Adaptive Morphological Operation for High-Performance Weather Image Processing

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Abstract

Morphological operations have been an integral part of enhancement of digital imaging programs, especially for filtering noise for improving the quality of image by utilizing the two most basic morphological operations, named as erosion and dilation, altogether. The main role of dilation is to fill the defined region in an image with pixels, while erosion removes pixels from the region. As we know, the method of erosion followed by dilation or dilation followed by erosion is indeed an attractive approach amongst researchers to deal with filtering noise problems. However, this approach needs more computation time and has a high percentage of losing essential pixel area. To cover these issues, this paper introduces a new approach called adaptive morphological operation to boost the performance of image enhancement. Based on 2011, 2013, 2015, and 2016 weather image datasets collected from WITH radar, which is installed on the rooftop of Information Engineering building, University of the Ryukyus, the experimental results confirm that the proposed approach is more efficient than the conventional approach.

Keywords-Adaptive Morphological Operation, Dilation, Erosion

1. Introduction

It is never possible to be able to collect a perfect real dataset due to data corruption because of sensor or acquisition devices, and data transmission. Simply, the corruption acts like diseases that gradually swallows human's life. Likewise, the data corruption constantly forces algorithms struggle with prediction or classification work and face performance degradation in terms of mainly prediction accuracy. Thus, any kind of noise is inescapable in data collection and data preparation processing for the next advanced processes.

Thus, in the case of rainfall radar images, the shape of the rainfall region in the radar images tends to be variable and is easily covered with noise. Therefore, it is difficult to apply a fixed method to detect the rainfall region. It is necessary to develop a new method that can be applied to meteorological images that vary spatiotemporally.

Morphological filters have been using as a powerful tool for removing noises, shape detection, boundary detection, etc., by applying the two most basic approaches (erosion and dilation). In more details, erosion removes pixels from the predefined region in an image, while dilation fills that region with pixels. These two operations occupy the completely inverse relations. In the way, erosion followed by dilation or dilation followed by erosion is kind of dual operation in noise filtering problems. According to our experimentations, this dual process still lacks maintaining the indispensable pixels with absorbing high computational time.

For these issues, in the work of this paper, we focus on not only the reduction in noise but also in computational time of morphological approach by assigning the appropriate morphological operation (dilation or erosion) based on the adjustment of the local pixel density in an image, instead of applying two operations directly to that region. This simple and intuitive concept is named as an adaptive morphological operation.

The process by these two different operations, a sense comes to us is that if the pixel density of the region is high, then dilation operation is selected for that region. Otherwise, erosion has to take the responsibility for that region. Therefore, the new adaptation approach measures the pixel density of a targeted region before applying one of those two operations to that region. By doing so, this new approach reduces computational time obviously and fairly prevents the important pixels from wearing away.

2. Related Works

Morphological filters are the central theme of image enhancement, such as noise reduction, shape detection, etc. The authors of [1] proposed a system that utilized morphological operation for removing the salt and pepper noise from the input image with different structuring elements. The main methods of morphological filters that are erosion followed by dilation and dilation followed by erosion are applied to remove this kind of impulsive noise.

The authors of [2] primarily studied mathematical morphological operations such as dilation, erosion, opening, closing, fill and majority operations, which were used to accomplish filtering noise and enhance the appearance of binary images. As reported by the experimental results, they proved that noise could be

effectively removed from binary images using combinations of erode-dilate operations.
Likewise, reference [3] tackled the problems of speckle noise removal and edge detection using the basic operations of mathematical morphology (dilation and erosion).

The authors of [5] designed a new decision based morpho filter for de-noising salt and pepper noise. The authors of [6] proposed an adaptive mathematical morphology for impulse noise. In this work, the authors emphasized on adjusting the size and shape of structuring element based on the local information of an image for de-nosing impulse noise. The authors of [7] designed a medical image enhancement using morphological transformation system to improve the quality of an image. Besides, this study utilized a mask of an arbitrary size and keeps changing its size until an optimum enhanced image is obtained from the transformation operation.

The systems described in reference [1], [2], [3], [5], [6] and [7] only emphasized how to remove noise by using the combination of two basic morphological operations and a mask of different shape and size. However, they only focus on improving the quality of image by de-noising an image. They did not mention about the reduction in computational time of conventional morphological and adaptive morphological approach.

3. Conventional Morphological Operations

Erosion and dilation are indeed the two most basic morphological operations for removing or attaching single pixels layer referring to structuring element. In this research, morphological operations are aimed at binary images with two possible pixel values, 0 and 1 [6]. Binary images can be described as follows:

$$I_B(x, y) \in \{0, 1\} \quad (1)$$

Where I denotes a binary image, and (x, y) is coordinate. Section 4.1, 4.2 and 4.3describes structuring element, dilation and erosion in details, respectively.

3.1. Structuring element

Besides, the structuring element is specified by a matrix that contains only the values 0 and 1. In other words, it is a small binary image. Thus, it can be a 3 ×3 square or 9 × 9 square image. Structuring element can be expressed as follows:

$$H(i, j) \in \{0, 1\} \quad (2)$$

Where H means structuring element and (i, j) is coordinate.

$$H = \begin{vmatrix} & ■ & \\ ■ & ■ & ■ \\ & ■ & \end{vmatrix}$$

Figure1. 3 × 3 binary structuring element. 1 is marked with ■ and 0 cells are empty.

This research primarily uses the 3 × 3 structuring element as illustrated in Figure 1.

3.2. Dilation

Dilation grows or thickens an object in an image. As a set operation, it is defined as

$$I_B \oplus H \equiv \{(p + q) \mid \text{for all } p \in I, q \in H\} \quad (3)$$

The point set $I_B \oplus H$ produced by a dilation is the sum of all possible pairs of coordinate points from the original sets I_B and H.

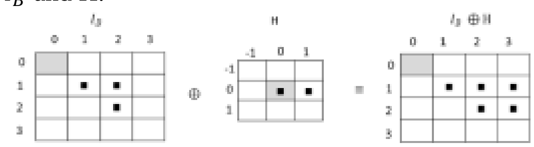

Figure 2. Simple Binary Dilation

$I_B \equiv \{(1, 1), (2, 1), (2, 2)\}$, $H \equiv \{(0, 0), (1, 0)\}$
$I_B \oplus H \equiv \{(1, 1) + (0, 0), (1, 1) + (1, 0),$
$(2, 1) + (0, 0), (2, 1) + (1, 0),$
$(2,2) + (0,0), (2,2) + (1,0)\}$

The image I_B is dilated with the structuring element H and $I_B \oplus H$ the result of dilation operation. The structuring element H is replicated at every foreground pixel of the original image, I_B.

3.3. Erosion

The quasi-inverse of dilation is the erosion operation, again defined in set notation as

$$I_B \ominus H \equiv \{p \in \mathbb{Z}^2 \mid (p + q) \in I, \text{ for all } q \in H\} \quad (4)$$

This operation can be expressed as follows. A position p is contained in the result $I_B \ominus H$ if (and only if) the structuring element H-when placed at this position p-is fully contained in the foreground pixels of the original image.

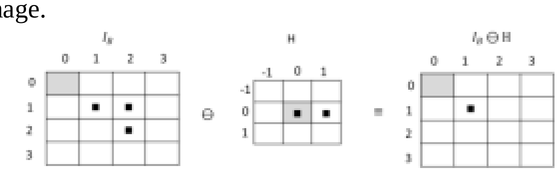

Figure 3. A simple example for binary erosion

$I_B \equiv \{ (1,1), (2,1), (2,2) \}$, $H \equiv \{ (0,0), (1,0) \}$
$I_B \ominus H \equiv \{ (1,1)\}$ because $(1,1) + (0,0) = (1,1) \in I_B$ and $(1,1) + (1,0) = (2,1) \in I_B$

As stated in conventional morphological operations, dilation and erosion are often used together in practice. Therefore, the methods that are erosion followed by dilation and dilation followed by erosion are widely used approaches for various image enhancements with different structuring elements.

4. Problems and Solutions

This paper mainly emphasizes on removing noise from rainfall radar images that is apparently a mixture of noises closely similar to salt and pepper noses as illustrated in Figure 4, the left hand-side image (original rainfall radar image). When we apply erosion with 3×3 structuring element to noisy rainfall image, it could perfectly remove out all noises from no rainfall area as shown in Figure 4, the right-hand side image.

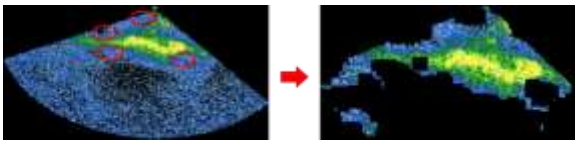

Figure 4. Noisy radar image and noise clean rainfall radar image

However, unfortunately, the erosion function operation left the image with big holes by wiping out the essential rainfall areas as illustrated in Figure 4, the right-hand side image, as those hole-areas occupy light rainfall areas having lower pixel density than heavy rainfall areas. In the rainfall radar images, the pixel density of heavy rainfall area is mostly thicker than light rainfall area as well as the pixel density of light rainfall area is thicker than no rainfall area.

To overcome the problem of leaving hole-areas, the method of erosion followed by dilation approach or dilation followed by erosion can accomplish the problems discussed above as well as remove all noise perfectly, as reported by Figure 5, the left-hand side image.

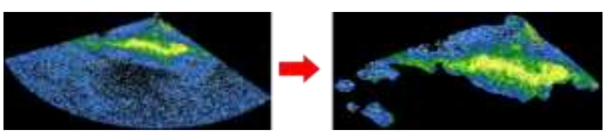

Figure 5. Noise cleaned rainfall image by the conventional approach

However, the repeatedly sequential function of erosion followed by dilation or dilation followed by erosion raises time complexity, the usage of memory, and gradually losing the essential rainfall pixel. Thus, the computational complexity of erosion and dilation for each pixel can be described in N + 2 operations, where N denotes the number of pixels in the structuring elements. Besides, this conventional method cannot completely fill back the holes with pixels as near as the original ones.

Let us first take a closer look at the essential areas, as shown in Figure 6. Figure 6 (a) and (b) have different problems. Figure 6 (a) shows the rainfall areas occupy the thicker pixel density. Those areas that are parts of rainfall region already have the proper enough pixel density. If we apply erosion operation to those areas, it will truly remove out the important pixels from those areas and leave them with holes. Therefore, protecting from eliminating the important pixels, the function of dilation is only enough to operate on those areas, instead of running two approaches on the same area directly.

Figure 6. (a) and (b) Pixel density of a radar image

For the second case, the pixel density in the red rectangle regions, as illustrated in Figure 6 (b), is fairly low compared with the red rectangle regions in Figure 6 (a). Literally, the noises like salt and pepper are more likely to be naturally injected into those kinds of areas. Thus, for those areas, the function of erosion is more appropriate to take a role of removing noise, instead of assigning dilation to those area.

As discussed above, some regions more prefer erosion to dilation operation, while some regions are reasonable to use dilation operation with respect to structuring element. According to this analysis, an adaptive approach comes to us to handle those problem. The adaptive approach measures the pixel density of targeted region and examines which morphological operation (erosion or dilation) is perfect to take a role of removing noise. As the adaptive approach chooses properly one of two operations (dilation or erosion) according to the local pixel density, it intuitively solves the problem of time complexity, removing noise and protecting the essential rainfall area from wiping out during the repeatedly filtering noise process.

5. Adaptive morphological operation

This paper primarily focuses on upgrading computation time, filtering nose and protecting from wiping the important pixel area out during the noise filtering process. As discussed in the previous section, the adaptive morphological operation is a simple solution by selecting the appropriate one of two operations (erosion and dilation) respecting with the average pixel density of a targeted region in a binary image. Before selecting one of those two operations, it specifies the size of the interested filter region, R(x, y) as shown in Figure 7. The computation of the density of the filtered region is given by:

$$D(R) = \frac{1}{(x \times y)} \sum_{x=0}^{19} \sum_{y=0}^{19} R[x,y] \quad (5)$$

The size of the interested filtered region is also an important parameter of the filter because if the size is large, then the computation time is high, while if the size is small, the filtering noise may not work with a satisfied result. In the work of this paper, the size of the region is defined as 20× 20 square matrices

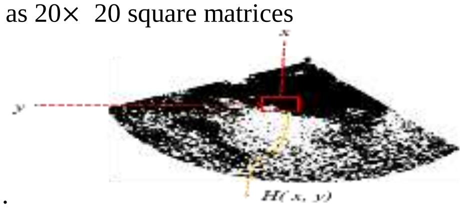

Figure 7. Filtered region R(x, y)

$$R'(x,y) = \begin{cases} R \oplus M & , \ if \ D(M) > threshold \\ R \ominus M & , \ otherwise \end{cases} \quad (6)$$

where $R'(x,y)$ is the new noise clean region after applying one of those two operations and in this research, R is the targeted region of a binary image, and the threshold is defined 10% according to our experimentations.

Algorithm 1 implements an adaptive morphological operation for a binary image. First, it converts radar image into the weighted image in order to avoid destruction of the pixels during transforming from a gray image into a binary image. The rainfall radar image has the intensity of rainfall levels represented by 15 different colors as shown in Figure 8. For the purpose of using weighted value, those colors are categorized into five groups, heavy raining, semi raining, fair raining, normal raining, and no raining. The heavy raining group includes red, pink and light pink. The next three colors, yellow-orange, yellow and light yellow are in semi raining group. The third group includes dark green, light green, and green. The fourth group has dark blue, blue and light blue and the rest colors are for the fifth group. Then, we specify the weighted value, 200, for heavy raining, 150 for semi raining, 100 for fair raining, and 70 for normal raining.

Dilation (*q*,*H*)

Input: a pixel of binary image, *q*.
a binary structuring image, *H*.
Output: q', the dilated region = $q \oplus$ H
1. $q' \leftarrow 0$
2. for all (p) ∈H *do*
3. $q' \leftarrow q \oplus$ H
4. Return q'

Erosion (*q*, *H*)

Input: a pixel of binary image, *q*.
a binary structuring image, *H*.
Output: q', the eroded region = $q \ominus H$
1. $q' \leftarrow 0$
2. for all $p \in H$ do
3. $q' \leftarrow q \ominus H$
4. Return q'

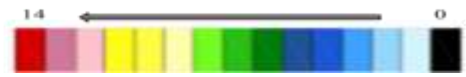

Figure 8. The intensity of rainfall levels

After converting into weighted value image, it is ready to transform into a grayscale image and then into a binary image. Then, according to the density of the region, it selects the appropriate operation.

Algorithm 1 : Adaptive Morphological Operation (*I*, *H*)

Input: Rainfall radar image, *I*, size of *M*×*N*;
a binary structuring image, *H*.
Output: I'
1. $I_w \leftarrow I$ *// convert image I into weighted image* I_w
2. $I_G \leftarrow I_w$ *// convert image* I_w *into gray image* I_G
3. $I_M \leftarrow median\ (I_G)$ *//apply median filter to gray image*
4. $I_B \leftarrow$ Binary(I_M) *// convert into binary image*
5. Create map I': $M \times N \rightarrow \{0, 1\}$
6. for all (p) ∈M×N *do*
7. for all q ∈$M \times N$
8. define R(x,y) in an image and compute the density every N
$$D(R) = \frac{1}{(20 \times 20)} \sum_{x=m}^{x+20} \sum_{y=n}^{y+20} R[x,y]$$
9. if ($D(R)$> 10%) $q' \leftarrow$Dilation (*q*, *H*)
10. else Erosion$q' \leftarrow$ (*q*, *H*)
11. End
12. End

After that, the adaptive noise filtering approach starts to remove all noises from the image with high computational speed. At the final stage, the final noise clean binary image is converted into a color image by using a mapping approach.

6. Experimental results and analysis

In this section, we will discuss the experimentation of filtering noise from rainfall radar images. The results prove that the efficiency of the adaptive morphological operations by comparing with the conventional morphological approach based on 2011,2013, 2015 and 2016 radar images. In details, the total numbers of rainfall radar images are 116, 693 images (3.20 GB).

The performance of the adaptive approach is measured by using two factors: computation time, and the amount of important pixel value protected from wiping out as the accuracy. First, Figure 8(a) and (b), 10(a) and (b), 11(a) and (b), and 12(a) and (b) demonstrate the comparative study of conventional approach, adaptive approach, weighted value conventional approach, and weighted value adaptive approach using four radar images. As reported by those four images, the adaptive approach is more efficient than the conventional approach as expressed in each verbal expression and computation time. Likewise, it is obvious that the weighted value adaptive approach also achieves the accomplishment of higher computation time and accuracy than the weighted value conventional approach.

After discussing a comparative studying of the performance of weighted value adaptive approach using four rainfall radar images aiming at having closer look difference between among approaches, we did the experimentation again using 116, 693 (3.20 GB) radar images to prove that the performance of new approach with more confident results as demonstrated in Figure 13 and 14.

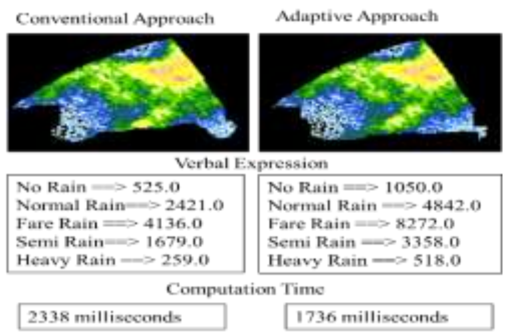

Figure 9(a). A comparative study of conventional approach and adaptive approach

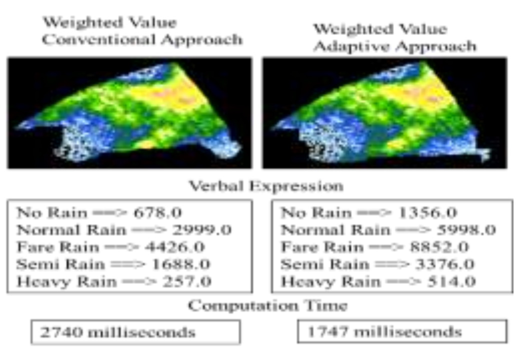

Figure 9(b). A comparative study of weighted value conventional approach and weighted value adaptive approach

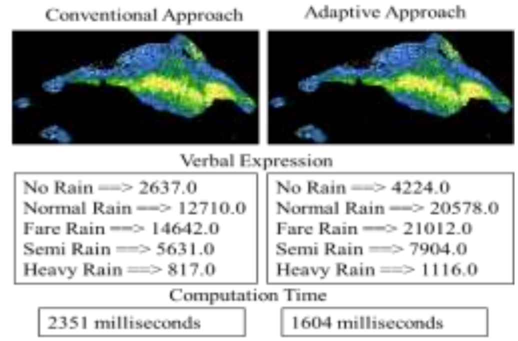

Figure 10(a). A comparative study of conventional approach and adaptive approach

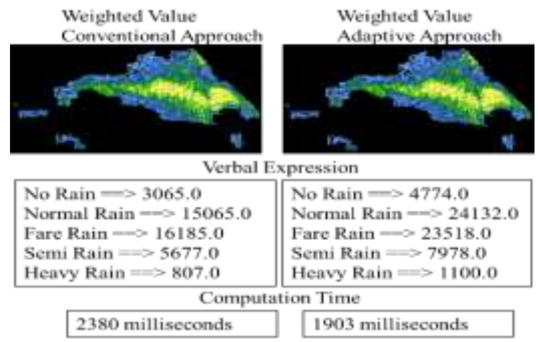

Figure 10(b). A comparative study of weighted value conventional approach and weighted value adaptive approach

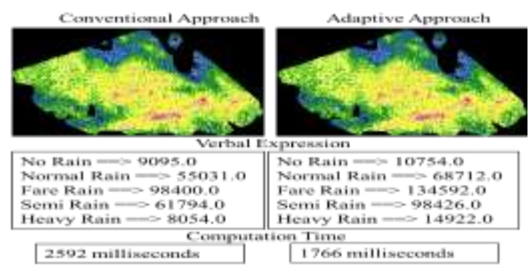

Figure 11(a). A comparative study of conventional approach and adaptive approach

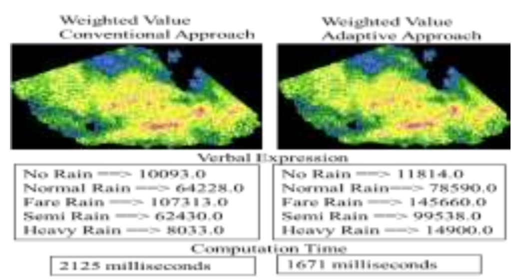

Figure 11(b). A comparative study of weighted value conventional approach and weighted value adaptive approach

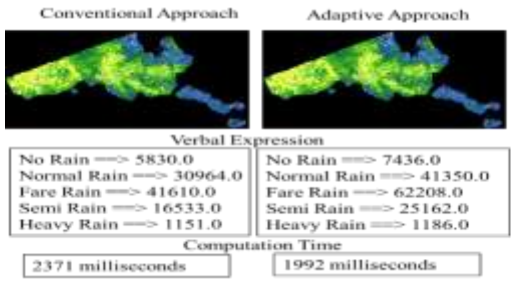

Figure 12(a). A comparative study of conventional approach and adaptive approach

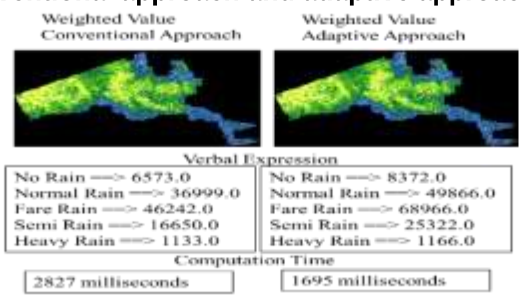

Figure 12(b). A comparative study of weighted value conventional approach and weighted value adaptive approach

In Figures 13 and 14, the performance of two algorithms (adaptive and conventional approaches) is analyzed using 116, 693 images. As illustrated these figures, it is obvious that the adaptive noise filtering is more effective than the conventional approach because the adaptive approach filters the noise as perfect as the conventional approach. Furthermore, it maintains more pixels of essential rainfall areas than the conventional approach.

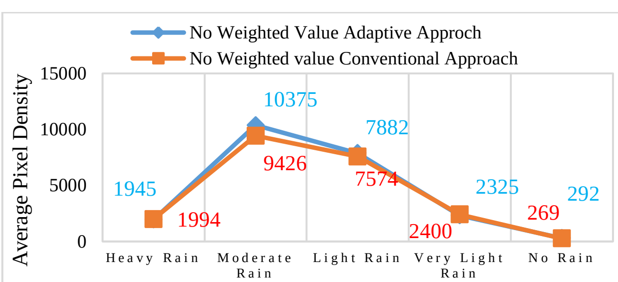

Figure 13. A comparative study of conventional approach and adaptive approach over four-year rainfall radar images

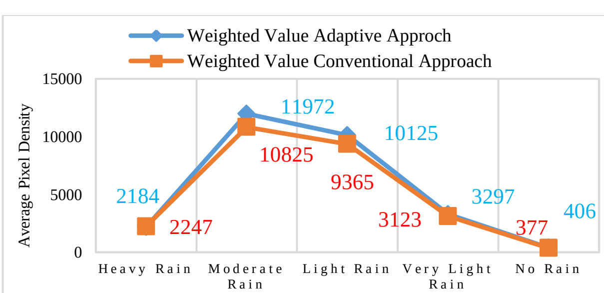

Figure14. A comparative study of weighted value conventional approach and weighted value adaptive approach over four- year rainfall radar images

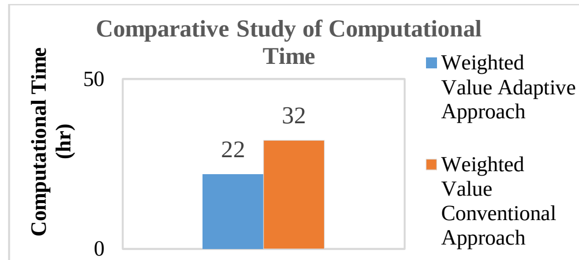

Figure 15. Computation time of weighted value adaptive approach and weighted value conventional approach over four-year rainfall data

As stated in Figure 15, the adaptive concept fairly boosts the computational time of repeated sequential noise filtering approach. The adaptive approach takes 22 hours for the noise filtering process using 3.20 GB radar images, while the conventional approach needs 32 hours. It reduces about 10 hours.

7. Computational Complexity

Suppose N × N is an image I, S × S is a structuring elements , H. The computation of conventional method, erosion I × S and dilation I × S of I by H would require $N^2 \times S^2$ for erosion and $N^2 \times S^2$ for dilation. Thus, the addition of two operations can be described as O ($2N^2S^2$).

For the adaptation approach, each time it needs only one function (erosion or dilation) and the execution of density. Therefore, the computation of adaption approach can be specified as O(N^2S^2 + (N*N/20))→ O (N^2S^2 + $N \log N$) . Because $2N^2S^2$ is always bigger than N^2S^2 + N*(N/20), we can conclude that O ($2N^2S^2$)>O (N^2S^2 + $N \log N$).

8. Conclusion

In this study, we propose the adaptive morphological approach aiming at upgrading the computational time and improving the noise filtering performance of conventional morphology. According to experimental results, weighted value adaptive approach accomplishes the task of filtering noise with 10 hours faster than the weighted value conventional approach as stated in Figure 15. As stated in Figure 13 and 14, adaptive approach maintains the important region 1.05 times (105%) more than the conventional approach, and similarly, weighted value adaptive approach protects the essential pixels 1.07

(107%) times more than weighted value conventional approach.

Finally, those results experimentally prove that the adaptive morphological approach is more efficient than the conventional approaches for noisy radar images. However, this adaptive approach considers only the pixel density of the targeted region in an image, not all the local information. For the future work, we will emphasize on improving the capability of noise filtering approach utilizing not only the density but also other local information of an image.

9. References

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