The document introduces a new nonlinear image filtering technique called the Generalized Varying Weight Trimmed Mean (GVWTM) filter for removing both additive and impulse noise from corrupted images.

**On a New Nonlinear Image Filtering Technique**

The proposed VWTM filter generalization effectively removes additive and impulse noise from images by incorporating the center pixel, making it robust and efficient compared to other methods.

**I. INTRODUCTION**

The section discusses various noise filtering techniques, focusing on nonlinear filters like the GTM and GVWTM filters for improved performance.

* Images often suffer from noise, which affects signal processing, data compression, and pattern recognition, necessitating effective noise filtering techniques.
* Linear local averaging filters, being low pass filters, fail to preserve image edges and details, making nonlinear techniques more effective.
* The median filter, while popular for edge preservation and impulse noise removal, is not optimal as it uniformly suppresses both true signals and noise.
* The α-trimmed mean (α-TM) and modified trimmed mean (MTM) filters improve upon the median filter but still have limitations, particularly in handling impulse noise and additive noise.
* The generalized trimmed mean (GTM) filter outperforms α-TM and MTM filters by using a "median basket" to select and weight pixels, including the center pixel, for better noise removal.
* The generalized varying weight trimmed mean (GVWTM) filter combines GTM and VWTM filters, dynamically varying the weight of the center pixel to enhance impulse noise detection and removal.

**II. GENERALIZED VARIYING WEIGHT TRIMMED MEAN FILTER**

The section discusses various advanced image filtering techniques, including α-TM, MTM, GTM, VWTM, and GVWTM filters, focusing on their effectiveness in noise reduction.

* The α-TM filter generalizes the median filter by averaging a predetermined number of pixels above and below the median pixel.
* The MTM filter selects pixels around a predetermined threshold and averages them, useful for removing additive noise but less effective for impulse noise.
* The GTM filter improves α-TM and MTM by incorporating weighted averaging of the center pixel and pixels in the median basket.
* The VWTM filter dynamically weights and averages pixels based on their absolute difference from the median value, effectively suppressing impulse noise.
* Weight functions in VWTM, such as exponential and polynomial functions, ensure the median value has the largest weight.
* The GVWTM filter combines the advantages of GTM and VWTM, dynamically adjusting the center pixel's contribution based on its difference from the median pixel.
* The GVWTM filter is effective in suppressing impulse noise and canceling additive noise by involving the center pixel in the filtering process.
* The section highlights the limitations and strengths of each filter, emphasizing the superior performance of the GVWTM filter in various noise conditions.

**III. IMPULSE DETECTOR AND THE IMPULSE NOISE REMOVAL ITERATIVE METHOD**

The section discusses a switching scheme using the GVWTM filter to detect and replace impulse noise in images.

* The proposed algorithm uses a switching scheme based on the GVWTM filter to detect and replace impulse noise corrupted pixels.
* The filtering output is determined by comparing the initial input value with the GVWTM filtering result, using a threshold to identify noise.
* Iterative procedures improve filtering performance, especially for highly corrupted images, by continuously comparing the filtering output with the initial input.
* The proposed method is shown to be more efficient than previous median-based iterative schemes for impulse noise detection and replacement.

**IV. NUMERICAL EXPERIMENTS**

The section discusses the performance of the GVWTM filter compared to other filters on images corrupted with Gaussian and impulse noise.

* The standard 8-bit, gray-scale “Lena” image (512×512) is used to test the GVWTM filter against median, α-TM, and MTM filters.
* All algorithms are implemented using a 3×3 window, and a 3-entry median basket is used for α-TM, MTM, and GVWTM filters.
* The Lena image is degraded with additive Gaussian noise, resulting in a PSNR of 22.17 dB.
* GVWTM filtering with smaller α converges faster but yields less optimal PSNR, while larger α converges slower but yields more optimal PSNR.
* For images corrupted with Gaussian noise, GVWTM filter outperforms other filters, with PSNR values of 30.14 dB and 28.37 dB for two different noise levels.
* For images corrupted with impulse noise, GVWTM filter also performs better, with PSNR values up to 36.47 dB using a switching scheme.
* The performance of GVWTM filter improves with reasonable center pixel weights for lightly corrupted images and smaller weights for heavily corrupted images.
* The section includes comparative tables and figures showing the PSNR performance of different filters under various noise conditions.

**V. CONCLUSIONS**

The GTM and GVWTM filters effectively suppress additive and impulse noise in images, with GVWTM adjusting center pixel weight based on luminance. Simulations show robust, efficient performance.