A UNIFIED FRAMEWORK FOR FAULT DETECTION OF FREIGHT TRAIN IMAGES UNDER COMPLEX ENVIRONMENT

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INTRODUCTION

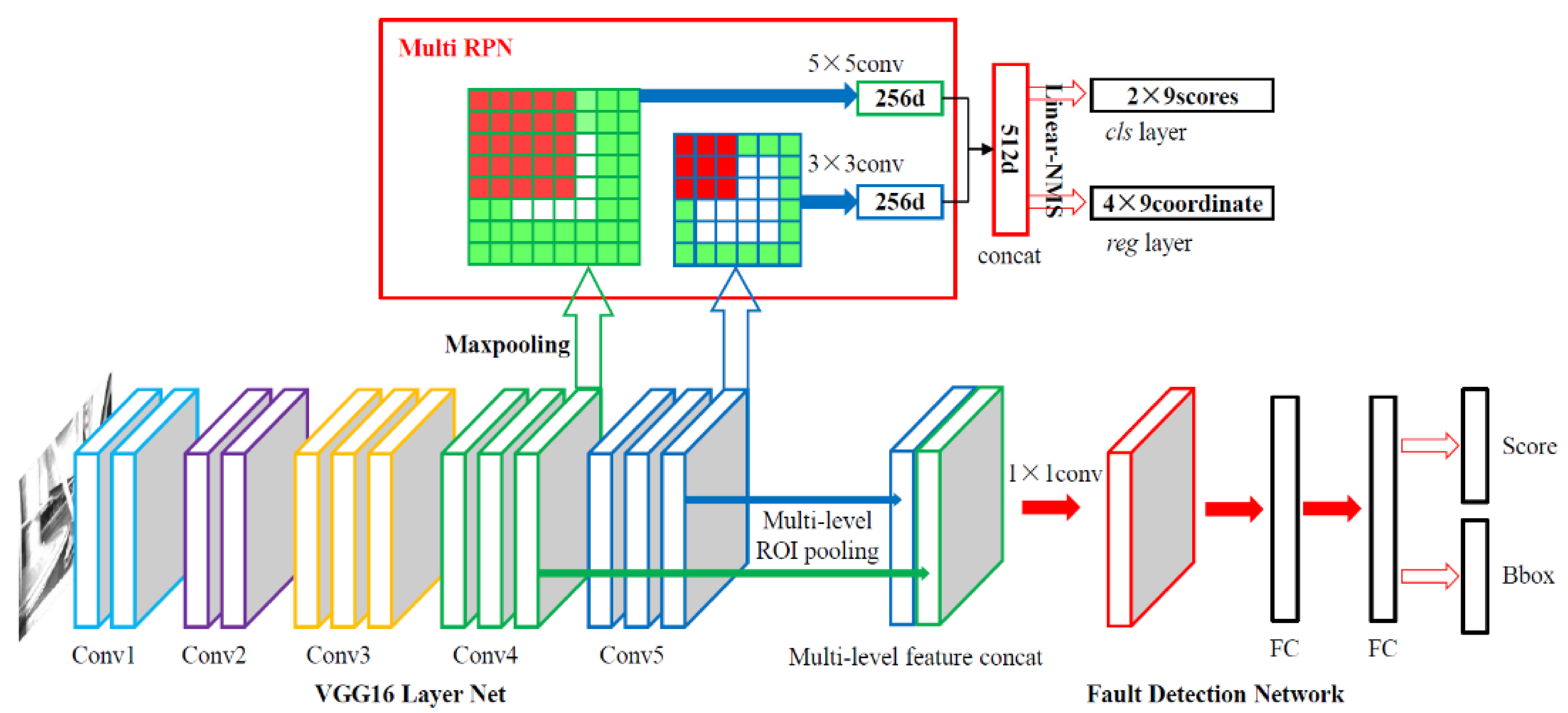
Fault detection for the vehicle braking and steering systems is an important task to ensure the security of freight trains. For a long time, it has been performed by the skilled workers, which has many drawbacks such as low detection probability and poor efficiency. This paper proposes a novel unified framework for fault detection of the freight train images based on convolutional neural network (CNN) under complex environment.

- The multi region proposal networks (MRPN) with a set of prior bounding boxes are introduced to achieve high quality fault proposal generation.
- A linear non-maximum suppression (NMS) is used to retain the most suitable anchor while removing redundant boxes.
- A powerful multi-level region-of-interest (RoI) pooling is proposed for proposal classification and accurate detection.

The experiments indicate that the proposed framework can achieve high performance on four fault benchmarks, substantially outperforming the state-of-the-art methods.

METHOD

(a) Pipeline of fault detection of freight train image



(b) The pseudo code of linear-NMS

```
Input : A = {a_1, ..., a_N}, R = {r_1, ..., r_N}, T_NMS
        A  is the list of initial detection boxes
        R  contains corresponding detection scores
        T_NMS  is the NMS threshold
begin
    C ← {}
    while A ≠ empty do
        j ← argmax R
        M ← a_j
        C ← C ∪ M; A ← A − M
        for a_i in A do
            if iou(M, a_i) ≥ T_NMS then
                A ← A − a_i; R ← R − r_i
            end                                   NMS
            r_i ← r_i f(iou(M, a_i))
                                                  liner-NMS
        end
    end
    return C, R
end
```

● ***Multi region proposal generation***

To search for fault region proposals, a network is slid over two feature maps (Conv4_3 and Conv5_3) in the VGG16 model.

- A 5×5 convolution is applied to extract local feature over a 2×2 max pooling layer employed on Conv4_3 feature maps.
- A 3×3 convolution is used to extract local feature over Conv5_3 feature maps at each sliding position.

● ***Multi-level fault detection network***

To better utilize the multi-level convolutional features and enrich the differentiate information of each anchor, we perform multi-level RoI pooling over the Conv4_3 and Conv5_3 feature maps. We apply concatenation on each feature and encode the concatenated feature with 512×1×1 convolutional layer to combine the multi-level pooled features and match the first fully-connected layer of the VGG16 network.

CONCLUSION

In this paper, we present a novel unified framework for fault detection of freight train images of the vehicle braking and steering system with a powerful deep learning method in an end-to-end manner. The proposed framework consists of a MRPN with a set of characteristic prior anchors for high quality fault proposal generation and a powerful multi-level fault detection network for proposal classification and accurate localization. Specially, a linear-NMS method is applied to effectively remove redundant boxes. Experiments on four benchmarks show that the proposed method can achieve high performance with a fast detection speed over 4 fps (including all steps), substantially outperforming the previous methods.

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PERFORMANCE

● ***Detection results of different databases***

Methods	Cut-out cock handle			Dust collector			Fastening bolts			Bogie block key			Detection speed /s
	CDR/%	MDR/%	FDR/%	CDR/%	MDR/%	FDR/%	CDR/%	MDR/%	FDR/%	CDR/%	MDR/%	FDR/%	
Cascade detector(LBP)	92.12	7.88	15.29	98.12	1.88	8.82	96.79	3.21	4.73	97.89	2.11	1.31	0.036
HOG+Adaboost+SVM	97.41	2.59	9.41	99.53	0.47	2.59	98.58	1.42	2.89	99.1	0.90	2.14	0.049
FAMRF+EHF	98.71	1.29	5.41	98.94	1.06	2.82	99.11	0.89	6.41	**99.24**	0.76	1.52	0.725
SSD(VGG16)	**99.88**	0.12	23.06	100	0	26.71	97.69	2.31	0.05	98.07	1.93	0	0.153
R-FCN(ResNet-50)	99.17	0.83	2.59	100	0	19.41	99.89	0.11	0.05	96.41	3.59	0	0.177
+Soft NMS	99.88	0.12	29.88	100	0	26.82	99.74	0.26	0	64.45	35.55	0.03	0.179
Faster-RCNN(ZF)	98.82	1.18	4.00	100	0	14.94	99.42	0.58	0.05	98.86	1.14	0	0.073
Faster RCNN(VGGM)	98.82	1.18	7.41	100	0	13.53	99.79	0.21	0.05	97.45	2.55	0	0.079
Faster RCNN(VGG16)	99.06	0.94	1.41	100	0	3.65	99.95	0.05	0	95.76	4.24	0.10	0.238
+Soft NMS	99.17	0.83	0.82	100	0	4.12	99.95	0.05	0.05	77.98	22.02	0	0.243
Our method	99.18	0.82	**0.47**	**100**	**0**	**0.35**	**100**	**0**	**0**	98.76	1.24	**0**	0.244

● ***Results of railway equipment detection***