

Effect of applying smoothing filters on improving disparity maps in stereo images Efecto de la aplicación de filtros de suavizado en la mejora de mapas de disparidad en imágenes estéreo

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Summary. This work develops an application of different classical filtering techniques in order to demonstrate their impact on the generation of disparity maps with OpenCV, commonly used to create 3D reconstructions. The experimentation stage was developed using the Semi-Global Block Matching (SGBM) algorithm as a standard option, due to its wide recognized characteristics, being applied to the set of stereo images from the KITTI 2015 dataset, applying the median, Gaussian and bilateral filters. The evaluation metrics were the visual quality of the final result, the mean absolute error (MAE) and the computation time. The results demonstrate the effectiveness of the bilateral filter compared to other options, since it manages to mitigate noise with a reasonable computation time, preserving edge consistency and proving to be a practical alternative for computer vision applications and 3D scene reconstruction.

Keywords: Disparity Map, Computer Vision, Image Filtering, Stereo Vision, Semi-Global Block Matching.

Resumen. Este trabajo desarrolla una aplicación de diversas técnicas de filtrado clásicas para demostrar su impacto en la generación de mapas de disparidad con OpenCV, herramienta comúnmente utilizada para crear reconstrucciones 3D. La fase experimental se llevó a cabo utilizando el algoritmo *Semi-Global Block Matching* (SGBM) como opción estándar —dada su reconocida eficacia— y aplicándolo al conjunto de imágenes estéreo del *dataset* KITTI 2015, empleando filtros de mediana, gaussianos y bilaterales. Las métricas de evaluación fueron la calidad visual del resultado final, el error absoluto medio (MAE) y el tiempo de cómputo. Los resultados demuestran la eficacia del filtro bilateral frente a otras opciones, ya que logra mitigar el ruido en un tiempo de cómputo razonable, preserva la consistencia de los bordes y se perfila como una alternativa práctica para aplicaciones de visión por computadora y reconstrucción de escenas en 3D.

Palabras Clave: Mapa de disparidad, visión por computadora, filtrado de imágenes, visión estéreo, correspondencia de bloques semiglobal.

1 Introduction

Computer vision is considered in many areas as a cutting-edge tool in the field of autonomous robotics applications, feature extraction, pattern recognition and in industrial inspection applications. In applications where feature knowledge requires depth information allowing the understanding of the 3D geometry of a specific environment or object, it plays a relevant role in many problems today [1-2]. A common way to make this depth calculation from 2D images is through images captured by stereo cameras. These capture two images with a controlled phase shift similar to what human eyes do [3].

This problem is constantly addressed in the literature, however, current algorithms that generate the so-called disparity maps (difference between pairs of phased images) generate noise, regions lacking definition and discontinuous areas where edges defining important textures are found. These defects greatly impact the accuracy with which 3D reconstructions are made [4].

Therefore, a practical and low computational impact strategy is needed to achieve an improvement in the quality with which disparity maps are constructed. This can be achieved through a one-stage post-processing filtering strategy. Some filters such as (i) median [5]; (ii) Gaussian [6]; and (iii) bilateral filters

usually have advantages and certain considerations when working with edges, noise and computational cost, as seen in Table 1 [7].

Table 1. Filters and expressions.

Filter	Equation
Median	• $Median(S) = \frac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2}$ (when n is even) • $Median(S) = \frac{x_{\frac{n+1}{2}}}{2}$ (when n is odd)
Gaussian	$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$
Bilateral	$I'(p) = \frac{1}{w_p} \sum_{q \in \Omega} I(q) f(\ p - q\) f(\frac{ I(p) - I(q) }{r})$

This paper aims to demonstrate the impact of applying different filters in post-processing and to observe the quality of the generated disparity maps. To do this, we will use the Semi-Global Block Matching (SGBM) algorithm available in the OpenCV Python library, using images from the public stereo image dataset to perform the comparison in the application of the filters [8].

The following sections of the article are composed as follows: Section 2 presents an analysis of the current methods reported in the literature; Section 3 presents the overall methodology of the proposal, as well as details of the dataset used. Section 4 analyzes the results found, and Section 5 presents the conclusion and future work.

2 State of the art

This section presents an analysis of previous work that includes classical methods used to construct disparity maps, such as Block Matching (BM) and SGBM, which involve noise and discontinuities. Likewise, various works in the literature show simple filters that help with improvements without increasing the complexity of the proposals. Some efficient methods already in progress are also analyzed, which improve results by sacrificing resources and gaining greater computational complexity. This analysis can be seen in Table 2.

Table 2. Analysis of state-of-the-art works with different filters.

Work	Method	Filtering technique	Details
Hirschmüller (2005) [8]	Semi-Global Block Matching (SGBM)	Without filtering	Original SGBM proposal, accurate but noisy in homogeneous regions.
Zhang et al. (2013) [9]	Classic dense stereo	Bilateral filter	Enhance the preservation of edges, but with high computational cost.
Yoon & Kweon (2006) [10]	Adaptive stereo correspondence	Guided adaptive filters	Noise mitigate on planar zones, with complexity increase
Hosni et al. (2012) [11]	Local and global methods	Cross-based cost aggregation	Efficient strategy to reduce noise, good preservation of edges
Chang & Chen (2018) [12]	Deep Learning-based methods	Neural networks	It has high accuracy, but requires large computational power and a data set for training.

In summary, Table 2 shows that classical algorithms perform well in generating disparity maps, but they generate noise in textureless regions or those with edges. Advanced techniques exist, but they are computationally expensive. In contrast, simple filters are used as an efficient alternative that improves the quality of disparity maps with a low impact on complexity.

3 Methodology

As part of the methodology, the dataset of stereo images used as an assessment of the proposed strategy is described. This dataset is freely distributed and is called KITTI Stereo 2015 in its version 13.03.2017 where the ground truth for disparity maps is improved. This dataset contains 200 images in pairs and 200 paired test images, each in PNG format. Specifically, it works with the Stereo/optical Flow dataset, available at [13].

3.1 Approach and Experimental process

The proposal consists of 4 stages mainly as shown in Figure 1. In the first stage, the stereo image pairs from the KITTI 2015 dataset are read, then in the second stage the disparity map is generated with a known and proven technique, this being the Semi-Global Block Matching (SGBM) algorithm implemented with *OpenCV* libraries in Python.

For the experimental process, the proposal was implemented in *Python* version 3.9.12 with the development environment (IDE) *Visual Studio Code* 1.103.2 (x64), as well as the *OpenCV* libraries for the creation of the disparity maps; *Matplotlib* for the visualization; *Numpy* for the numerical part; and *Pandas* for the evaluation metrics.

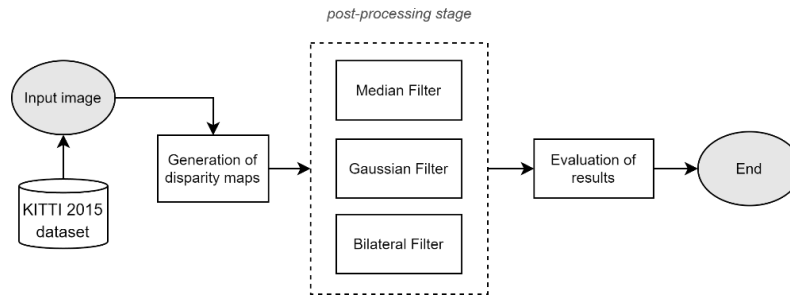


Figure 1. Image processing stages for filter analysis.

The following stage is considered the central contribution of this work where a post-processing stage is added where different filters will be applied to smooth the features obtained in the disparity map. In the last stage, the results are evaluated by comparing the final disparity map when a particular filter is applied to it, comparing the output for the median, Gaussian, and bilateral filters. This process is observed in the form of pseudocode in Algorithm 1 (see Figure 2). The hardware used as a platform for experimentation in terms of computing time was an Asus ROG Strix 16 laptop, with Intel Core i7-13650HX (13th generation, 14 cores), with 16 GB DDR5 RAM.

Algorithm 1 Methodology for evaluating filters in disparity maps

Input: Stereo images (I_L, I_R) ,
Output: $DM_f, \Delta t, MAE$

```

 $I_L, I_R \leftarrow cv2.imread()$  Load stereo images
 $cv2.StereoSGBM$  Configure parameters and create object
 $DM_{raw} \leftarrow SGBM(I_L, I_R)$  Calculate initial disparity map
 $DM_{vis} \leftarrow DM_{raw}$  Normalize for display
 $F \leftarrow \text{Filter}$ 
foreach  $F \in \{none, median, gaussian, bilateral\}$  do
  if  $F = none$  then
     $DM_f \leftarrow DM_{vis}$ 
  else if  $F = median$  then
     $DM_f \leftarrow MedianBlur(DM_{vis}, k)$ 
  else if  $F = gaussian$  then
     $DM_f \leftarrow GaussianBlur(DM_{vis}, k, \sigma)$ 
  else if  $F = bilateral$  then
     $DM_f \leftarrow BilateralFilter(DM_{vis}, d, \sigma_c, \sigma_s)$ 
   $\Delta t$  Execution time (sec)
end
 $MAE = mean(|DM_f - DM_{gt}|)$  Mean Absolute Error (MAE)
return  $DM_f, \Delta t, MAE$ 
  
```

Figure 2. Disparity map evaluation algorithm.

The evaluation metrics used were based on the analysis of computation time for each of the different filters applied, keeping the algorithm constant to create the disparity map. The Mean Absolute Error (MAE) analysis was also performed and complemented with a visual inspection of the results obtained.

4 Experimental Results and Discussion

At this stage, the Python work and programming environment is used, where the experimental space is structured by means of folders where the images are distributed in *IL* and *IR*, in addition to the disparity maps available in the dataset as ground true *MDgt*. With a folder where all the outputs of the experimental process are stored for the results when no filter is applied, the Gaussian, median and bilateral.

Following the process of Algorithm 1 (see Figure 2), the stereo images are loaded in pairs, converted to grayscale, and the filtering stage begins as appropriate. Subsequently, to run the *OpenCV* SGBM algorithm, the KITTI 2015 dataset recommends some parameters to improve results. First, the *minDisparity* parameter is set to 0 since the objects are located in front of the scene; the *numDisparities* parameter is configured between 128 and 256 to encompass both distant and near objects; *blockSize* is regularly set and adjusted between 3 and 9 px. The *uniquenessRatio* value is commonly used between 10 and 15. There is an intensity *normalization* parameter, typically between 31 and 63, for the *preFilterCap* parameter; and finally, the parameter in which the algorithm is run. For this dataset, the *cv2.STEREO_SGBM_MODE_SGBM_3WAY* mode is recommended.

In the experimental process, 400 pairs of images are evaluated for each filter, in total 1600 images are processed, where the results of the average processing time and the Mean Average Error are summarized in Table 3 and in the graphs in Figure 3.

Table 3. Average computing time and average MAE result.

Filter	Average time (sec)	Average MAE
None	0.0256	8,723.78
Median	0.0233	8,724.29
Gaussian	0.0260	8,723.67
Bilateral	0.0232	8,723.74

We can see that the base values when no filter is applied have a MAE value of 8,727.78 and an average execution time of 0.0256 sec. Based on this, the Median filter slightly reduces noise (see Figure 4) and is a little faster.

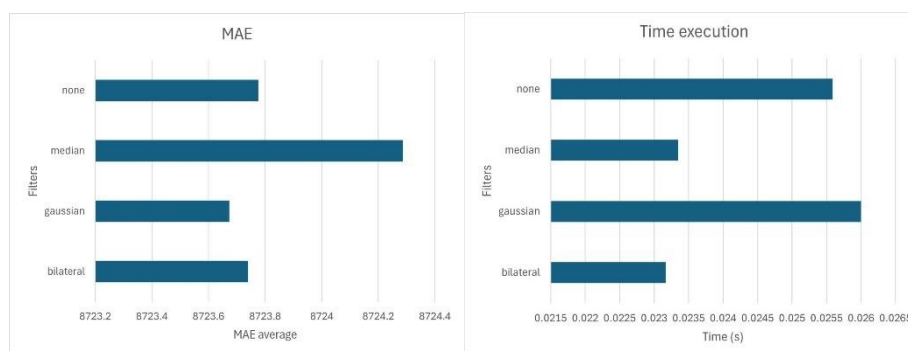


Figure 3. Comparative graph of the results in computation time and MAE.

In the case of the Gaussian filter, it doesn't significantly improve accuracy and is slightly slower than the previous two. Finally, the bilateral filter reduces noise and performs as quickly as the median filter.

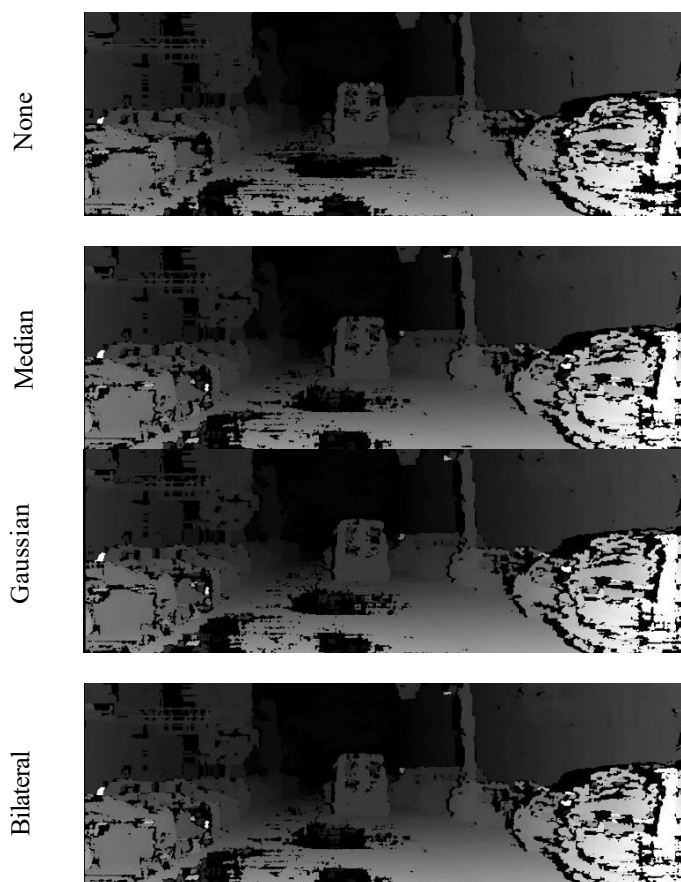


Figure 4. Visual comparison of the application of the filter on disparity maps.

4.1 Discussion

The results obtained from the process in general, and from the sample presented as a summary, show that an image post-processing process significantly impacts the results obtained in the final disparity map. Some filters perform better in particular characteristics, such as the bilateral filter, which notably results in edges, and requires more computation time compared to the other filters. This could be applied where quality versus response time is essential. On the other hand, the Gaussian and median filters improve quality in the presence of noise with a balance in computation time. However it is necessary to improve this comparison and expand the research to other algorithms and more sophisticated filters, and segment the analysis of efficiency versus computation time.

5 Conclusions and Future Work

The strategy proposed to demonstrate the difference and impact of a disparity map post-processing step in this work reveals a significant impact on the quality of the obtained disparity maps, improving their visual quality and also impacting computation time. In summary, the filter that presented the best balance between final quality and computation time was the bilateral edge-preserving filter, which aids in better 3D reconstruction of scenarios.

This work highlighted an opportunity to expand the comparison process with different datasets in different scenarios and lighting conditions that may affect the process, implementing more advanced filters, and even incorporating deep learning techniques or different algorithms, allowing for more complete and robust evaluations.

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