

# Using CNNs to Estimate Depth from Stereo Imagery

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## Motivation

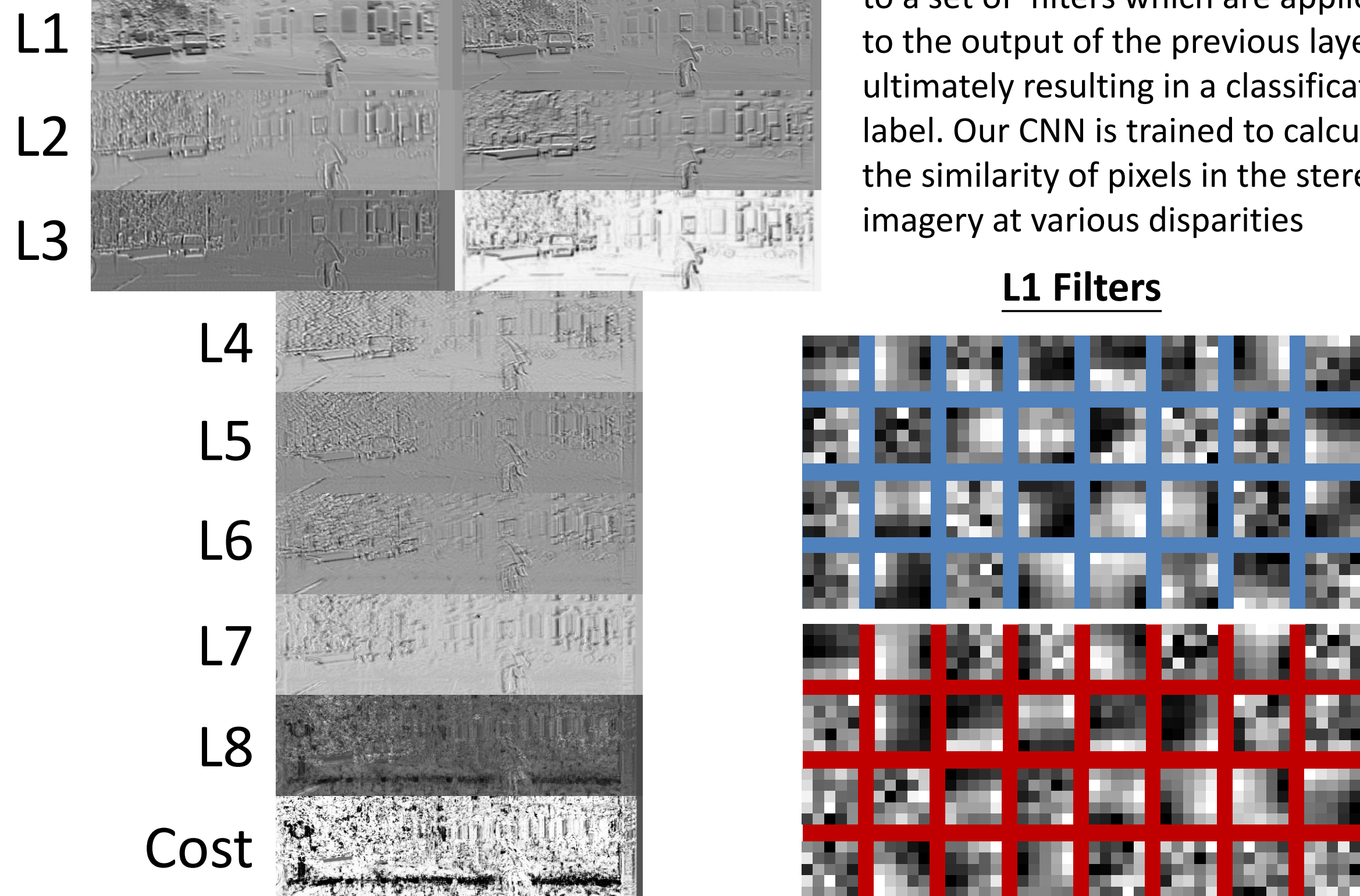
- 3D TV / Free Viewpoint TV
- Virtual Reality / Head-mounted displays
- Augmented Reality
- Computer Vision
- Autonomous Vehicles



## Convolutional Neural Network

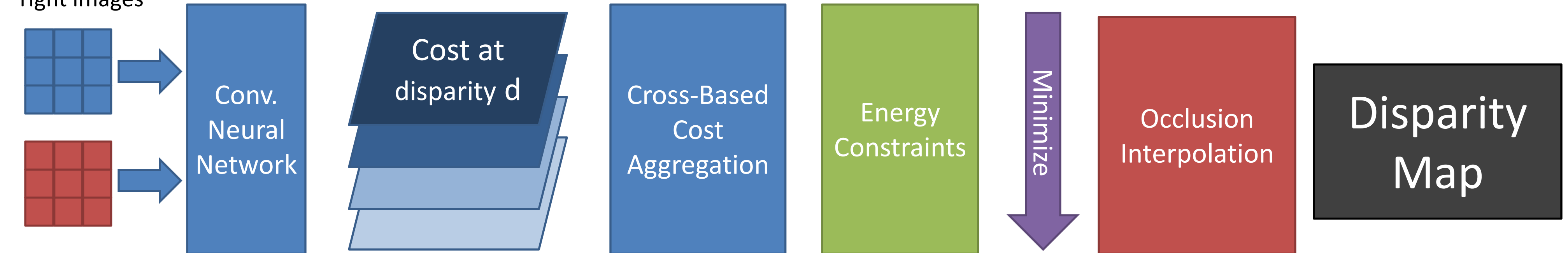


Convolutional Neural Networks are interconnected layers of artificial neurons (perceptrons) that are trained to create a model for image classification. Each layer corresponds to a set of filters which are applied to the output of the previous layer ultimately resulting in a classification label. Our CNN is trained to calculate the similarity of pixels in the stereo imagery at various disparities



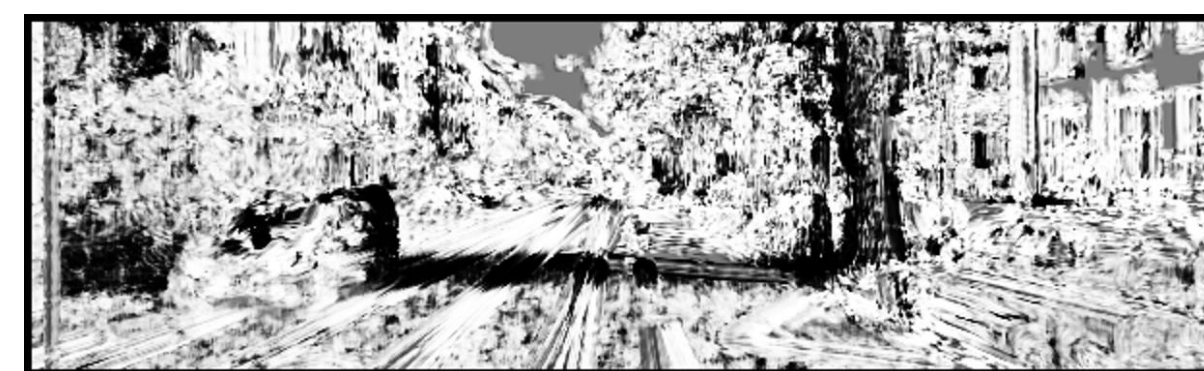
## Cost Function Technique<sup>[8]</sup>

9x9 patches from left and right images

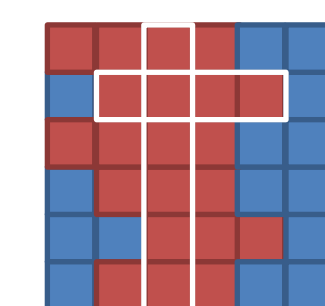


### Cross-Based Cost Aggregation

Cost



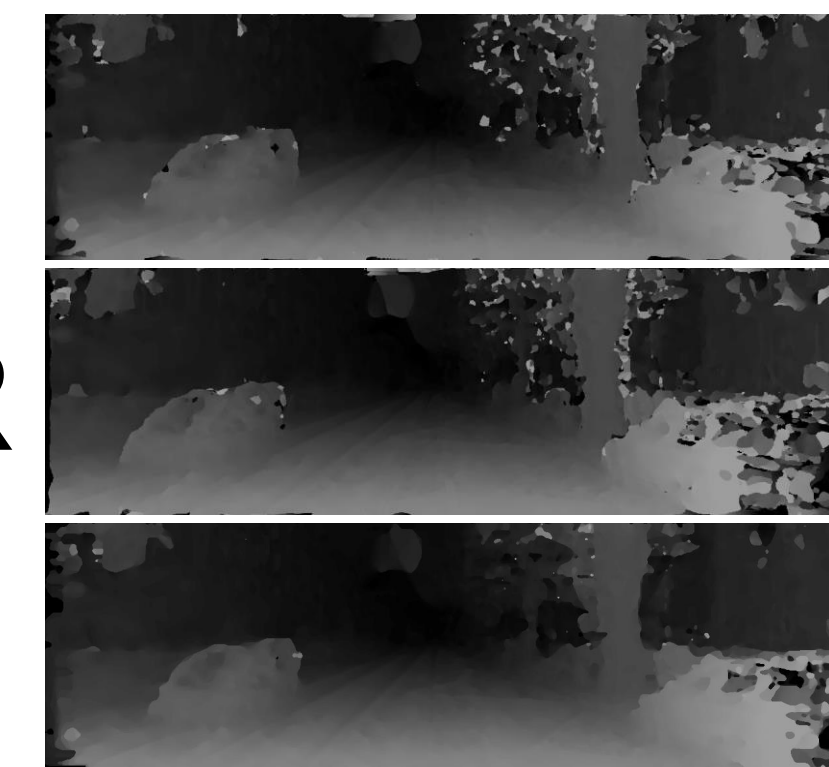
CBCA



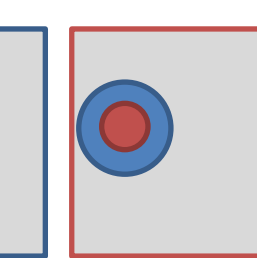
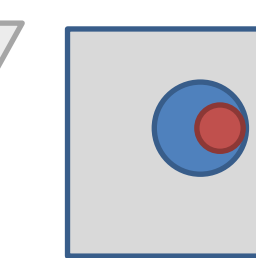
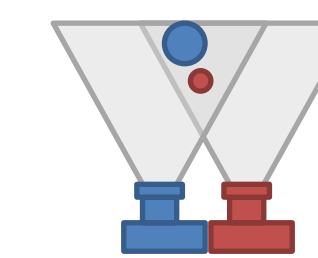
Support region (red) created by union of horizontal crosses along the vertical cross. The cross length are determined by intensity difference and length constraints. This allows for context-based blurring

### Occlusion Interpolation

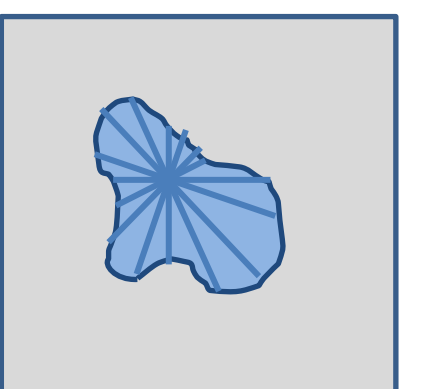
L  
R



Interpolation uses the depth information from the right image corresponding to the disparity in the left to fill in holes. Regions where the right and left depth map don't agree after occlusion interpolation are filled by the median of the closest good pixels in 16 directions



Regions occluded in the left image (blue) are filled in with data from the right (red)



## Experimental Results



Major objects in the scenes like the road, signs, and cars are accurate in the disparity maps. The right and left edges are not as clean as the center of the image due to the lack of redundant data. The CNN approach performs far better than the naïve plane-sweep approach.

## References

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