



Cost Volume Refinement for Depth Prediction

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Abstract

Light-field cameras data redundancy allows, to predict the depth of each point visible from the camera. A large subset of methods for depth prediction from light fields relies on cost-volume estimates. Generally, this volume is used to regress a depth map, which is then refined for better results.

In this paper, we argue that refining the cost volumes is superior to refining the depth maps. We propose three cost-volume refinement algorithms and show their effectiveness:

- A method for combining cost-volumes with other prediction methods.
- A method for artifact removal on cost volumes robust to smooth surfaces and object complexity.
- A fast smoothing method for noise and discontinuity reduction on cost volumes robust to sharp depth changes

Classification Artifact Removal

We noticed that multi-label classification methods tend to be robust to artifacts, but also to reduce accuracy due to lack of precision or miss-assignment between close labels. To take advantage of the artifact detection while maintaining accuracy, we define:

$$C_{k+1}(\mathbf{u}, z) = C_k(\mathbf{u}, z) + \lambda_k |L_{\mathbf{u}} - \mathcal{D}(C, \mathbf{u})| \cdot (L_{\mathbf{u}} - z)^m$$

which increases $\cot C$ according to multi-label prediction *L* using an even polynomial, and linearly according to its difference to a simple depth prediction *D*.



Independent Predictor Combination

We define a generic method that can make use of any depth prediction obtained from non cost-based light-field method, or from any domain specific knowledge:

$$C_{k+1}(\mathbf{u}, z) = C_k(\mathbf{u}, z) + \lambda_k G(P_{\mathbf{u}} - z)$$

we increase the original cost C according to the difference between depth z and the independent prediction P using a gaussian kernel G.

As an example, we use a facial reconstruction convolutional network to improve the result of a portrait picture:



Iterative Local Smoothness

Two common issues with depth predictions from cost volumes are noise and local artifacts. We vastly reduce these by taking into account the predictions of the neighborhood of each image point:

$$S_{0} = C_{k}$$

$$S_{j+1}(\mathbf{u}, z) = C_{k}(\mathbf{u}, z) + \lambda_{k} \sum_{v \in \mathcal{I}_{\mathbf{u}}} G(\mathcal{D}_{S^{j}}(v) - z) \cdot W_{S^{j}}(v)$$

As this is a recursive problem, we solve it by estimating new cost volumes iteratively.



