Automotive - Advanced Driver Assistance Systems

Technische Universiteit Eindhoven University of Technology

Online Self-Supervised End-to-End Learning of FCNs* for Free-Space Detection

* FCN: Fully Convolutional neural Network

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Motivation

- A key component for ADAS is **fast free-space detection** to determine where the vehicle can drive in dynamic environments.
- A fundamental challenge is that traffic scenes come in a
  - **wide variety** (urban/rural, highway/city-center) under
  - **varying imaging conditions** (good/bad weather, day/night).
- Therefore, we propose a system that is **fast**, **flexible** and **robust**.
- We achieve this by tuning a small FCN [1,2] online (while driving) on weak labels generated from disparity analysis.

Methodology

We tune an FCN [1,2] while driving using weak labels from disparity analysis. The FCN is pre-trained offline on similar traffic scenes for faster convergence. Our full system diagram is in Fig.1, more details in [5].

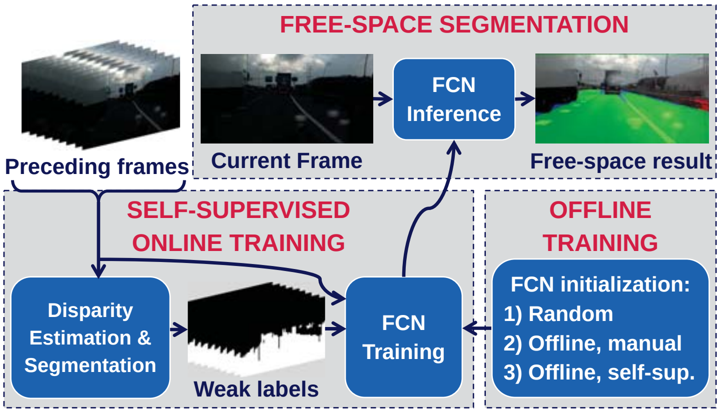

Fig.1: System diagram with data examples.

OFFLINE:

- Pre-train FCN on traffic scenes.

ONLINE, while driving:

- Generate **weak labels** (Fig.2) :
  - Stereo camera with disparity estimation
  - Analyze with disparity Stixel World [3]
- **Tune** the FCN with the new data
- **Segment** free space in current frame (Fig.3)

Fig.2: Left to right: dark **input** image, noisy **disparity** signal, corresponding **weak labels** for online training. Manual groundtruth in red.

Training on automatically generated weak labels provides similar results as training on manual labels, reducing the need of large scale annotation.

Experiments and Validation

QUALITIATIVE (Fig.3): The disparity Stixel World (left) is generally correct but has trouble with rain. The small FCN without online tuning (middle) fails to generalize to exceptional cases (cyclist, canal). With our online tuning method (right), that same FCN outperforms both methods.

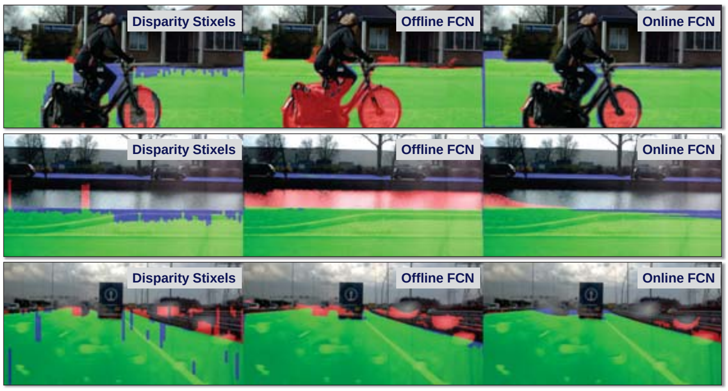

Fig.3: Left to right: Stixel World; offline trained FCN; online tuned FCN.
Green: **true free space**; Red: **missed obstacles**; Blue: **false obstacles**

QUANTITATIVE (Fig.4):

- Our method provides improved results from weak labels.
- Fast and small FCN requires our tuning for difficult images.
- Tuning improves Fmax with 5%.
- With pre-training, the FCN reaches baseline performance 40x faster

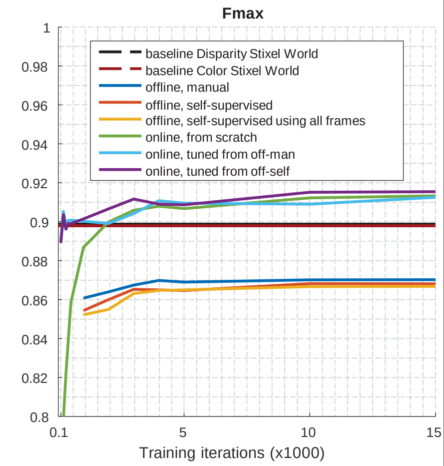

Fig.4: FCN training convergence.

Conclusions

Our self-supervised online trained FCN outperforms [3] and [4] on our public data (265 frames). Our method provides

- **robust free-space segmentation** in
- **difficult imaging conditions**, while relying on a
- **small** and **fast FCN,** by focusing on
- a small amount of **weakly-labeled** but **currently relevant data**.

References

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[5] W.P. Sanberg, G. Dubbelman, P.H.N. de With, *arxiv.org/abs/1604.02316*, April 2016