Abstract

In practical applications especially with safety requirement, some hand-held actions need to be monitored closely, including smoking cigarettes, dialing, eating, etc. Taking smoking cigarettes as example, existing smoke detection algorithms usually detect the cigarette or cigarette with hand as the target object only, which leads to low accuracy. In this paper, we propose an application-driven AI paradigm for hand-held action detection based on hierarchical object detection. It is a coarse-to-fine hierarchical detection framework composed of two modules. The first one is a coarse detection module with the human pose consisting of the whole hand, cigarette and head as target object. The followed second one is a fine detection module with the fingers holding cigarette, mouth area and the whole cigarette as target. Some experiments are done with the dataset collected from real-world scenarios, and the results show that the proposed framework achieve higher detection rate with good adaptation and robustness in complex environments.

1. Introduction

In practical applications especially in industrial scenarios, some hand-held human actions need to be monitored closely, including smoking cigarettes, dialing, eating, etc. Under most circumstances, smoking cigarettes is an important problem of safety. Places like chemical plants, industrial workshops and petrol stations, all require strict control of smoking cigarettes, which may bring about fire, explosion, etc. For instance, a spark in some chemical plants may lead to a disaster of a lot of human life. Additionally, in most scenarios, it is not permitted to use smart phone or eating something during on-duty. In this paper, we take smoking cigarettes as a typical example to discuss how to detect this kind of hand-held action. With the rapid development of deep learning [9], more and more detection methods are utilized in the field of smoking cigarettes detection [6]. However, most of these methods adopt only one single detection model, which may conquer one kind of problem but meanwhile lead to another problem. In other words, due to the inherent attributes of the target object, methods utilizing one single model are scarcely possible to cover all kinds of problems that may occur under real-world scenarios.

Intuitively, methods of detecting smoking cigarettes can
be roughly devided into two kinds: one kind of method fo-
cuses on the cigarettes itself while the other focuses on the
overall human smoking pose, as shown in Figure 1. Typi-
cal distribution of real-world scenarios’ smoking cigarettes
can be roughly classified into three classes: (a) images hav-
ing no cigarettes but human body pose are similar to smok-
ing cigarettes; (b) images having cigarettes and are easy to
be detected correctly; (c) images having sticks similar to
cigarettes but having no cigarettes. As for these different
kinds of scenarios, current mainstream methods can hardly
cover all these cases and achieve a high accuracy. This is
because the class (a) and (c) are exactly two opposite direc-
tions for training models: a model focusing its attention on
class (a) is natively inclined to neglect the small cigarettes
compared to the much bigger human body, and vice versa.
For instance, as is shown in Figure 2, if one method focuses
more attention on the cigarette itself, it’s more inclined to falsely take sticks that are similar to cigarettes as the final
target; but also, as is shown in Figure 3, if one method fo-
cuses its attention on the overall human body and smoking
pose so as to amend the former stick mistakes, it again may
bring about other problems: it may overlook the cigarettes
and take the bigger pose and human body as final target in-
stead.

To adress these issues, the hierarchical coarse-to-fine
detection framework is proposed in this paper as a new
application-driven AI paradigm. In this framework, the
coarse detection module detects the target of human smok-
ing pose consisting of the whole hand, cigarette and head, while the followed fine detection module detects the tar-
et of cigarette consisting of the fingers holding cigarette,
mouth area and the whole cigarette. With the hierarchical
framework, both the overall pose and details are considered,
which confirms the high accuracy. The rest of the paper is
arranged as follows. The related work is introduced in Sec-
tion 2. In Section 3, the proposed application-driven AI
paradigm is presented in detail. The experiments are done
and results are given in Section 4. Finally, in Section 5, the
conclusion is drawn.

2. Related Work

Some methods have been proposed to handle the prob-
lem of detecting smoking cigarettes. The method [12] pro-
poses a smoking image detection model based on a convo-
lutional neural network, referred to as SmokingNet, which
automatically detects smoking behaviors in video content
through images, this method can detect smoking images
by utilizing only the information of human smoking ges-
tures and cigarette image characteristics without requiring
the detection of cigarette smoking. The method [10] pro-
poses a novel algorithm for automatic detection of puffs in
smoking episodes by using a combination of Respiratory In-
ductance Plethysmography and Inertial Measurement Unit
sensors. The detection of puffs was performed by using a
Figure 5. Examples of the coarse detection model’s annotation. The target object consists of the whole hand, cigarette and head.

Figure 6. Examples of the fine detection model’s annotation. The target object consists of the fingers holding cigarette, mouth area and the whole cigarette.

deep network containing convolutional and recurrent neural networks. The method [8] designs a series of convolutional neural network modules to reduce the amount of model parameters and pick up the inference speed to meet real-time requirements as well as improving the accuracy of small target object (cigarette) detection.

Generally, in these methods, an object detection model is adopted to localize the smoking action in an image. In nowadays, the object detection models constructed on CNNs are popularly used, such as YOLOv5 [3], faster rcnn [7], retinanet [5], cornernet [4]. For the video or temporal image sequence composed of consecutive image frames, the object detection model may be applied to each image to give the detection result, and the combination of consecutive images’ results gives the final result of the video or temporal image sequence.

The mainstream approach for smoke detection can be divided into two kinds [1, 2, 8, 11]: one method, simple and easy to think of, is to detect the smoke itself, ignoring all kinds of context information, which simplifies this method’s processing procedure but meanwhile leads to more wrong detections; the other method, which takes care of more context and specific scenarios, involves in more other human bodies, including hand, mouth, upper body, body pose, etc. However, these two methods, having their own advantages, both have some certain intrinsic vulnerabilities. The first method may take all kinds of sticks, which are similar to cigarettes, as cigarettes by mistake. The second method, which to a certain degree decreases the first method’s mistakes, may take some poses similar to smoking cigarettes as target by mistake. In this paper, the two kinds of methods are combined in order to avoid their individual disadvantages.

3. The Proposed Application-Driven AI Paradigm

3.1. The hierarchical object detection framework

In this paper, we propose a coarse-to-fine two-stage method to deal with this dilemma. Our method utilizes two detection modules: the first module focuses on a coarse object of human smoking pose, while the followed second one focuses on the fine object of the cigarette. Overview of the two stages is shown as Figure 4 and detailed as follows.

3.2. Coarse detection module

The coarse detection module roughly detects an object including whole hand, cigarette and head, as shown in Figure 5. In this detection, we take a typical human pose of smoking cigarettes as target. A pose of smoking consists of several parts, but the typical and essential one is to hold a cigarette and feed it into mouth, which we take as the target of the first stage’s detection module. In this way, hands and whole head, as context of a typical pose of smoking cigarettes in an image, can filter out most targets that can be easily misdetected as smoking cigarettes.

3.3. Fine detection module

The second module detects a finer object consisting of the fingers holding cigarette, mouth area and the whole cigarette. Following the coarse detection module, the second module detects a much smaller object as shown in Figure 6. In this way, the second module’s results, which are based on the first module’s input, can natively utilize the first module’s design philosophy to filter out a majority of mistakes, meanwhile the well designed finer object can filter out other kinds of false detections: for instance, due to the relatively bigger target, the first module may improperly take hands and whole head as the target of smoking cigarettes.
cigarettes and ignore the cigarettes. This is because in the bigger target, the cigarette itself is a much smaller object compared to hands and human head, after several CNN layers, the feature map may just take the cigarette as an irrelevant noise of the overall target. Hence the second module concentrates more on a rather small target: the fingers holding cigarette, mouth area and the whole cigarette. In this smaller area, the module will give more attention to the cigarettes, while still give consideration to other body parts of fingers and mouth, which in all are pivotal components of a pose of smoking cigarettes.

3.4. Detection model

In our proposed framework, various kinds of object detection models can be adopted either for the coarse detection module or the fine detection module, and it’s not limited to one certain object detection model. In this paper, we utilized the basic object detection model YOLOv5 [3] and faster rcnn [7] to construct the coarse detection model and fine detection model for our ablation study experiments.
4. Experiments

In this section, we will firstly introduce our dataset, which we collected from all kinds of real-world scenarios, including chemical plants, industrial workshops and petrol stations, etc. Then we will describe the details of our experiments.

4.1. Dataset

4.1.1 Coarse detection model’s dataset

We collected images from public webs, manual simulation and certain real-world scenarios, including chemical plants, industrial workshops and petrol stations, etc. A glimpse of our dataset is shown as Figure 7. These images cover various gestures, angles, facial features, ages and illuminations of smoking cigarettes, which can enhance the detection models’ generalization ability while simultaneously maintaining a rather high accuracy. The smoking poses in these images are annotated by the way as shown in Figure 5.

4.1.2 Fine detection model’s dataset

Based on the coarse detection model’s dataset, the fine detection model’s dataset is constructed by applying the coarse object detection and fine annotation. A glimpse of the fine detection model’s dataset is shown as Figure 8. And cigarettes are annotated by the way as shown in Figure 6.

4.1.3 Additional dataset

Smoking cigarettes, as a safety event which requires intense and precise attention and monitoring, sometimes requires high precision under some circumstances while sometimes requires high recall under other circumstances. In view of this realistic dilemma, we additionally collected images without cigarettes inside but are very likely to be classified as smoking cigarettes. In this way, the dataset can enhance the models’ generalization ability to certain degree, which will increase precision and recall simultaneously.
Table 1. Accuracy on test data for different frameworks. Single Model I focuses on the overall human smoking pose, Single Model II focuses more on the cigarette itself, and Coarse-to-fine Models is our proposed framework.

| Models          | Frameworks     | Accuracy |
|-----------------|----------------|----------|
| Yolov5          | Single Model I | 0.714    |
|                 | Single Model II| 0.753    |
|                 | Coarse-to-fine Models | 0.921    |
| Faster RCNN     | Single Model I | 0.704    |
|                 | Single Model II| 0.734    |
|                 | Coarse-to-fine Models | 0.913    |

4.2. Experimental settings

The coarse detection model’s input size is 1280x1280, and batch size is 64, and we train the model on an 8*V100 machine. In view of the fine detection model’s target is detected based on the coarse model’s output, which most of the time is rather small, we set the fine model’s input size as 320x320, and batch size 100, and we train the model on a 4*2080Ti machine. For both models, we use warmup epochs as 2, momentum for warmup epochs is 0.5, learning rate is set as 0.0032, and momentum is 0.843.

4.3. Experimental results

In this section, we conduct experiments on our collected dataset. Both the coarse model and fine model are trained using yolov5m and faster rcnn. Additionally, to compare with our coarse-to-fine models, the single model focusing on human smoking pose and the one focusing on cigarettes are trained using yolov5m and faster rcnn.

After training the models, we conduct ablation study on the models to show the superiority of our framework. We manually choose 450 positive images containing positive targets, and 400 negative images which contain no positive targets but are very likely to be detected as smoking cigarettes.

The results of YOLOv5 and faster rcnn are shown as Tabel 1, Single Model I focuses on the overall human smoking pose, while Single Model II focuses more on the cigarette itself. The results of both YOLOv5 and faster rcnn have the same regular pattern. In detail, for the 450 positive images, Single Model I, Single Model II and our Coarse-to-fine Models both achieve satisfactory results; as for the other 400 negative images, however, the two single models both detect many targets as smoking cigarettes, while the images have no smoke at all, which makes much more mistakes than our coarse-to-fine model.

In Figure 9, we show several typical mistakes of detecting images containing false positive targets as smoking cigarettes. For instance, take the top left image in Figure 9 as an example, Single Model I detects the target as a true positive target, in which the person inside feeds nothing into the mouth but the action pose is similar to smoking cigarettes; however, in our method, the fine model correctly ignores this target and detects nothing as a true positive target, in other words, the person with the smoking pose but without cigarette is detected as a true negative target, which is classified correctly. In this way, a method utilizing one single model focusing on overall human smoking pose makes a mistake while our method does it precisely correctly.

Furthermore, take the top right image in Figure 9 as an example, Single Model II detects the target as a true positive target, in which the person inside is holding a pen only, the action pose is not similar to smoking cigarettes but the pen itself looks like a cigarette; however, in our method, the coarse model, which focuses on the overall human smoking pose, correctly ignores this target and detects nothing as a true positive target. In this way, a method utilizing one single model focusing on cigarette itself makes a mistake while our method does it precisely correctly.

5. Conclusion

In this paper, we propose a hierarchical object detection framework for hand-held action detection, which is composed of a coarse detection model to localize the human action pose and the fine detection model to identify the object itself. Taking smoking cigarette detection for example, the dataset is collected from various practical application scenarios, and annotated in both coarse manner and fine manner. Based on typical basic models YOLOv5 and faster rcnn, the coarse model and fine model are trained, and compared with single model frameworks. The experimental results show that the coarse-to-fine framework achieves better results and effectively reduces false alarms than the single model frameworks. Our framework, as a new application-driven AI paradigm, can be further generalized to handle various kinds of hand-held action detection such as smoking, dialing and eating.

References

[1] Tzu-Chih Chien, Chieh-Chuan Lin, and Chih-Peng Fan. Deep learning based driver smoking behavior detection for driving safety. Journal of Image and Graphics, 8(1):15–20, 2020. 3
[2] Guijin Han, Qian Li, You Zhou, and Yue He. Cigarette detection algorithm based on improved faster r-cnn. In 2019 IEEE Symposium Series on Computational Intelligence (SSCI), pages 2766–2770. IEEE, 2019. 3
[3] Glenn Jocher, Ayush Chaurasia, Alex Stoken, Jirka Borovec, NanoCode012, Yonghye Kwon, TaoXie, Jiacong Fang, inyihxy, Kalen Michael, Lorna, Abhiram V, Diego Montes, Je-bastin Nadar, Laughing, tkianai, yxNONG, Piotr Skalski, Zhiqiang Wang, Adam Hogan, Cristi Fati, Lorenzo Mannana, AlexWang1900, Deep Patel, Ding Yiwei, Félix You,
Jan Hajek, Laurentiu Diaconu, and Mai Thanh Minh. ultra-
lytics/yolov5: v6.1 - TensorRT, TensorFlow Edge TPU and
OpenVINO Export and Inference, Feb. 2022. 3, 4

[4] Hei Law and Jia Deng. Cornernet: Detecting objects as
paired keypoints. In Proceedings of the European confer-
ence on computer vision (ECCV), pages 734–750, 2018. 3

[5] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and
Piotr Dollár. Focal loss for dense object detection. In Pro-
cedings of the IEEE international conference on computer
vision, pages 2980–2988, 2017. 3

[6] Alessandro Ortis, Pasquale Caponnetto, Riccardo Polosa,
Salvatore Urso, and Sebastiano Battiato. A report on smok-
ing detection and quitting technologies. International jour-
nal of environmental research and public health, 17(7):2614,
2020. 1

[7] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun.
Faster r-cnn: Towards real-time object detection with region
proposal networks. Advances in neural information process-
ing systems, 28, 2015. 3, 4

[8] CHEN Ruilong, LUO Lei, CAI Zhiping, and MA Wentao.
Algorithm for real-time smoking detection based on deep
learning. Journal of Frontiers of Computer Science & Tech-
nology, 15(2):327, 2021. 3

[9] Jürgen Schmidhuber. Deep learning in neural networks: An
overview. Neural networks, 61:85–117, 2015. 1

[10] Volkan Y Senyurek, Masudul H Imtiaz, Prajakta Belsare,
Stephen Tiffany, and Edward Sazonov. A cnn-lstm neu-
ral network for recognition of puffing in smoking episodes
using wearable sensors. Biomedical Engineering Letters,
10(2):195–203, 2020. 2

[11] Fangfei Shi, Hui Zhou, Chunyang Ye, and Jianbin Mai.
Faster detection method of driver smoking based on decom-
posed yolov5. In Journal of Physics: Conference Series,
volume 1993, page 012035. IOP Publishing, 2021. 3

[12] Dongyan Zhang, Cheng Jiao, and Shuo Wang. Smoking im-
age detection based on convolutional neural networks. In
2018 IEEE 4th International Conference on Computer and
Communications (ICCC), pages 1509–1515. IEEE, 2018. 2