Unsupervised flow estimation (change this)

Joe Withers

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1 Abstract

2 Introduction

unsupervised learning of optical flow
using FlowNetS, similar approach to *ref* - extended to ?.
results show... - either comparison to other methods, or comparison to with and without occlusion constraints (or any other additions to the implementation).

3 Related literature

3.1 Traditional optical flow estimation (re-name)

In traditional gradient-based optical flow estimation, the common assumption is brightness consistency. The brightness consistency constraint, *eq*, can be used as a data driven error term in an optimization problem. However, this equation is underdetermined and therefore further constraints are required to estimate optical flow. *Horn and Schunck* impose the global smoothness of the flow as a regularization term, giving a global energy function seen in *eq*. *include some extensions of horn and schunck*. These global energy functions can be minimized using continuous optimization methods using such as gradient descent. Alternatively, these can be minimized using discrete optimization...*variation method*

3.2 Supervised CNN flow estimation

Convolutional neural networks are capable of. . .
Recent works have seen CNN's. . .
*FlowNet**DispNet* introduced using CNN's to predict optical flow estimation.
FlowNet uses convolutional layers and pooling layers to extract features and then uses up-convolutional layers to output a dense optical flow estimation. This CNN architecture is trained end-to-end in a supervised learning environment, using ground-truth optical flows.
DispNet. . .
Further work. . .
D.Teney 2016. . .
FlowNet2.0 stacks networks to incrementally predict optical flow. . .

In a supervised training environment, CNN's require large labelled datasets to learn optical flow estimation. Real world datasets with ground truth optical flow labels are difficult to obtain. In the case of *FlowNet, . . . *, they created synthetic datasets which they train on. Training on unrealistic datasets may impose an upper limit on the accuracy on the optical flow estimation on real data.
*. . . * attempts to. . .
Another approach is to use unsupervised learning.

3.3 Unsupervised CNN flow estimation

More recently we have seen works for unsupervised learning of optical flow using a CNN.
Yu. Harley 2016. . .

A. Ahmidi 2016...
Z.Ren 2017 uses *FlowNet* in an unsupervised learning domain. This paper uses a differentiable bilinear warping function to calculate the photometric error of the optical flow estimation. Also, a first order smoothness constraint is imposed on the estimated flow. This method allows for end-to-end training using backpropagation since the bilinear warping function is differentiable.
Extending this, *UnFlow 2017* uses *FlowNet2.0* and considers occlusion in the loss function by estimating the flow in both directions and...
Furthermore, *UnFlow 2017* imposes second order smoothness on the flow which is shown in *...* to give better results.
Lai 2017 uses an adversarial network in contrast to the brightness constancy error from warping with the estimated flow.
These approaches, although currently not as good as the supervised CNN learning have good potential for optical flow estimation going forward as they require no ground truth flow datasets. This also means that these approaches are not constrained by the implicit upper bound of performance from training on synthetic datasets.

4 Implementation

4.1 unsupervised loss function

4.1.1 photometric loss

differentiable warping function - reference to section
Charbonnier loss

4.1.2 smoothness constraint

first order smoothness constraint
second order smoothness constraint?

4.1.3 occlusion error term?

4.2 network architecture

diagrams
introduce how loss functions are used in the architecture.

4.3 Differentiable warping

bilinear interpolation

4.3.1 Testing the warp function

using ground truth flow and comparing error of warped image

5 training

back-propagation
plots of error over epochs
tables

5.1 analysis

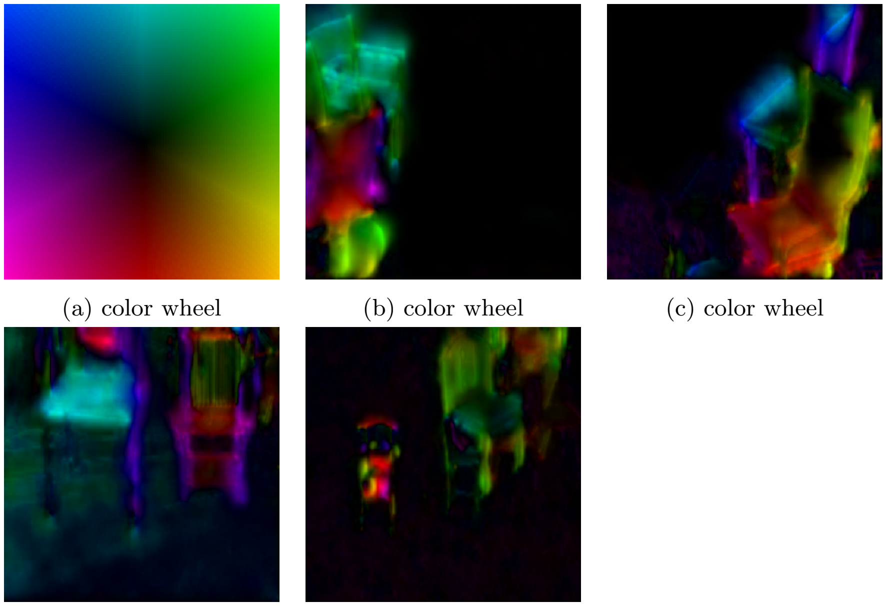
6 Training datasets

6.1 Flying chairs

6.2 etc

6.3 Data augmentation

7 Results



(a) color wheel (b) color wheel (c) color wheel

(d) color wheel (e) color wheel

Figure 1: flow training data

qualitative - graphical results

quantitative - end-point / interpolation/ angular / etc error tables

8 Analysis

9 Conclusion

10 Future work