MAN-MADE OBJECT RECOGNITION FROM UNDERWATER OPTICAL IMAGES USING DEEP LEARNING AND TRANSFER LEARNING

Xian Yu, Xiangrui Xing, Han Zheng, Xueyang Fu, Yue Huang, Xinghao Ding*

Key Laboratory of Underwater Acoustic Communication and Marine Information Technology, Ministry of Education, Xiamen University, China

School of Information Science and Engineering, Xiamen University, China

{*yhuang2010@xmu.edu.cn}

Objective Avoid having to collect and annotate large-scale underwater images with deep network and transfer learning

INTRODUCTION

Challenges

Poor image quality

Non-uniform lighting   Low contrast

Data collection **difficulties**

Complex environment   Expensive labeling costs

Innovation

Excellent **deep learning** method with sufficient labeled **in-air** images

But in-air images and underwater images follow **different** distributions

Transfer learning with only the labeled in-air images

Source domain——in-air images

Target domain——-underwater images

METHODS

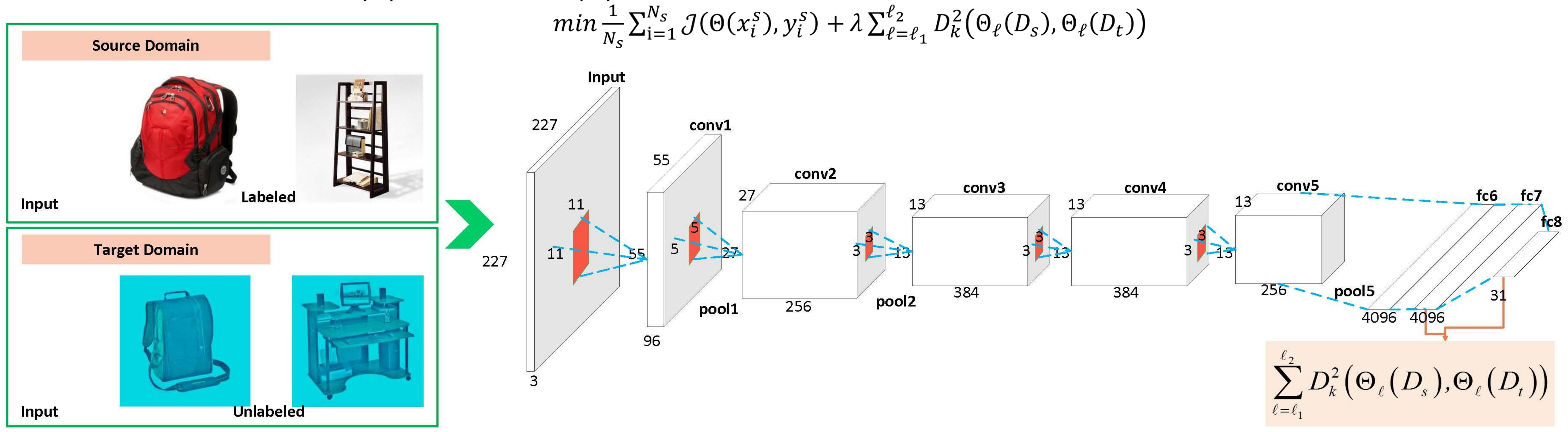
Underwater datasets generation

Color is the most dominant feature, we adopt the color transfer method [1] to manipulate the color values of real underwater image to generate images with same appearances, as I_{color}. Then we applied **turbidity** simulation on top of color transfer according to the underwater imaging physical model. For example, the direct transmission: $D = I_{color}e^{-\eta z}$, and the backscattering: $B = B_{\infty}(1-e^{-\eta z})$. Then the resultant underwater image is generated by: $I_{underwater} = D + B - D \cdot B$, where $\cdot$ represents the element-wise multiplication.

Underwater object recognition framework

The maximum mean distance (MMD) [2] is applied to the high-level layers as the regularization and transfer learning element based on normal AlexNet as: $D_k^2(p,q) = E_{x_p^s x_q^s} k(x_p^s, x_q^s) + E_{x_p^t x_q^t} k(x_p^t, x_q^t) - 2E_{x_p^s x_q^t} k(x_p^s, x_q^t)$. Then the objective function can be defined as:

$$\min \frac{1}{N_s}\sum_{i=1}^{N_s} \mathcal{J}(\Theta(x_i^s), y_i^s) + \lambda \sum_{\ell=\ell_1}^{\ell_2} D_k^2(\Theta_\ell(D_s), \Theta_\ell(D_t))$$



EXPERIMENTS

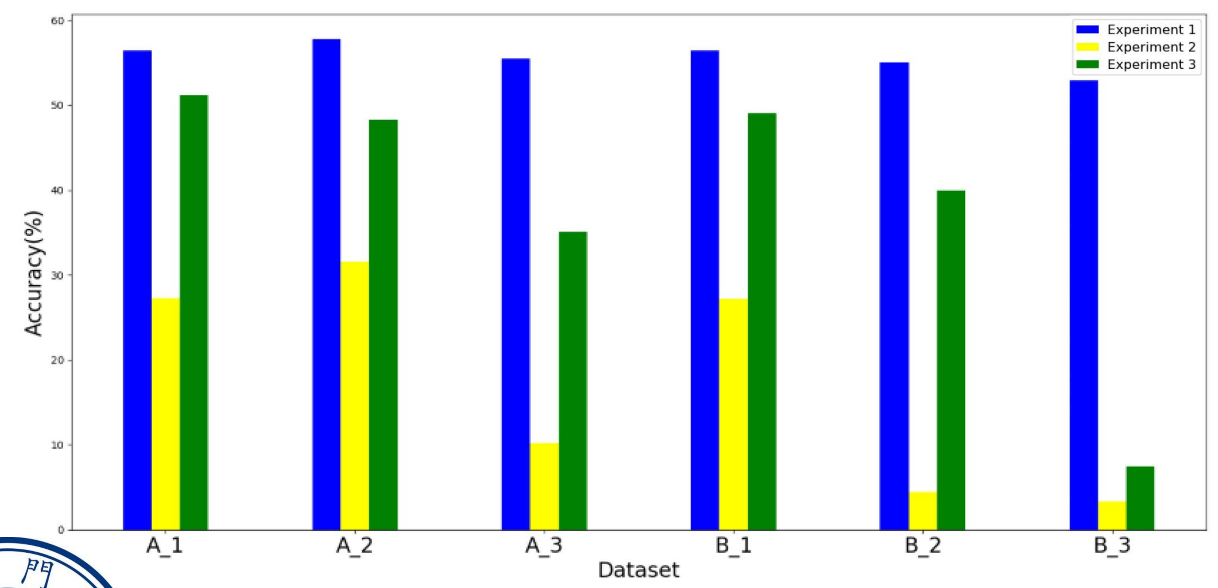
Datasets

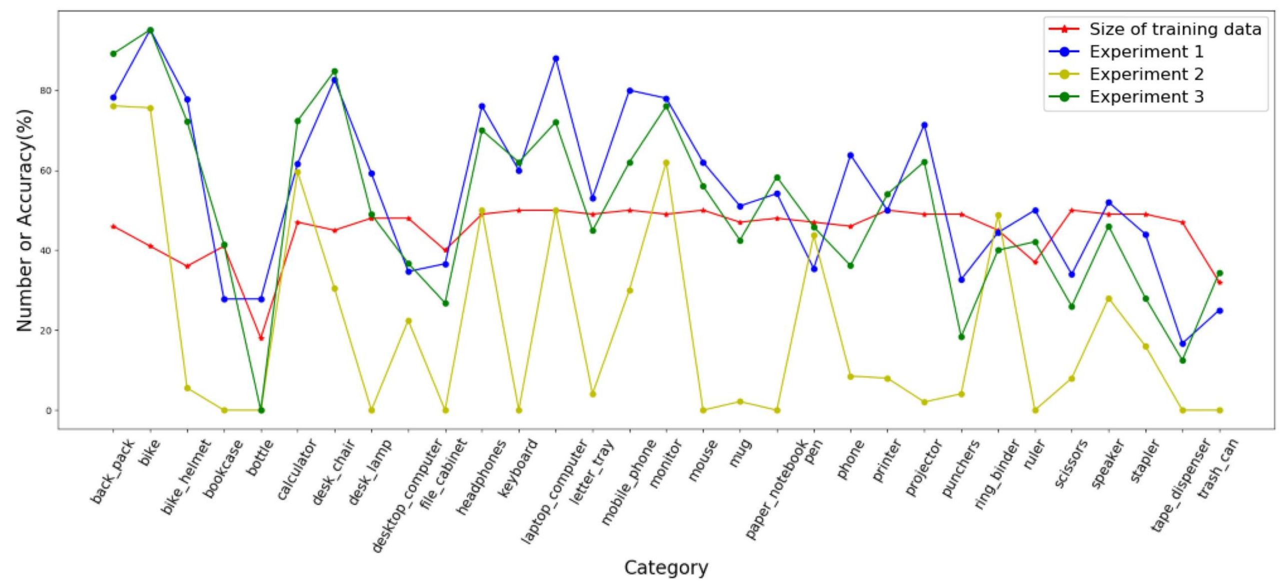
The **Amazon** dataset consists of objects from 31 classes with irregular shapes captured from different views [3]. We generate three simulated underwater datasets with three different values of turbidity for each reference image by adjusting turbidity factor z.

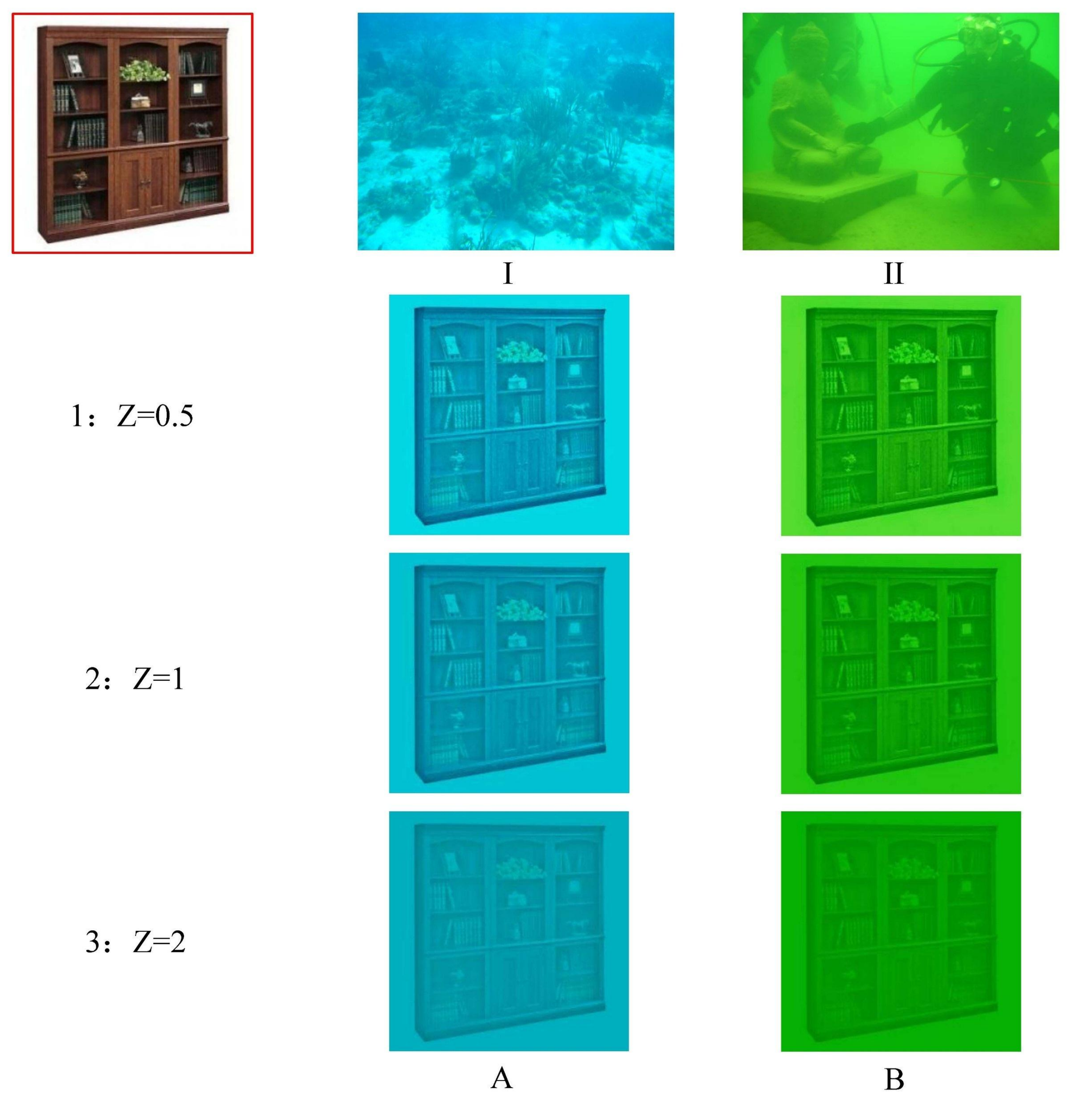
Experimental Details and results

We compare the accuracies of the **three experiments** for datasets with different turbidities and reference settings, where Exp. 1 and 2 adopt the raw AlexNet, and Exp. 3 adopt the proposed network.

Experiment 1 (Blue)		Experiment 2 (Yellow) & Experiment 3 (Green)	
Training	Test	Training	Test
Simulated underwater data	Simulated underwater data	In-air data	Simulated underwater data







CONCLUSIONS

Remove the need to carry out the tedious and difficult task of collecting and annotating large-scale underwater images with deep network and transfer learning by using in-air images to effectively classify man-made object from underwater optical images.

ACKNOWLEDGEMENTS

This work was partly supported by the grants from National Natural Science Foundation of China (No. 81671766, 61172179 and 61103121) and Natural Science Foundation of Fujian Province of China (2017J01126)

REFERENCES

[1] Nguyen et al., Illuminant Aware Gamut-Based Color Transfer, TEAJWS, 2014.

[2] Sinno Jialin Pan et al., A survey on transfer learning, IEEE TKDE, 2010.

[3] Kate Saenko et al., Adapting visual category models to new domains, ECCV, 2010.

Xian Yu postgraduate in SmartDSP Lab, Xiamen University, China. My research interests include machine learning, deep learning, transfer learning and active learning.
Please feel free to contact me if you are interested in my work. E-mail: yuxian94@qq.com