S9195-Deep Sensor Fusion for Visible Stereo and Thermal Stereo for Autonomous Driving

Vijay John, Yuquan Xu , Seiichi Mita, Smart Vehicle Research Center



DENSO Crafting the Core

Kazuhisa Ishimaru, Sakiko Nishino Research Division 2.0





Title of Content

- ADAS and Automated Driving
- World 3D Reconstruction
- 3D Deep Sensor Fusion
- Future Plan
- Conclusion

Popular ADAS Applications

ADAS Applications are booming

- Adaptive Cruise Control (ACC)
- Adaptive Front Lights (AFL)
- Driver Monitoring System (DMS)
- Forward Collision Warning (FCW)
- Intelligent Speed Adaptation (ISA)
- Lane Departure Warning (LDW)
- Pedestrian Detection System (PDS)
- Surround-View Cameras (SVC)
- Autonomous Emergency Braking (AEB)

Vehicle Platform





General Framework for ADAS and AD



Deep Understanding of Environment

World 3D Reconstruction

Dense Stereo Sensor

Stereo Vision Concept

<Stereo Vision>

<Process>



Matching Cost



Finding true disparity value for every pixel from Matching Cost Space

Cost Calculation Method



Optimization: Multi Viterbi Path

Exploiting the neighbors' matching cost can be translated into Mathematical Optimization about the **Shortest Path Problem**



Viterbi algorithm can find the global optimum

Fast Implementation of Multi Path Viterbi





Huge Networks with Parallel Optimization



Proposed Method: Multi Path Viterbi



MPV Optimize the Accumulates Information Step by Step

Benchmark: Street Data



Conventional method: SGBM





Multi Path Viterbi

Stereo Vision – Results (Urban)

Image Size: $1 2 8 0 \times 9 6 0$ Calculation Time : $15ms \checkmark$ FrameGPU:GeFORCE GTX 1080

Nagoya Urban Road







Stereo Vision – Results (Highway)

Calculation Time :15ms / Frame GPU : GeFORCE GTX 1080





Tokyo Metropolitan Highway



Stereo Vision – Snowy and Dark Weather

Calculation Time: 15ms/Frame GPU : GeFORCE GTX 1080





World 3D Representation



3D Deep Sensor Fusion

Sensors Properties

Electromagnetic Range Wave: Camera ,Laser, Radar

Sensor Fusion is necessary to cover Detail and Far Detection



Learning Framework for Perception

Training a learning framework for perception tasks



Single Sensor-based learning

- Single sensor-based learning is not robust or descriptive enough
- Challenges
 - Environmental
 Variation (occlusion, illumination variation, etc.)
 - High Inter-Class and Intra-Class Variability



Intra-class Vehicle Variations



There are many vehicle varieties with different orientations

Intra-class On-Road Objects Variations

We have a large number of On-Road Objects





We have a lot of variety of on road objects!!!!

Intra-Class Free Space Boundary Variations

We have the different type of road boundaries



We have a lot of variety of Free Space Boundary!!!!

Environmental Variation

Illumination variation as observed by a monocular camera image with appearance features



Sensor Fusion-based learning

- Sensor Fusion-based learning with
 Complementary Sensors addresses these issues
- Monocular Camera appearance features and depth features are Complementary Features



Complementary sensors

Monocular Camera	Depth Camera	
Monocular Camera ⇒ Rich Appearance Information	Depth Camera ⇒ Depth Information (3D Data)	
Inexpensive	Stereo-based Depth Inexpensive	
Illumination Variation	Illumination Invariant due to robust stereo algorithm [1]	

Depth information from stereo camera robust to illumination variation [1] Xu et al. Real-time Stereo Disparity Quality Improvement for Challenging Traffic Environments, IV 2018

Complementary Sensor Fusion for Deep Learning

Appearance and **Depth Features** are Fused within a Deep learning Framework for Environment Perception

Sensor fusion with complementary features



How to Fuse Sensors Data ??

Sensor Fusion : Raw Data Level Fusion



Bad

Sensor Fusion : Feature Level Fusion



Proposed Model



Entire Intensity Encoder Feature Maps (m,n,n) are transferred to Free Space and Object Decoder Feature Maps (o,n,n) for Concatenation (m+o,n,n)

Final Proposed Architecture



Learning Chi-Net

Disparity Image



- Trained with 9000 Samples from Japanese Highway dataset
 - Manually annotated free space and objects
- Trained on Keras with theano backend
- Trained with Nvidia Titan X GPU



Results for Japan Highway









Small Objects Detection



Raining Weather









Movie: Tokyo Expressway



ChiNet vs Baseline

Algorithm	Acc.	Time
ChiNet	97.35	192ms
U-Net [1]	94.2	82ms
FuseNet[2]	95.2	125ms

Implemented on GeForce Titan X using Keras with Theano backend





Evaluation Result

Comparison : "Intensity" vs "Intensity and Depth"

Intensity image only



Intensity and Disparity fusion



Evaluation Result

Comparison : "Intensity" vs "Intensity and Dept

Intensity image only





Learned Features by Chi-Net

Intensity Image

Some of Learned Image Feature

- Vehicle Lower Part
 - Free Space



- Edge
- Free Space



Strong

Weak

Depth





Learned Features by Chi-Net

Intensity Image

Some of Learned Depth Features



Future Plan

Distribution of Camera Data



After Mean Centering



We have different distribution even after mean centering

Sensors Properties

Electromagnetic Range Wave: Camera ,Laser, Radar



Challenges of Camera for different Environment



Thermal Camera





Normal Camera





Challenges of Camera for different Environment

Thermal Camera

Normal Camera



Challenges of Camera for different Environment





Thermal Camera Images



Stability against a variety of light conditions

Thermal Stereo













Thermal Stereo Results for Night





Thermal Stereo Results for Night









Sensor for Future ADAS and Automated Driving



Automated Driving Computer and Sensors

Process and Integration



Conclusion

- Sensor fusion of appearance and depth features for environment perception
- Increased robustness and perception accuracy
- ChiNet advantages
 - Precise object boundary detection
 - Detection of small objects in the road
 - Detection of far-away objects
- Computational time
 - Reduction of computational time to ~15 ms possible with optimized CUDA libraries and advances in GPU computing

