IPPR: TGV Based Fusion

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1 Introduction

In this report we will explain our implementation of total generalized variation in the context of multi-view stereo fusion. More specifically, we will comment on how the optimization based on finite differences approach minimizes the energy, allowing to fuse partial/noisy information into a single disparity map.

In multi-view stereo, disparity estimations might be inconsistent from one view to the other. For this reason, many approaches try to combine partial information by considering the consistency among other views. In our particular case, the different views were already aligned but contained artificial salt-and-pepper noise.

When it comes to the fusion itself, TGV optimizes the energy which takes into consideration a regularization and data term. In particular, the implemented approach minimizes such energy by means of finite differences (i.e. following the ideas of the primal-dual algorithm to reach an approximate solution).

2 Implementation

When it comes to the implementation we made use of the reshape/ravel method to move between a flattened and unflattened representation. This allowed us to make us of efficient broadcast operations provided by numpy. Due to the growing size of such matrices, special care was taken by using sparse representations when necessary, which allowed us to keep the memory footprint to a minimum. This was specially important when computing K, which was of size *6MNx3MN*. To achieve this the *bmat* method from the scipy package was used.

Before describing the evaluation procedure and the corresponding results we will mentioned the supporting hardware and software used to develop and evaluate our implementation:

- **CPU:** Intel i7 8550U @ 1.8 GHz x8
- **OS:** Ubuntu 19.10
- **Language:** Python 3.7 (Conda)

Beyond specific implementation details, we will now mentioned the upcoming evaluation procedure. First, we will evaluate how the different weighting parameters α_1 and α_2 affect the end result in a qualitative manner. Afterwards we will link such results to the quantitative accuracy results and evaluate any possible correlation. Furthermore, we will briefly execute some samples runs with different step values to see if this affects the results in any meaningful way.

Finally, we will also compare the quality of the results to the energy over time and analyze if there is anything meaningful to discuss regarding the convergence of the primal-dual algorithm.

3 Results

As previously mentioned, we will first take a look at the effect of the different alpha values have on the regularization term and the resulting fusion. For this we will evaluate the following combinations during 300 iterations:

- **Combination 1:** [α_1=0.8, α_2=0.2]
- **Combination 2:** [α_1=0.5, α_2=0.5]
- **Combination 3:** [α_1=0.2, α_2=0.8]

The Figure 1 shows the results for the three combinations. As it can be quantitatively noticed, as the effect of α_2 increases the influence of the gradient term of the regularization and the image becomes significantly noisier. This makes sense when look at Figure 2, where the final gradients produced in these combinations become stronger. In contrast, when the difference with the fusion term weights higher, the optimization tries to find a balance between the gradient of the fused disparity map and the gradient term, causing a piece-wise constant smoothing.

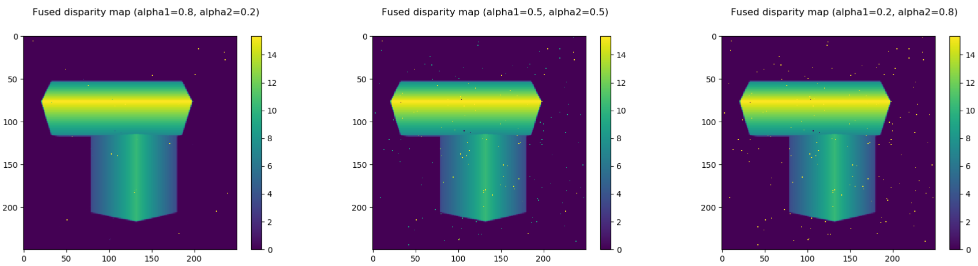

Figure 1: Comparison of different weighting when it comes to fusion results. Combination 1 to 3 from left-to-right order.

It could be interesting to see the effect in scenes with more complex geometry (no so many piecewise-constant areas), where the regularization term might affect the quality of the final reconstruction by oversmoothing high-frequency details.

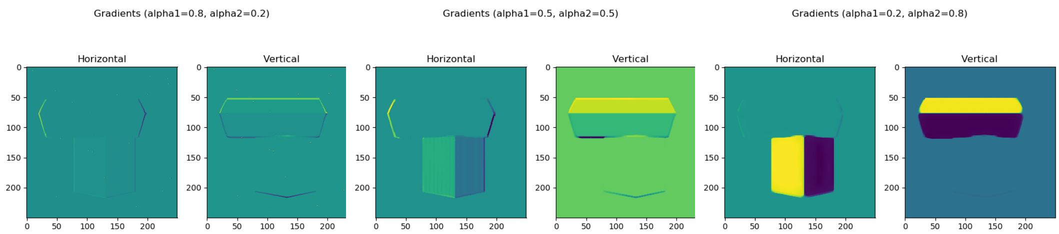

Figure 2: Comparison of different α when it comes to energy minimization over time. Combination 1 to 3 from left-to-right order.

The Table **??** shows the accuracy of each combination using a accuracy threshold of 0.00001. As can be seen the accuracy decreases as the influence of the gradient term increases. This makes sense if we consider the fact that the image is clearly noisier. It is interesting to note that all the results show a really high accuracy level given the initial noisy disparity maps.

Combination	Accuracy
1	0.991912
2	0.990608
3	0.979648

Table 1: Accuracy comparison when using different weighting for the regularization/data term. Higher data terms results in less accurate results w.r.t. ground-truth.

The Figure 3 shows the energy over time for the different configurations. As can be observed all of them quickly converge after approximately 20 iterations. When zoomed in we couldn't notice any significant difference in terms of convergence speed due to different weighting in the regularization term.

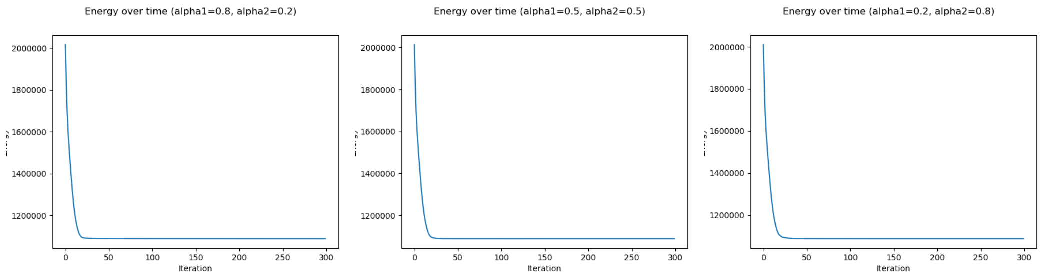

Figure 3: Comparison of different α when it comes to energy minimization over time. Combination 1 to 3 from left-to-right order.

To conclude the report we show the disparity map displayed in 3D in the following Figure:

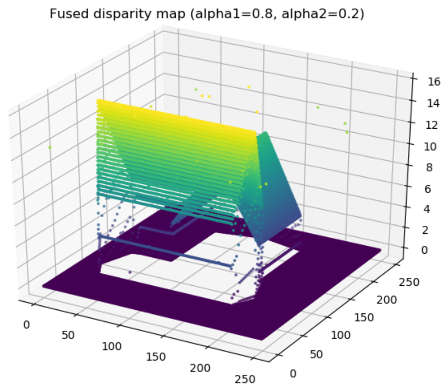

Figure 4: Comparison of different α when it comes to energy minimization over time. Combination 1 to 3 from left-to-right order.

4 Conclusion

To conclude this report, we will mentioned a few takeaways from this experience:

- The approximation using the primal-dual algorithm produces high-accuracy results.
- A higher α_2 over emphasizes gradients and produces noisier results compared to a balanced weighting scheme.