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Doing More with Less: Optimizing Image Quality and Stereo Depth at the Edge

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Overview



- John Deere Background
- Image Quality Considerations
- Stereo Method Comparisons
- Q&A









Technology at John Deere







What Makes A Good Image For Computer Vision & Machine Learning?















See & Spray Select – Use Case



Configuration

- 120 ft boom
- •96 nozzles
- 34 cameras
- 5 controllers
- @ 12.5 mph





Color Correction







Ambient Light Inconsistency





• The change of color temperature through the day will cause the image to appear differently at different times of the day, hence make it challenging to develop an algorithm that deal with the color inconsistency.

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Stuck Material On The Lens





[4]

- Stuck Material maybe hard to detect especially when dealing with translucent material.
- Not all stuck material necessarily impact the image processing.









Stuck Material On The Lens







Dealing With Shadows









 $\mathsf{Atla}_{\ensuremath{\mathbb{F}}}$ Workflow for Image Quality and Computer Vision



[5] Atlas Algolux



[6] Visionary.AI

• Tunning the ISP settings may be challenging or impossible to get the optimum setting to deal with issues such as shadows.



Stereo Vision







Stereo Correspondence



Disparity: $dx = x_1 - x_r = 274 - 242 = 32$

Distance: D = fB/dx = (focal length x baseline) / disparity



Left Image

Right Image



Stereo Disparity Image





[7]



Stereo At John Deere





Various Baselines and Imagers





Various Image & Video Processors (FPGA or GPU)



Block Matching Example – Minimal Filtering

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OpenCV StereoBM [8]



Semi-Global Block Matching





OpenCV StereoSGBM [9]



Neural Net Based Stereo Approach (Machine Learning – RAFT)





iRaftStereo_RVC [10]



Alternate Block Matching Example





Alternate BM



Stereo Method Differences





Reference Image

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Block Matching



AI Matching (RAFT)



Pixel by Pixel Disparity Differences



Additional Examples with Various Stereo Comparisons





- "Alternate BM" most efficient method & meets requirements for several John Deere applications.
- ML approach has higher precision capability, but greater chance of error for low confidence areas.
- Many use cases are already doing a Computer Vision or Machine Learning Algorithm On Image(s)

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Conclusions & Recommendations

Strive to do More with Less

- Start with the Worst Case & Strive for the Best Case (Data, Application Requirements, & Compute)
- Characterize Your Image Conditions for Outdoor **Environments**
- Higher Computation Stereo Has More Resolution & Accuracy Potential, But Also Potential for Error
- Higher Computation Stereo Improves Edges Do you use Depth for your Edges?



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- 9. <u>OpenCV Semi Global Block Matching</u> from <u>opencv/stereosgbm.cpp</u>

10. RAFT Stereo from princeton-vl/RAFT-Stereo

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