The AutoBio Challenge Report

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Abstract

The AutoBio challenge is a project aimed at assist researchers in biological laboratories to avoid tiny mistakes that may lead to failure in the experiments. The whole challenge is devided into three hierarchical problems. In our project, we made attempt to accomplish the first two, which are transparent object segmentation and liquid tracking. Here we will give a brief introduction about our work, including backgrounds, our ideas, implementation methods, experiment results and analysis.

1 Introduction

The success rate of biological experiments is low on the whole, especially for viruses, bacteria, yeast, and others,for various operational reasons.Unnecessary manual operation means that whether the operation is standardized will have a huge impact on the experimental results, and the failure caused by these small operational deviations is often difficult to trace the cause of the failure. Therefore, we hope to record the experimenter's operation through the monitoring system, remind the operator in time when a wrong operation is found, and avoid subsequent failures or eliminate irrelevant factors.

Our work can be divided into three parts:Instance segmentation, liquid tracking, and collaboration.For the first part, we compared the training effects of several existing models with limited computing resources, and carefully designed suitable datasets.

2 Related Work

2.1 MMsegmentation

MMsegmentation [1] is an open source semantic segmentation toolbox based on PyTorch. It is a part of the OpenMMLab project,featuring modular design and high efficiency.

2.2 Segmenting Transparent Object in the wild

This work [4] proposes a large-scale dataset for transparent object segmentation, named Trans10K,and a novel boundary-aware segmentation method, termed TransLab, which exploits boundary as the clue to improve segmentation of transparent objects.After that,they propose a novel transformer-based segmentation pipeline termed Trans2Seg,which helps us a lot in the first part.

2.3 Liquid Perception and Multiple Object Tracking

While transparent object perception is tricky problem, liquid perception, what's more, is rather more challenging, since liquid doesn't have a fixed shape. There are several approaches to enhancing liquid perception, such as using colored liquid and applying background subtraction, heating liquid and using thermal camera to make liquid more out-standing, all having their obvious limitation. A paper published in 2022 [2] has reported a gratifying progress on this topic. They can predict an accurate mask for liquid from a single static image, without any manual annotation.

Table 1: **IoU for Instance Segmentation on the basic dataset**

class	MMsegmentation	Trans2Seg
pipette	0.7741	0.849111
PCR-tube	0.0347	0.1031606
tube	0.0325	0.0665664
waste-box	0.6714	0.9235
vial	0.0758	0.129849
measuring-flask	0.1309	0.145382
beaker	0.1290	0.143419
wash-bottle	0.1034	0.571596
water-bottle	0.0656	0.190795
erlenmeyer-flask	0.0132	0.0391308
culture-plate	0.0249	0.05547
spoon	0.5573	0.97322
electronic-scale	0.0032	0.065178
LB-solution	0.0605	0.088212
stopwatch	0.0000	0.010385

Tracking is another important issue. Multi-Object Tracking (MOT) is the most popular tracking algorithm recently. One of the best known is DeepSORT [3]. It combines a deep appearance feature extractor with the Kalman filter to implement object tracking. And most recently, FairMOT, aiming at fair and unbiased MOT, receives wide attention.

3 Experiments and Analysis

3.1 Instance Segmentation

For the first part,we need to design a network to segment the transparent objects in the picture.In order to improve efficiency, we first selected several existing models and trained them for 50 epochs on the basic data set.We compared mmsegmentation(with Resnet), trans2seg(with Resnet50) and translab,and the experimental results are shown in Table 1.

Through comparison, it can be found that trans2seg has significantly better performance than mmsegmentation with a simpler structure.In a similar way, we compared Trans2seg with different backbonesresnet50,resnet101,and resnet152.In the first 50 epochs of training, resnet152 showed an overwhelming advantage. Although the training efficiency is not directly proportional to the performance bottleneck, we chose resnet152 for follow-up experiments due to the limitation of training resources.Then we made a series of adjustments to the loss function and model parameters, and selected a set of parameters with the best performance in the previous period.

Finally, in order to improve the training efficiency, we redesigned the dataset.We can see that the model has extremely high training efficiency when segmenting objects with distinctive features such as pipette, waste-box, and spoon,but it is much more difficult for objects such as tubes and PCR-tubes that are stacked together and have no obvious features.In addition,differences in camera angles and how objects are placed can also have a huge impact on training results. Therefore, in the follow-up training, we have made substantial additions and deletions to the training set to improve the robustness of the model to specific objects without affecting the training time.

3.2 Liquid Tracking

for the second part,we need to design a network to track the only liquid in the given video and output its position(s). Essentially, we just need to keep track of the transparent container the liquid is in.

We've thought about some potential methods for improving. The pose of containers might be an important clue. Intuitively considering, an unusual pose of a container often implies liquid exchange between two containers. For example, when we are pouring water from one container to another, the poses of the two must have some association with their content states. So we think adding a 'pose'

Table 2: **IoU for Instance Segmentation on the basic dataset**

class	resnet101	resnet50	resnet152
pipette	0.87063	0.849111	0.915169
PCR-tube	0.164509	0.1031606	0.27880
tube	0.09609	0.0665664	0.1794
waste-box	0.9367	0.9235	0.9658
vial	0.3645	0.129849	0.279946
measuring-flask	0.27945	0.145382	0.35
beaker	0.1290	0.143419	0.180362
wash$_bottle$	0.7034	0.571596	0.8712
water$_bottle$	0.230329	0.190795	0.176143
erlenmeyer-flask	0.15142	0.0391308	0.29333
culture-plate	0.0744438	0.05547	0.1520
spoon	0.931851	0.97322	0.98974
electronic-scale	0.0716163	0.065178	0.106393
LB-solution	0.143872	0.088212	0.138583
stopwatch	0.004116	0.010385	0.00851

attribute can be a further attempt to make.besides,it is worth noting that sometimes the same liquid appears in different containers,and it is also easy for containers to overlap.

Based on the work of the first part, we tried to separate containers and solutions, and achieved some results.

References

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