An alternative confidence measure for local-matching stereo algorithms

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Abstract—We present a confidence measure applied to individual disparity estimates in local-matching stereo correspondence algorithms. It aims at identifying textureless areas where most local-matching algorithms fail. The confidence measure works by analyzing the correlation curve produced during the matching process. We test the confidence measure by developing an easily parallelized local-matching algorithm. We use our confidence measure to filter out unreliable disparity estimates. Using the widely used Middlebury dataset and our own evaluation scheme, our results show that the confidence measure significantly decreases the disparity estimate errors at a low computational overhead.

I. INTRODUCTION

Stereo vision is a very actively researched topic in the computer vision community. In robotic systems, stereo vision provides a low-cost alternative for range imaging compared to expensive laser range finders for applications such as 3D reconstruction, obstacle avoidance, etc. The major issue in such a system is the correspondence problem, which is: given two or more images of the same scene from different viewpoints, find which pixels correspond and by how much the pixel in one view is translated relative to a corresponding pixel in another view. A number of solutions have been produced to the extent that an online evaluation has been developed [1].

Solutions for the stereo correspondence problem consist of complex modules such as plane-fitting, edge-preserving smoothing, image segmentation etc. Among these solutions are local-matching algorithms which can be easily parallelized for real time applications. Although these algorithms are applicable in real-time systems, they generally produce more errors compared to other more complex non-real time approaches.

We present a method of assigning a confidence to a disparity estimate for local-matching algorithms. Our approach is expected to give low confidences to disparity estimates in textureless regions, where many local-matching algorithms fail. While our approach is similar to a number of previously developed confidence measures in that the confidence of a disparity estimate is a by-product of the matching process, our analysis focuses on the base of convergence (refer to figure 3) of a disparity estimate.

To evaluate our confidence measure, we implement a local-matching algorithm. We expect our confidence measure to be applicable across the different variations of these algorithms because of their uniform structure of local-matching algorithms . We run our algorithm on the widely used Middlebury dataset [1] in order to evaluate the performance of our confidence measure using our own evaluation scheme.

The remainder of the paper is structured as follows. Section II briefly covers the related literature. Section III discusses the local-matching algorithm implemented. Section IV discusses our confidence measure and how we use the measure for disparity refinement. Section V discusses our evaluation methodology and the results of our experiments. The paper is concluded in Section VI.

II. RELATED WORK

In stereo vision research, there has been several successful approaches in representing the confidence of a disparity estimate. The left-right consistency constraint [2]–[6] has been traditionally used to characterize pixel ambiguity. The constraint checks the left-image reference disparity estimate and compares the estimate with the inverse mapping of the right-image reference disparity estimate. This approach has been successful in detecting occluded regions. There have been approaches which analyze the matching score of the disparity estimate [7], [8]. The confidence of a pixel is based on the magnitude of the similarity value between the pixel in the reference image and a matching pixel in the target image. Other approaches analyze the curvature of the correlation curve [9], [10] and assign low confidence to disparity estimates resulting from a flat correlation curve. Approaches such as [11], [12] estimate the confidence of pixels with two similar match candidates. Research has also been conducted in determining pixel confidence based on image entropy [13], [14]. Low confidence scores are assigned to low entropy points in the reference image. Recently, a new approach has been

developed which extrapolates confidence *a posteriori* from an initial, given, possibly noisy disparity estimate [15].

III. Stereo algorithm

According to [16], stereo vision algorithms generally perform the following steps:

1) matching cost computation, where a matching cost used to quantify pixel similarity is formulated;
2) cost aggregation, where a support region is defined to spatially aggregate the matching cost;
3) disparity computation, where the best disparity hypothesis for each pixel is computed to minimize a cost function and
4) disparity refinement, where the computed disparity maps are post-processed to remove mismatches or to produce sub-pixel disparity.

We are interested in local-matching algorithms which generally perform the steps 1, 2 and 3. We include step 4 as our confidence measure. Our interest in local-matching algorithms is motivated by:

- firstly, they can be easily parallelized which allows them to be implemented on graphics processing units or field programmable gate arrays for real-time computations,
- secondly, they are generally used as an initial estimate for a number of the state of the art algorithms and
- thirdly, their uniform structure shown in Algorithm 1, allows our confidence formulation to be used across the different variations of these algorithms.

However, local-matching algorithms generally fail because of lack of texture in an image and occluded regions.

Algorithm 1 Stereo algorithm

INPUT: Stereo images, window size, disparity range.
OUTPUT: Disparity map, confidence map.

for each pixel in the left frame **do**
    set support region around the pixel (left frame)
    set search window in the right frame
    for each pixel in the search window (right frame) **do**
        set correlation window around the pixel
        correlate support region with correlation window
    end for
    find best match
    calculate disparity
    calculate disparity confidence
end for

It can easily be seen that local matching algorithms generally differ in steps 1 and 2, matching cost computation and cost aggregation. For a comprehensive study of matching costs and cost aggregation, the reader is referred to [17] and [18].

For our purposes, we use Birchfield and Tomasi's sampling insensitive [19] matching cost. We also perform the left-right consistency check to detect occluded regions and filter them
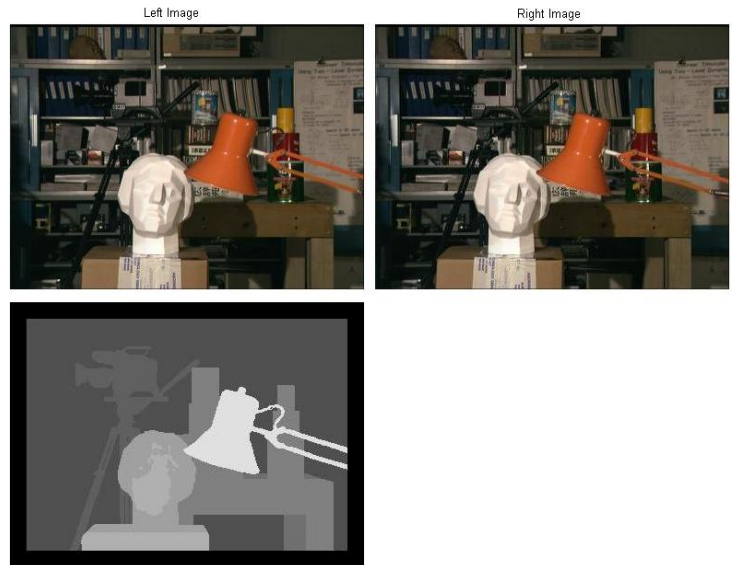

Fig. 1. Tsukuba image pair at the top and it's ground truth at the bottom with the left image as reference
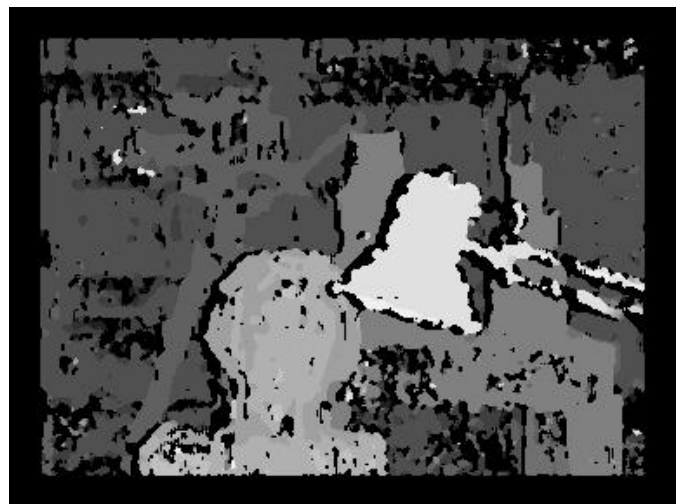

Fig. 2. Computed disparity map of the Tsukuba image pair. Close objects are bright while further objects are darker

out. Figure 1 shows Tsukuba image pair and it's ground truth. The resulting disparity map from our algorithm for the Tsukuba image pair with a 5x5 aggregation window and 15 disparities followed by a 5x5 median filter is shown in figure 2. It should be noted that the algorithm implemented is to be used as a testbed for our confidence measure and is not meant to be compared with the state of the art.

IV. Confidence measure

Our confidence measure is calculated as a function of x, y, d, where (x, y) are the image coordinates and d the disparity. A typical correlation curve is shown in figure 3. By analyzing the base of convergence, B of the disparity estimate, a confidence of the estimate can be inferred. Given a disparity,

d, the confidence of a disparity estimate can be computed as follows:

$$C(d) = \frac{B}{d_{max} - d_{min}}$$

$C(d)$ is the confidence for a given disparity, B is the base of convergence of the disparity estimate d, and $d_{max} - d_{min}$ is the disparity range. It is expected that in textureless regions, the correlation curve will have multiple local minima with small B values, therefore since $C(d)$ is proportional to B, we expect low confidences. A high confidence value would have few local minima in the correlation curve and a fully confident disparity estimate would arise where the local minima is the global minima of the correlation curve.

Our algorithm uses gradient ascent to determine B. Given a disparity estimate, d, we perform gradient ascent on both sides of the estimate and determine the two local maxima. The number of disparities covered by the two local maxima are defined as the base of convergence, B.
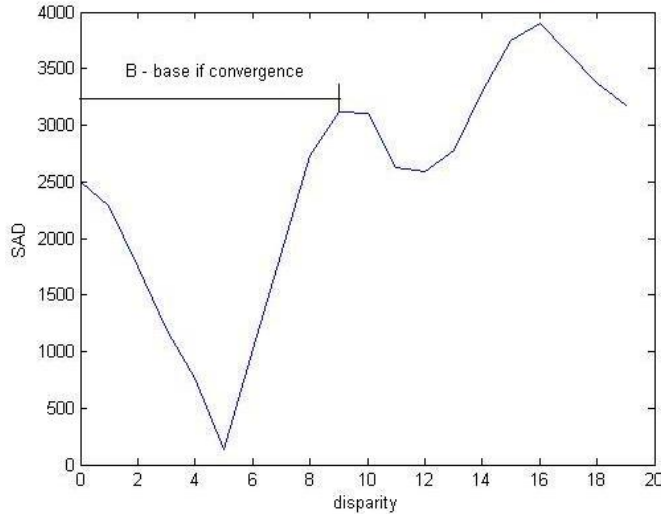

Fig. 4. Refined disparity map for the Tsukuba image pair with $T = 2$

disparity refinement would also include a hole filling step. Our algorithm does not perform hole filling because of the errors it might introduce, which leaves a sparse disparity map. Evaluating our sparse disparity map on the Middlebury stereo benchmark would not be sufficient because most errors would arise from the filtered out disparities. As a result, we use our own evaluation scheme. We used Matlab for our implementation.

We classify pixels as containing no information, unreliable information or good information. We define occluded pixels as containing no information, pixels with $C(d) \leq T$ as containing unreliable information and the rest of the pixels as good information. In our evaluation, we only consider pixels containing good information.

We calculate the root mean square error ($RMSE$) as follows:

$$RMSE = 100 \times \sqrt{\frac{1}{N_p} \sum_{(x,y) \in p} (d(x,y) - d_g(x,y))^2},$$

Fig. 3. Correlation curve and the base of convergence

where, p is the set of all pixels containing good information, N_P is the number of pixels containing good information, $d(x,y)$ is the estimated disparity at pixel (x,y) and $d_g(x,y)$ is the ground truth disparity at pixel (x,y).

A. Disparity refinement

After computing confidences for all our disparity estimates, we select a threshold, T, to create a mask of acceptable and unacceptable disparity estimates. Acceptable disparity estimates are defined as estimates satisfying, $C(d) > T$. By choosing, $T = 2$, the refined disparity map is shown in figure 4. One can visually see by comparing figure 2 and figure 4 that most of the noisy estimates arising from the local-matching algorithm are filtered out successfully.

Included in our evaluation is the percentage computational overhead for a chosen value of T. We include this metric instead of actual time in seconds because the actual time depends on the processor used to carry out the experiments. Percentage computational overhead on the other hand is independent on the processing power.

V. EXPERIMENTS

The Middlebury stereo benchmark provides a testbed to quantitatively evaluate stereo algorithms. Although the testbed is widely used in the computer vision community, it requires a dense disparity map. Generally, algorithms which perform

The Middlebury dataset is used for our evaluation. The results for the Middlebury dataset on the different image pairs with $T = 0$ are shown in Table I while results with an

TABLE I

Image pair	Window size	Disparities	T	RMSE
Tsukuba	5	15	0	7.56
Venus	5	19	0	29.84
Teddy	9	59	0	37.43
Cones	9	59	0	30.13

TABLE II

Image pair	Window size	T	RMSE	Overhead(%)
Tsukuba	5	2	6.56	2.33
Venus	5	4	21.94	18.35
Teddy	9	2	32.79	19.23
Cones	9	6	23.38	17.60

optimal value of T are shown in Table II.

In our experiments, it was noted that the $RMSE$ starts increasing after a certain value of T for a selected window size. This is due to the errors introduced by the window size. Local matching stereo algorithms assume constant disparity throughout the aggregation window, therefore errors known as the "fattening effect" arise. Also, since the images have pixel resolution, a window size greater than a pixel affects the resolution of our disparity estimates. Errors are introduced where the image details are smaller than the window size. Since our algorithm does not filter out these errors, they are fixed with a changing value of T. The larger the value of T, the smaller the value of N_p while the errors remain fixed. A plot showing the relationship between T and N_p with a 5x5 window size for the Tsukuba image pair is shown in figure 5.
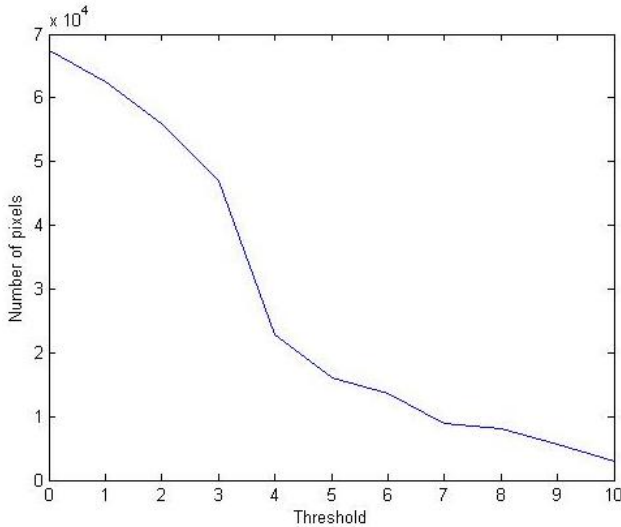

Fig. 5. Plot of number of pixels N_p vs Threshold (T) with a 5x5 window size for the Tsukuba image pair

To visually show the effect of the window size on our evaluation, figure 6 shows a plot of T vs $RMSE$ for varying window sizes. Different window sizes tend to shift

the curve up or down. As the window size increases, the curve shifts downwards until a point where a larger window size introduces more errors causing the curve to shift upwards.
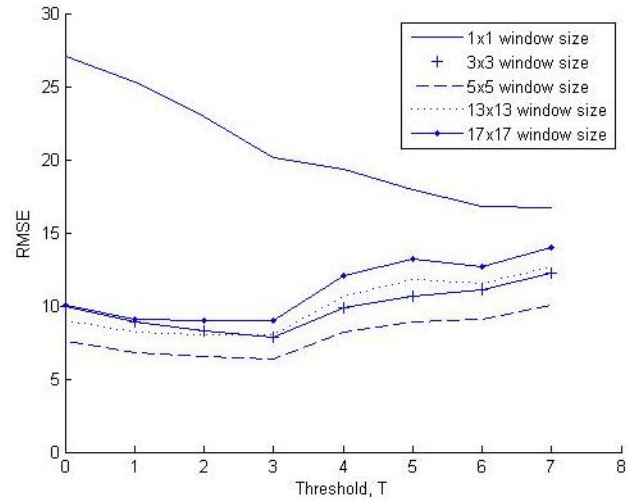

Fig. 6. Plot of Threshold (T) vs RMSE for varying window sizes

VI. CONCLUSIONS AND FUTURE WORK

We presented a confidence measure to detect textureless regions for local-matching algorithms. The effectiveness of our approach was demonstrated by implementing a local-matching algorithm and filtering unreliable depth estimates. Our quantitative evaluation scheme demonstrated that our simple confidence measure decreases the disparity estimate errors at a fraction of time complexity.

We plan to use the developed confidence measure to address the problem of temporal stereo which entails using previously computed disparity maps to seed new disparity maps. The confidence measure would aid in identifying good points to seed successive disparity estimates in the hopes of decreasing computation time in a stereo video sequence.

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