KI DELTA LEARNING
Scalable AI for Automated Driving

Transfer learning and self-attention in the context of unsupervised domain adaptation

Vinu Nair, Michael Essich, Cristóbal Curio

WP 2.4
WP 2.5
WP 3.1

Environment, Networks

Use-Case in Delta Learning

Our overall work target to study the domain shift from synthetic to real data as well as cross-sensor domain shift. Our work in these WPs complement these objectives by improving the unsupervised domain adaptation network to handle the following use cases for the tasks human pose estimation and object detection.

- **Traffic situation:** adapt the network for novel mobility classes in the dataset such as E-Scooters and hoverboard
- **Environment:** adapt the network to different lighting and weather conditions
- **Network:** adapt the network using partially supervised and unsupervised signals to increase the performance of task models

Technical Problem

- Updating the trained model for new tasks and capabilities requires training from scratch and access to old training data
- Existing transfer learning approaches are not practical in an automotive environment where new data is constantly available and joint training is expensive.
- The training of deep learning algorithms for vision tasks requires huge labelled datasets. The process of creating these labelled datasets is very time-consuming and therefore expensive

Technical Solution

- Use learning without forgetting (LwF) [1] for Object detection model to add new classes to existing models and to learn parameters that work well on old and new classes, using data from only the new class
- Use the unsupervised domain adaptation network to adapt for different lighting and weather conditions in the target domain
- Use of self-attention technique Convolutional Block Attention Module [2] (CBAM) to improve the data efficiency and performance of unsupervised domain adaptation network

Evaluation

- Learning without Forgetting (LwF) technique was evaluated by initial training of the object detection model with synthetic images containing only the e-scooter class. Then the model was trained with images containing only humans using the LwF method. Evaluation was done on images containing both the classes
- Environmental adaptation is not yet evaluated
- Evaluation of CBAM was done by training the pose estimation network on the simulated data and evaluating using the real data

Figure 1: Object detection : Detected bounding boxes (Red) and Ground Truth (Green), data augmentation using background images from the CARLA simulation.

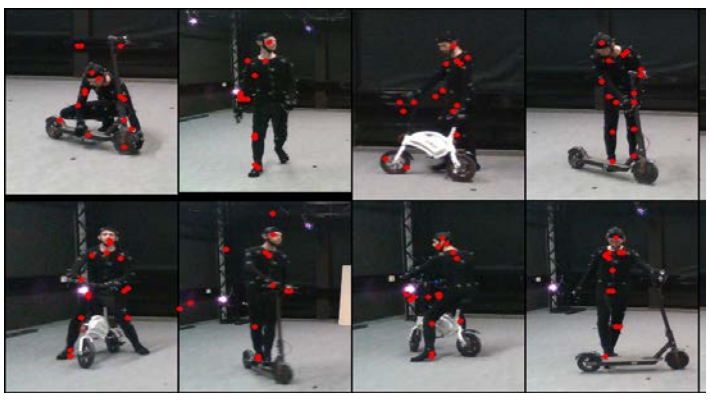

Figure 3: Human pose estimation: Detected key points on real data from the HSRT Motion Capture dataset

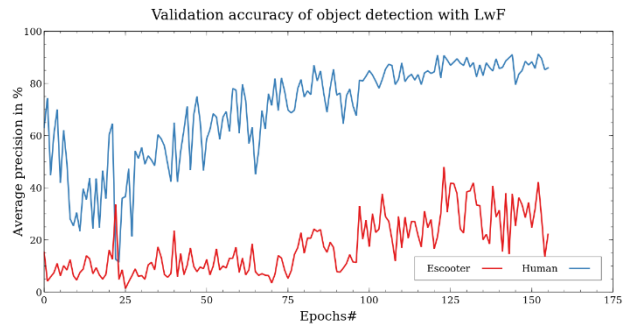

Figure 2: Object detection validation accuracy of Human (new class) and E-Scooter (old class) trained using Learning without forgetting

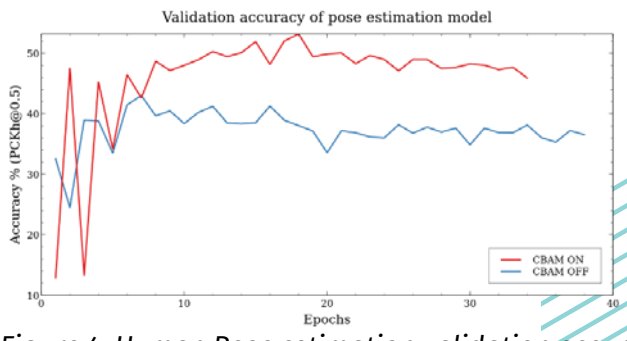

Figure 4: Human Pose estimation validation accuracy on real data improves with CBAM. Model was trained using only simulated data

References

[1]. Z. Li and D. Hoiem, "Learning Without Forgetting," in Computer Vision – ECCV 2016, Cham, 2016, pp. 614–629, doi: 10.1007/978-3-319-46493-0_37.
[2]. Woo, S., Park, J., Lee, J. Y., & So Kweon, I. (2018). Cbam: Convolutional block attention module. In Proceedings of the European conference on computer vision (ECCV) (pp. 3-19).

Hochschule Reutlingen
Reutlingen University

For more information contact:
vinu.vijayakumaran_nair@reutlingen-university.de

Partners

External partners

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KI FAMILIE

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