# Effects of Image Blurring on the Efficiency of Edge Detection Algorithms

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**Abstract.** Image smoothing is a vital pre-processing step in edge detection, primarily implemented using filters like the Gaussian filter to reduce noise and standardize pixel intensity variations. While essential for minimizing false positives and improving algorithm accuracy, it can lead to the loss of fine details. Given the limited research on the impact of blurring on edge detector efficiency, this study explores the effects of the Gaussian filter, particularly in comparison with the Canny edge detector, on precision, recall, and the F-measure. Experiments were conducted using the Berkeley Segmentation Dataset (BSDS500), adjusting the Gaussian filter's smoothing parameters from 0 to 5 and fixing the Canny detector's sigma at 2.25. Analysis revealed an inverse correlation between precision and recall, suggesting that increased smoothing reduces false positives but raises false negatives. The study found a moderate balance between precision and recall with the Gaussian method, and an overall reasonable balance according to the F-measure, though not outstanding. The results indicate a negative correlation between precision and recall as blurring intensity increases.

**Keywords:** Edge Detection · Blurring Methods · Performance.

## 1 Introduction

A crucial process in the pre-processing stage of edge detection is image smoothing, It attenuates noise and standardizes intensity variations between pixels [3]. This process often implemented through filters, such as the Gaussian filter. This technique is essential for minimizing false positives, allowing edge detection algorithms to operate with greater accuracy [8]. However, smoothing can result in the loss of fine details and subtle edges, posing a challenge in applications that demand high precision [2]. Considering the scarcity of studies in the literature, this study aims to conduct initial research into the effects of blurring on the efficiency of edge detectors, especially the Gaussian filter in relation to well-know Canny edge detector, which are, respectively, the most widely disseminated classical methods of smoothing and edge detection. The goal is to understand how blurring affects precision, recall, and the F-measure, while determining the quantitative effects of this pre-processing on the acquisition of image object contours. For this purpose, the Gaussian filter and the Canny detector were used, with smoothing parameters varied in discrete intervals.

### 1.1 Related works

Through a comprehensive literature review and an extensive search across major academic databases, it was noted that the works were not directly dedicated to the impact of blurring on edge detection, but authors like Lopez-Molina *et al.* made significant contributions. Notable among these is the Modified Sobel (M-Sobel) method, detailed in [4], which incorporates Gaussian smoothing at various scales to enhance edge detection accuracy, emphasizing the trade-off between precision and recall. Their subsequent studies [5] introduced a multiscale approach that combined Gaussian smoothing with coarse-to-fine edge tracking, aimed at improving the detection of true edges and reducing false positives. Furthering their research, Lopez-Molina *et al.* [6] developed multiscale gradient fusion, an approach inspired by human visual focus mechanisms, to balance precision and recall across multiple scales. These studies consistently highlighted the interplay between precision and recall, suggesting that multiscale methods could achieve a more balanced performance compared to single-scale techniques, despite the overall scarcity of specific studies on the impact of blurring on these metrics in edge detection methods.

## 2 Materials and Methods

The experiments have been conducted over the Berkeley Segmentation Dataset (BSDS500), which includes a subset of 200 natural images with more than 1000 reference annotations. Where adopted Estrada and Jepson displacement-tolerant correspondence, to the edge matching [1] (Available on KITT[4]). A spatial tolerance of 2.5% for the image diagonal length where defined. The smoothing parameters of the filter were varied in a discrete range from 0 to 5, while the parameter of the Canny detector was fixed with sigma = 2.25. This procedure resulted in a comprehensive data collection. Subsequently, this dataset was analysed with the aim of investigating the presence of trends or systematic relationships between the parameters. To assess the performance of an edge detection method

[4] Kermit Research Unit (Ghent University), The Kermit Image Toolkit (KITT), B. De Baets, C. Lopez-Molina (Eds.), Available online at https://github.com/giaracvi/KITT

on a specific image, we compared its results with the reference images, known as “ground truth”. We recorded the values of Precision, Recall, and the $F_{0.5}$ Measure for the “ground truth” that provides the highest $F_{0.5}$ value [7].

## 3 Results and discussion

It was observed that there is an inverse correlation between precision and recall. That is, as smoothing intensifies, there is a significant decrease in the number of false positives (Table 1). Conversely, there is a proportional increase in the number of false negatives. This correlation was less intense for the precision metric but showed an almost perfect correlation regarding recall.

**Table 1.** Correlations between Sigma, Precision (Prec), and Recall (Rec) for Gaussian

| **Filter** | **r: Sigma and Prec** | **r: Sigma and Rec** | **r: Prec and Rec** |
|---|---|---|---|
| Gaussian Blur | 0.6343 | -0.9830 | -0.5632 |

For the optimal sigma values that return the highest F-measure, in each image, the Gaussian blur presented a moderate balance between precision and recall, with mean and median parameter values close for precision (3.025 and 3.1, respectively) and a greater discrepancy for recall (1.162 and 0.7). This suggests consistency in identifying true positives, but a tendency to miss some false negatives. The F-measure, with parameter values of 1.64 and 1.3, indicates a reasonable balance between the two metrics, although not exceptional (Table 2).

**Table 2.** Optimal values of metrics for each method with Canny fixed at 2.25

| **Method** | **Precision** | **Recall** | **F-measure** |
|---|---|---|---|
| | Mean/Median | Mean/Median | Mean/Median |
| Gaussian | 3.025 / 3.1 | 1.162 / 0.7 | 1.64 / 1.3 |

## 4 Conclusion

This study has thoroughly investigated the impact of Gaussian blurring on precision and recall in edge detection, utilizing the Gaussian filter and Canny edge detector. Through experiments conducted with the Berkeley Segmentation Dataset (BSDS500), we established a negative correlation between precision and recall, particularly evident as blurring increases. While heightened blurring typically reduces false positives, enhancing precision, it also increases false negatives, reducing recall. This finding highlights the critical balance necessary between blurring intensity and edge detection accuracy.

Our analysis confirms that the optimal Gaussian parameter for the Canny detector, with $\sigma = 2.25$, is $\sigma = 1.5$, achieving a balanced F-measure in various imaging scenarios. These insights emphasize the complex trade-offs involved in edge detection processes and suggest directions for future research, such as exploring multiscale and alternative smoothing techniques to optimize both precision and recall in different application contexts.

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