



SHANGHAI JIAO TONG
UNIVERSITY



Image Cropping with Spatial-aware Feature and Rank Consistency

Chao Wang Li Niu* Bo Zhang Liqing Zhang*

Shanghai Jiao Tong University

WED-AM-174



Quick Preview

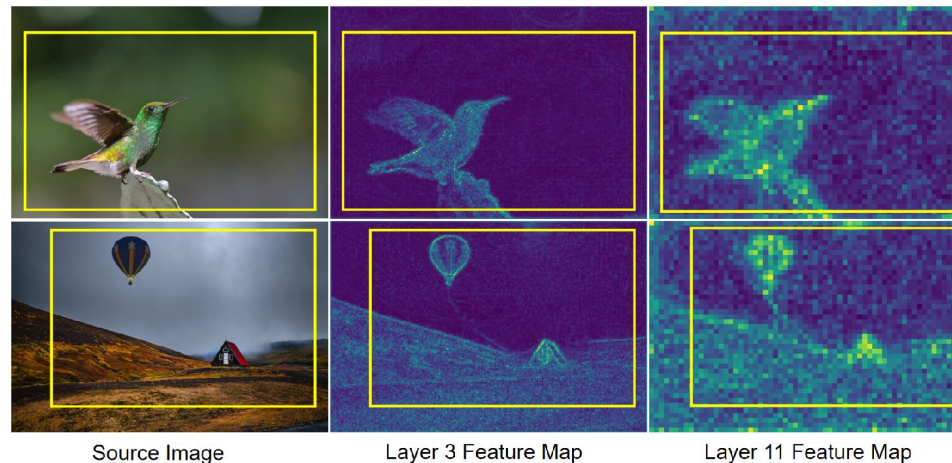
- Image cropping aims to find visually appealing crops in an image.



- Drawbacks of previous methods.
 - They are weak in capturing the spatial relationship between crops and aesthetic elements.
 - The potential of unlabeled data awaits to be excavated.

Quick Preview

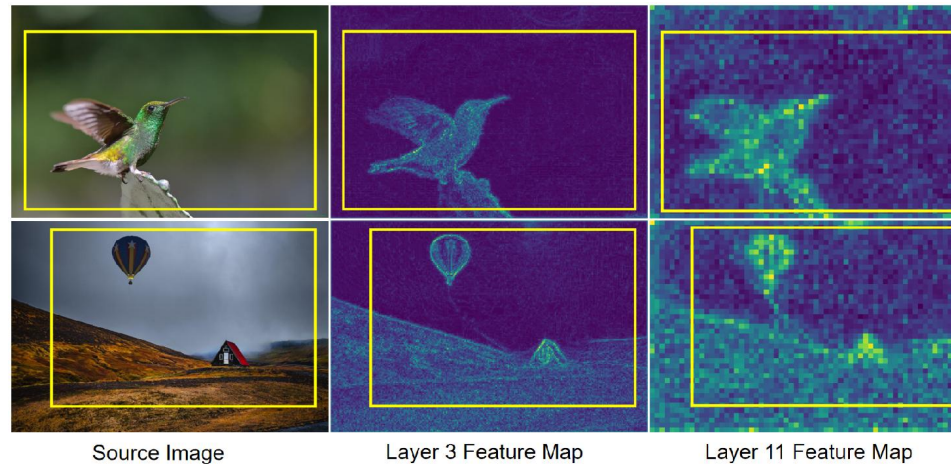
- We propose **spatial-aware feature** to encode the spatial relationship between candidate crops and aesthetic elements.



- We train a pair-wise ranking classifier on labeled images and transfer the ranking knowledge to unlabeled images to enforce **rank consistency**.
- Experimental results on the benchmark datasets show that our proposed method performs favorably against state-of-the-art methods.

Motivation of Spatial-aware Feature

- The spatial relationship between crops and aesthetic elements (e.g., salient objects, semantic edges) is very critical for image cropping.
- The crop should enclose the salient object, or should not cut through the semantic edges.



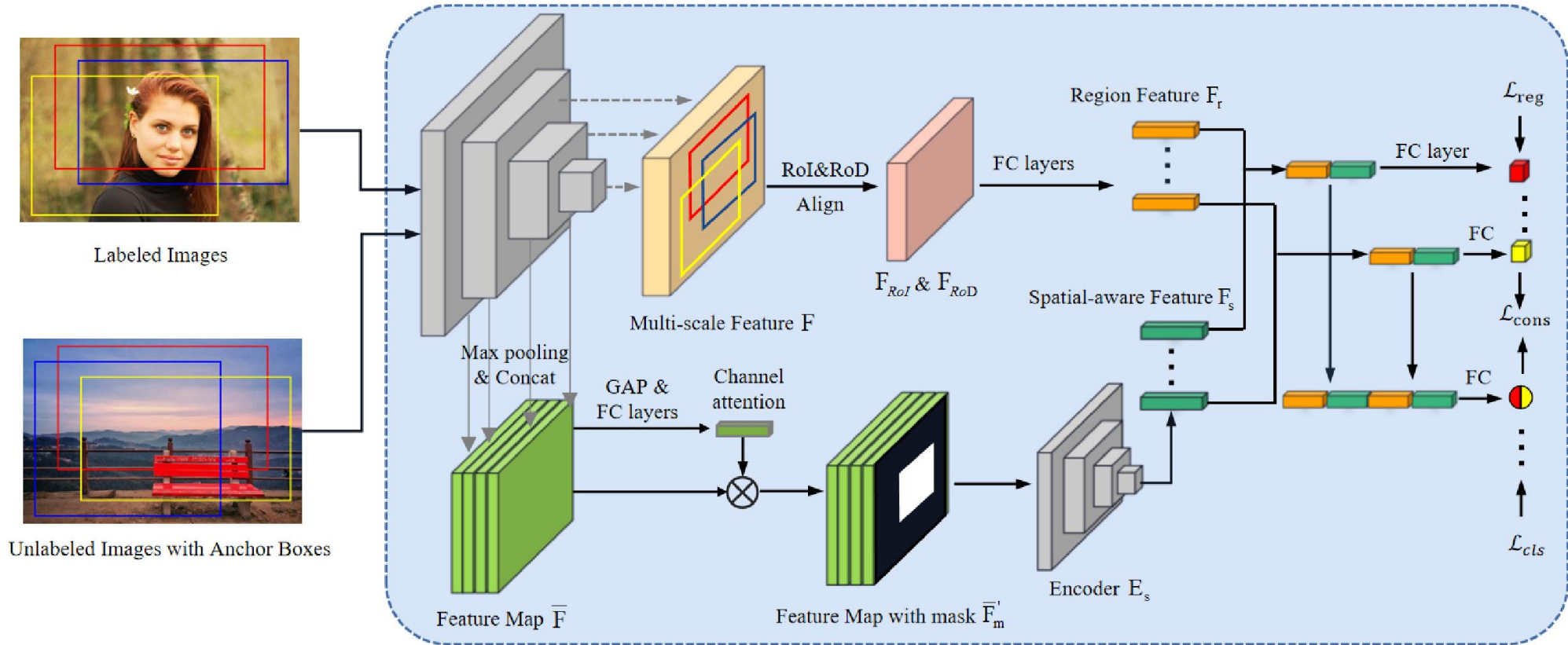
The feature map obtained using channel-wise max pooling can emphasize some aesthetic elements. The low-level feature maps emphasize semantic edges and the high-level feature maps emphasize salient objects.

Motivation of Rank Consistency

- The cost of crop annotation is very high.
- The rank of candidate crops should be consistent between labeled data and unlabeled data.
- We expect that the knowledge of comparing the aesthetic quality of two crops with similar content could be transferred to unlabeled data.
- Semi-supervised/Transductive Learning paradigms.

Proposed Method

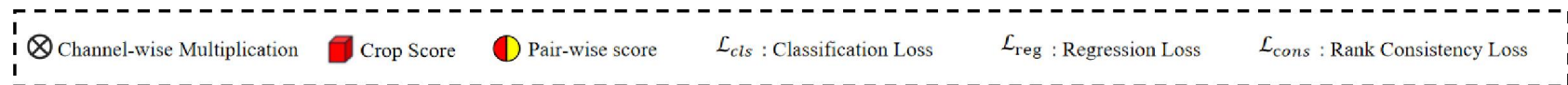
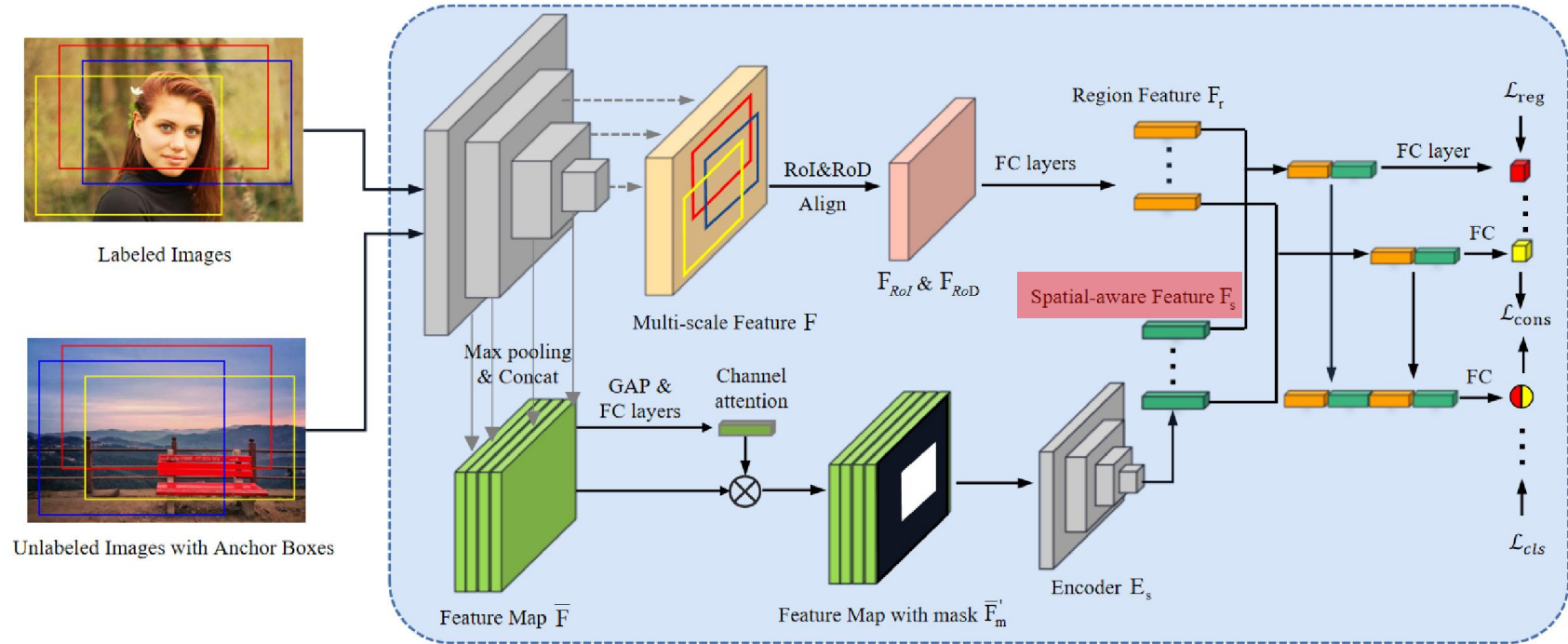
➤ Image Cropping with Spatial-aware Feature and Rank Consistency



Proposed Method

➤ Spatial-aware Feature

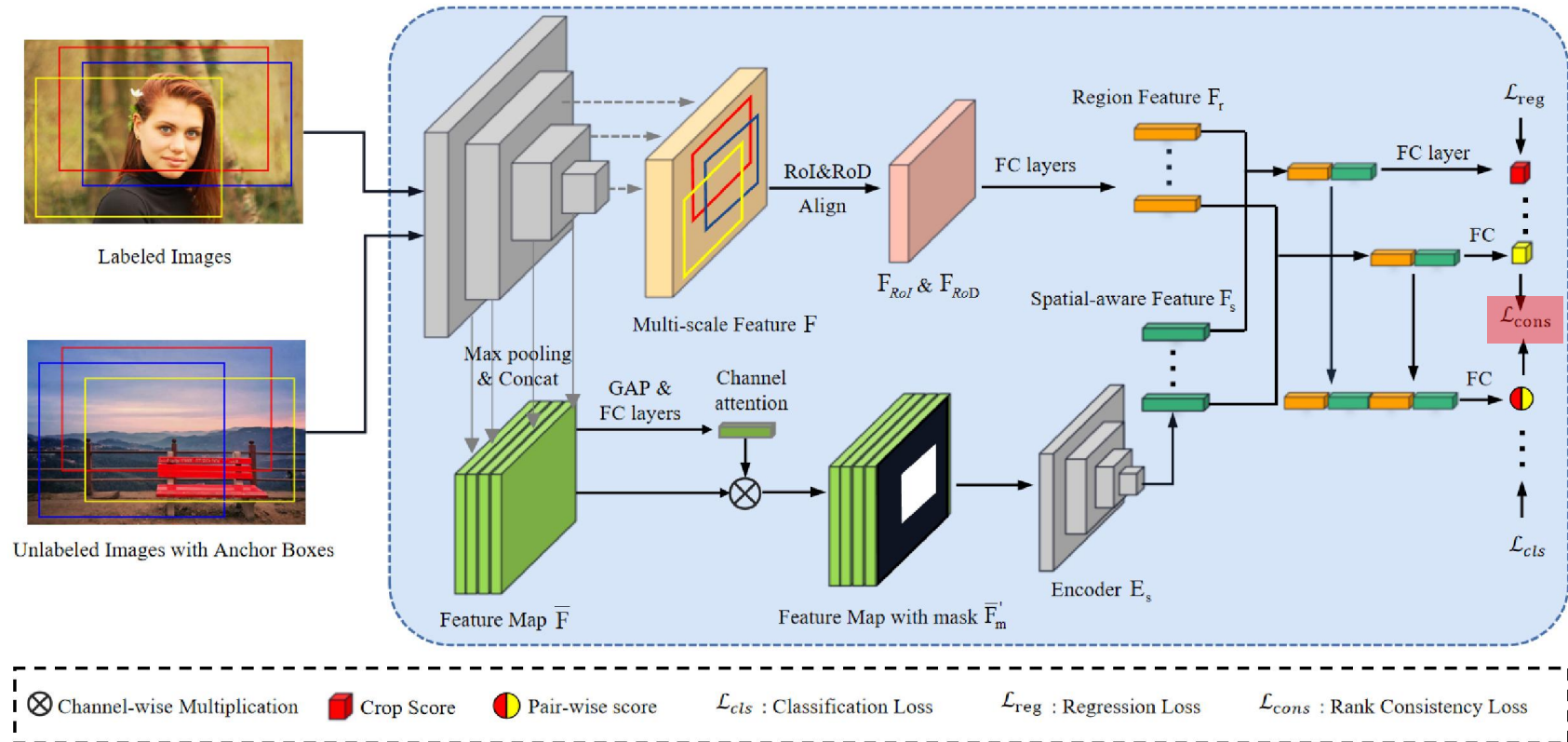
- Feature Maps Activation.
- Channel Attention Block.
- Spatial Relationship Modeling



Proposed Method

➤ Rank Consistency

- Pair-wise Ranking Classifier.



Proposed Method

- Training with a multi-task loss function in an end-to-end manner

$$\mathcal{L}_{total} = \mathcal{L}_{labeled} + \mathcal{L}_{cons}$$

$$\mathcal{L}_{labeled} = \mathcal{L}_{reg} + \lambda_{cls} \mathcal{L}_{cls}$$

Regression Loss

$$\mathcal{L}_{reg} = \frac{1}{N} \sum_i \mathcal{L}_{s1}(y_i - \hat{y}_i)$$

Classification Loss

$$\mathcal{L}_{cls} = \frac{1}{P} \sum_{n=1}^P -q_n \cdot \log p_n - (1 - q_n) \cdot \log(1 - p_n)$$

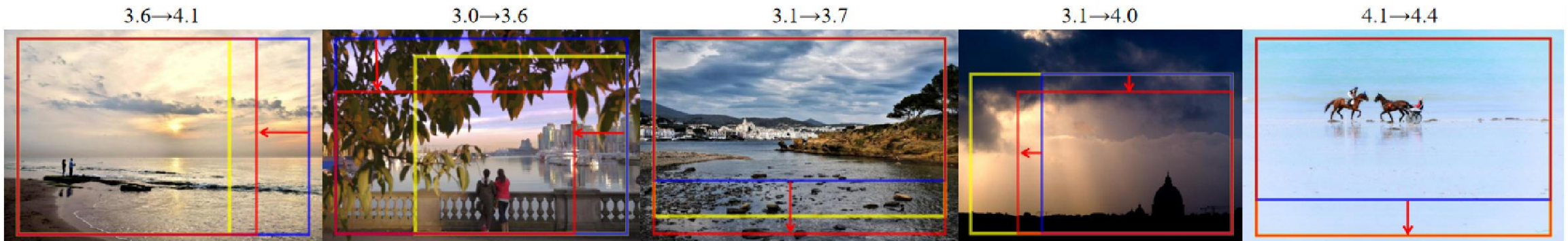
Consistency Loss

$$\mathcal{L}_{cons} = \frac{2}{(N^2 - N)} \sum_{i=1}^N \sum_{j=i+1}^N l(C_i, C_j)$$

$$l(C_i, C_j) = \max \{0, \delta + \text{sign}(p_n - 0.5)(\hat{y}_j - \hat{y}_i)\}$$

Proposed Method

- Spatial-aware Feature
 - Spatial-aware feature helps locate the crop better.

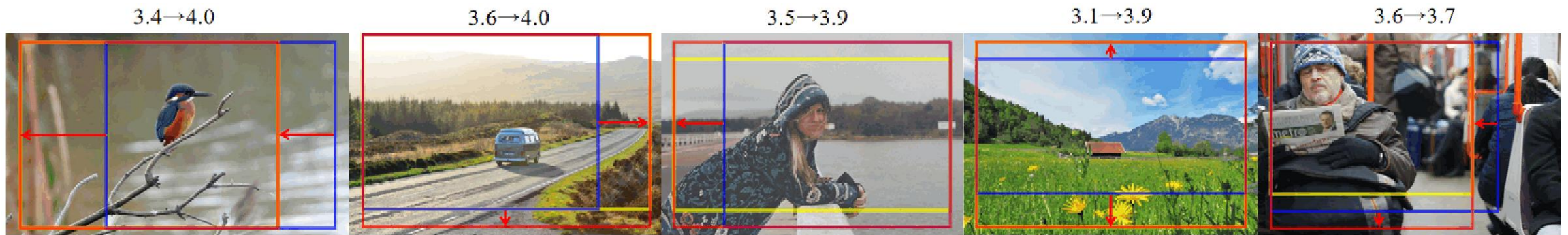


Predicted scores are lift by Spatial-aware feature. The annotated best crops are in yellow, the predicted best crops by the basic model and our proposed method are in blue and red respectively. The numbers above the images are their predicted scores.

Proposed Method

➤ Rank Consistency

- Rank consistency helps rank candidate crops more accurately.



Predicted scores are lift by Rank consistency. The annotated best crops are in yellow, the predicted best crops by the basic model and our proposed method are in blue and red respectively. The numbers above the images are their predicted scores.

Experiments

- Quantitative comparison on **GIACD** dataset.
 - **PCC** evaluates the linear correlation.
 - **SRCC** measures the ranking order correlation.
 - **Acc5/Acc10** measures the ability to return the best crops.

| Model | $Acc_{1/5}$ | $Acc_{2/5}$ | $Acc_{3/5}$ | $Acc_{4/5}$ | \overline{Acc}_5 | $Acc_{1/10}$ | $Acc_{2/10}$ | $Acc_{3/10}$ | $Acc_{4/10}$ | \overline{Acc}_{10} | \overline{SRCC} | \overline{PCC} |
|-----------------|-------------|-------------|-------------|-------------|--------------------|--------------|--------------|--------------|--------------|-----------------------|-------------------|------------------|
| A2RL [21] | 23.2 | - | - | - | - | 39.5 | - | - | - | - | - | - |
| VPN [52] | 36.0 | - | - | - | - | 48.5 | - | - | - | - | - | - |
| VFN [5] | 26.6 | 26.5 | 26.7 | 25.7 | 26.4 | 40.6 | 40.2 | 40.3 | 39.3 | 40.1 | 0.485 | 0.503 |
| VEN [52] | 37.5 | 35.0 | 35.3 | 34.2 | 35.5 | 50.5 | 49.2 | 48.4 | 46.4 | 48.6 | 0.616 | 0.662 |
| GAIC [57] | 68.2 | 64.3 | 61.3 | 58.5 | 63.1 | 84.4 | 82.7 | 80.7 | 78.7 | 81.6 | 0.849 | 0.874 |
| CGS [23] | 63.0 | 62.3 | 58.8 | 54.9 | 59.7 | 81.5 | 79.5 | 77.0 | 73.3 | 77.8 | 0.795 | - |
| CGS* [23] | 66.2 | 63.0 | 59.6 | 56.5 | 61.3 | 84.4 | 81.4 | 78.9 | 76.9 | 80.4 | 0.850 | 0.874 |
| Trans View [36] | 69.0 | 66.9 | 61.9 | 57.8 | 63.9 | 85.4 | 84.1 | 81.3 | 78.6 | 82.4 | 0.857 | 0.880 |
| Ours (w/o te) | 68.4 | 65.1 | 62.1 | 59.2 | 63.7 | 86.2 | 83.1 | 81.4 | 79.5 | 82.6 | 0.865 | 0.889 |
| Ours | 70.0 | 66.9 | 62.5 | 59.8 | 64.8 | 86.8 | 84.5 | 82.9 | 79.8 | 83.3 | 0.872 | 0.893 |

Experiments

- Quantitative comparison on **FCDB** dataset.
 - **IoU** and **Disp** measure the overlap and offset degree.

| Method | Training Set | IoU \uparrow | Disp \downarrow |
|----------------|--------------|----------------|-------------------|
| A2RL [21] | AVA | 0.663 | 0.089 |
| A3RL [22] | AVA | 0.696 | 0.077 |
| VPN [52] | CPC | 0.711 | 0.073 |
| VEN [52] | CPC | 0.735 | 0.072 |
| ASM [46] | CPC | 0.749 | 0.068 |
| GAIC [57] | GAICD | 0.672 | 0.084 |
| CGS [23] | GAICD | 0.685 | 0.079 |
| TransView [36] | GAICD | 0.682 | 0.080 |
| Ours (w/o te) | GAICD | 0.686 | 0.078 |
| Ours | GAICD | 0.695 | 0.075 |

Experiments

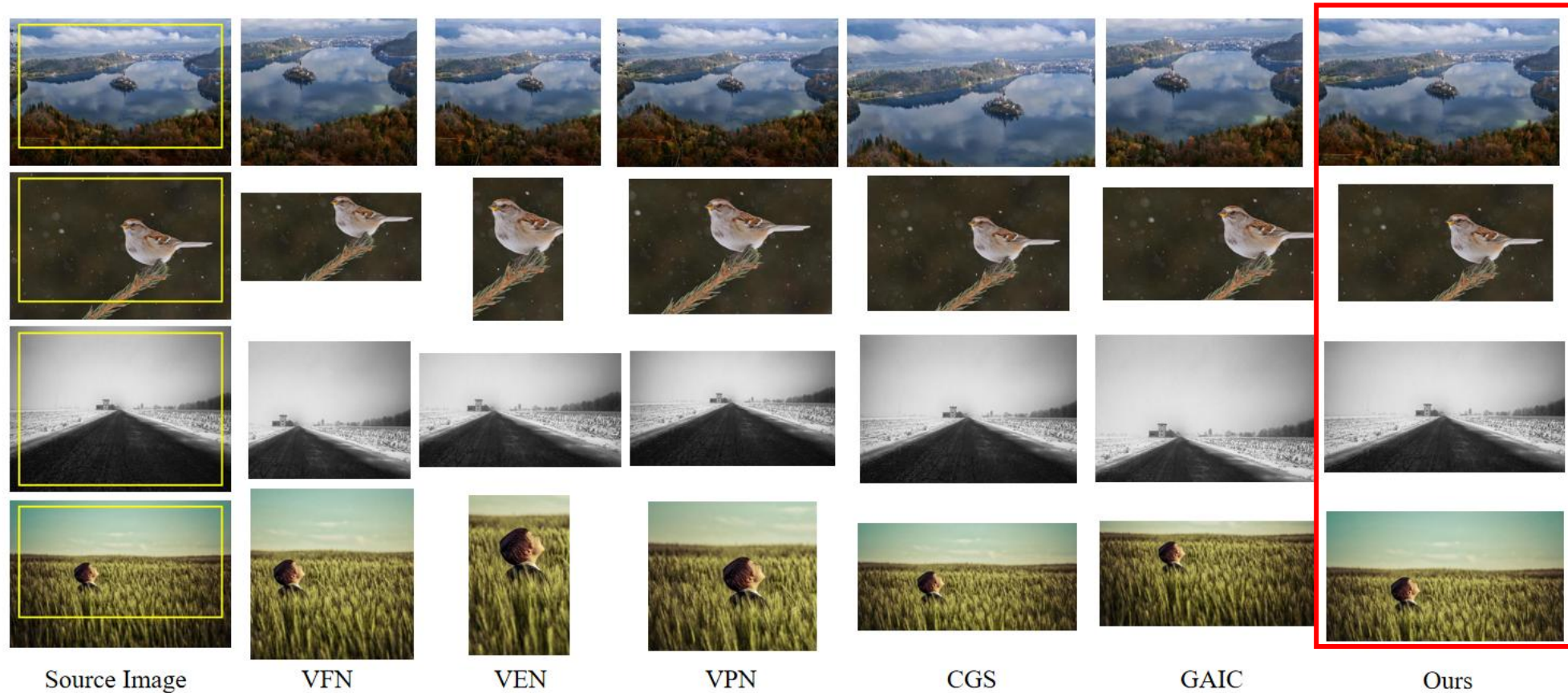
- Model complexity and runtime.
 - Our model is lighted-weighted and efficient for mobile device application.

| Method | Backbone | #Parameters | Runtime |
|-------------|-------------|-------------|---------|
| VFN | Alexnet | 14.88M | 2491ms |
| VEN | VGG16 | 40.93M | 5331ms |
| VPN | VGG16 | 65.31M | 149ms |
| CGS | VGG16 | 21.25M | 31ms |
| GAIC | MobileNetv2 | 5.91M | 24ms |
| Ours(basic) | MobileNetv2 | 5.91M | 25ms |
| Ours | MobileNetv2 | 7.10M | 32ms |

All models are run on the PC with Intel(R) Core(TM) i7-9700K CPU and one single NVIDIA GTX 1080Ti GPU.

Experiments

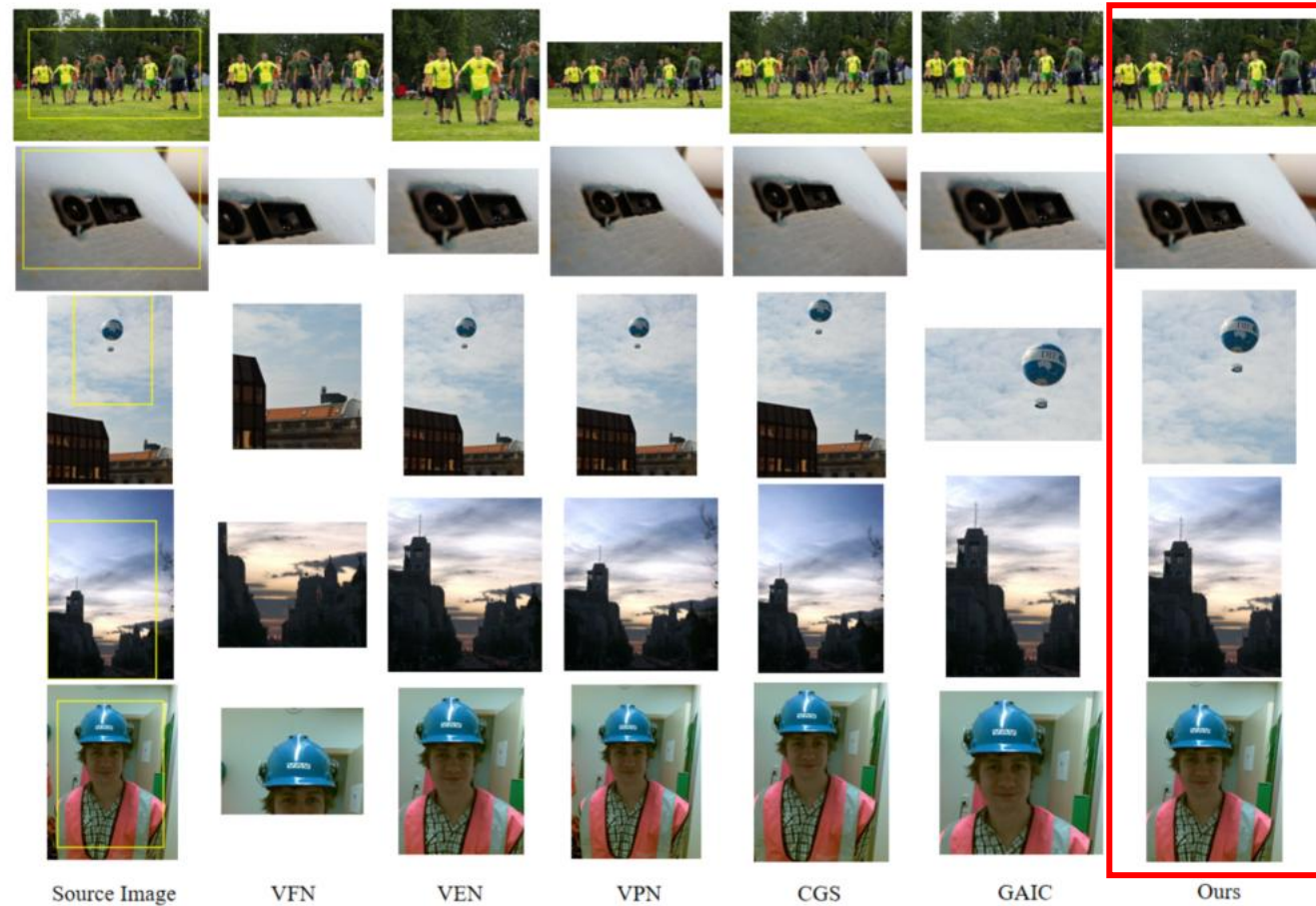
- Qualitative comparison on **GAICD** dataset.



The annotated best crop (yellow bounding box) in the source image is in the left column and top-1 crops obtained by different methods are in the rest of the columns.

Experiments

- Qualitative comparison on **FCDB** dataset.



The annotated best crop (yellow bounding box) in the source image is in the left column and top-1 crops obtained by different methods are in the rest of the columns.

Contributions

- **Spatial-aware Feature**: capture the spatial relationship between candidate crops and aesthetic elements.
- **Rank Consistency**: transfer ranking knowledge from labeled images to unlabeled images.
- Quantitative and qualitative comparisons have shown that our method obtains the state-of-the-art performance on benchmark datasets.



SHANGHAI JIAO TONG
UNIVERSITY



Thanks for watching !

Image Cropping with Spatial-aware Feature and Rank Consistency

Chao Wang Li Niu* Bo Zhang Liqing Zhang*

Shanghai Jiao Tong University

WED-AM-174