-right point p}\mp@subsup{p}{b}{*
    1: initial the max score S Sax =0
    2: }\mp@subsup{p}{obj}{}=(\mp@subsup{p}{tl}{}\cdoti+\mp@subsup{p}{tl}{}\cdotw,\mp@subsup{p}{tl}{}\cdotj+\mp@subsup{p}{tl}{}\cdoth
3: {\mp@subsup{p}{br}{}\mp@subsup{}}{}{\prime}=\mathrm{ select }\mp@subsup{p}{br}{}\mathrm{ from {pbr}}}=\mp@code{*}
            where }\mp@subsup{p}{br}{}\mathrm{ in (pobj.i土 
                and pbr.label == potl.label
    4: for }\mp@subsup{p}{br}{}\in{\mp@subsup{p}{br}{}\mp@subsup{}}{}{\prime}\mathrm{ do
    5: }\quad\mp@subsup{S}{IoU}{}=\operatorname{IoU}(\operatorname{bbox}(\mp@subsup{p}{tl}{},\mp@subsup{p}{obj}{}),\operatorname{bbox}(\mp@subsup{p}{tl}{},\mp@subsup{p}{br}{})
    if}\mp@subsup{S}{IoU}{}>\mp@subsup{T}{IoU}{}\mathrm{ then
        Scur}=\mp@subsup{S}{IoU}{}\times\mp@subsup{p}{br}{}.scor
        if S}\mp@subsup{S}{cur}{}>\mp@subsup{S}{\mathrm{ max }}{}\mathrm{ and }\mp@subsup{S}{cur}{}>\mp@subsup{T}{\mathrm{ score }}{}\mathrm{ then
            Smax}=\mp@subsup{S}{cur}{
            pbr}=\mp@subsup{p}{br}{
        end if
    end if
    end for
```



[^0]Bottom-Right Point


* Estimated Bottom-Right Point
$\mathrm{Rol}_{\mathrm{T}}$ P


## Experiments

| Method | AP | $\mathrm{AP}_{0.5}$ | $\mathrm{AP}_{0.75}$ | $\mathrm{AP}_{0.8}$ | $\mathrm{AP}_{0.85}$ | $\mathrm{AP}_{0.9}$ | $\mathrm{AP}_{0.95}$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Retinanet 101 | 0.459 | 0.729 | 0.497 | 0.389 | 0.253 | 0.110 | 0.012 |
| Faster-RCNN 101 | 0.580 | 0.805 | 0.664 | 0.578 | 0.434 | 0.233 | 0.056 |
| Cascade-RCNN 101 | 0.647 | 0.831 | 0.723 | 0.660 | 0.552 | 0.375 | 0.149 |
| CornerNet | 0.646 | 0.783 | 0.717 | 0.674 | 0.587 | 0.429 | 0.225 |
| CenterNet | 0.666 | 0.820 | 0.742 | 0.685 | 0.592 | 0.429 | 0.205 |
| HCPN w/o PPM | 0.697 | $\mathbf{0 . 8 7 0}$ | 0.775 | 0.714 | 0.610 | 0.429 | 0.222 |
| HCPN | $\mathbf{0 . 7 0 6}$ | 0.868 | $\mathbf{0 . 7 7 8}$ | $\mathbf{0 . 7 2 3}$ | $\mathbf{0 . 6 2 3}$ | $\mathbf{0 . 4 5 7}$ | $\mathbf{0 . 2 6 1}$ |
| HCPN (Bar Only) | 0.810 | 0.934 | 0.873 | 0.837 | 0.757 | 0.635 | 1 |
| Revision (Bar Only) | 0.330 | 0.598 | 0.316 | 0.217 | 0.112 | 0.032 |  |
|  |  |  |  |  |  |  |  |

## Conclusions

- we presented HCPN, a new framework for precise object detection.
- The experiments proved that our method effectively combining the strengthens of region and point based methods on chart component detection task.

Thanks


[^0]:    Step 1

