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Sand Soil Image Processing Using the Watershed Transform and Otsu Thresholding Method Based on Gaussian Noise

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Abstract

Image processing technology is one of the technologies that can help facilitate and speed up human work, especially in the process of determining the grain size distribution of soil in a civil building plan. Its utilization has been widely used to study, analyze, and understand the structure and framework of the soil. Image analysis is carried out as an initial or fundamental step in image processing to discover and comprehend information. With so many image segmentation methods, it is necessary to conduct research to determine which method is best for sandy soil image segmentation based on one of the image segmentation quality criteria, namely gaussian image noise. By testing the watershed transform method and the Otsu thresholding method as two of the area-based methods that are considered suitable for segmenting sandy soil images before and after distorted Gaussian noise based on the calculation of the mean square error (MSE) value. The results showed that the watershed transform method is better for segmenting sandy soil images when compared to the Otsu thresholding method. This is indicated by the average squared error (mse) of 3.08 for the watershed transform method and 4.09 for the Otsu Thresholding method. In addition to the comparison of quality tests of sandy soil based on gaussian noise with standard deviation values of normal distribution and noise intensities of 10, 20, and 30, it proves that the watershed transform method is still better at segmenting noise-distorted sandy soil images than the Otsu thresholding method. However, in terms of processing time, the Otsu Thresholding method is faster or better than the Watershed Transform method of the results or conclusions brief. There are no citations, tables or figures in abstract.

Keywords: Sand Soil Imagery, Gaussian Noise, Image Processing, Otsu Thresholding, Watershed Transform.

1. Introduction

Technology has been widely used in various fields of life and has an important role in modern life, one of which is image processing technology (Ni, 2021). Image processing technology is one of the technologies that can help simplify and speed up human work, especially in the process of extracting the distribution of grain size in a civil building plan (Ni, 2021). And has been widely used to study and analyze the structure of the soil framework, among others (Love & Matthews, 2019; Ye et al., 2018; Zavadskas et al., 2017).

Image has an important role in the processing because the image represents an object, be it an object, place, person, and so on (Shukla, 2017; van Es, 2017; Zhang et al., 2018). Meanwhile, soil consists of mineral particles that range from less than one micron to several millimeters (Afrin, 2017; Daryati et al., 2019; Powrie, 2018). There are various types of soil particle sizes consisting of clay, silt, sand, gravel, and other materials that can affect soil engineering behavior.

The image of sandy soil as an object of research is processed into an image using a digital camera, so it is called "sand soil image".The stages of sand soil image analysis are carried out through a segmentation process as the initial step or basic stage to find out and understand sand soil image information (Fellenius, 2017; Shukla, 2017; Zhang et al., 2018). Segmentation divides an image into a group of homogeneous pixels in some way or method (Love & Matthews, 2019; Morais et al., 2019; Ravikumar & Arulmozhi, 2019). In sandy soil image segmentation, it is necessary to use the right method to get good soil grain segmentation results. The method used is the Watershed Transform method and the Otsu Thresholding method which are considered suitable for image segmentation because they are the two most commonly used methods by researchers and produce good results (Yuheng & Hao, 2017). The application of these two methods is often found in medical images (MRI, cell images, mammograms, etc.), satellite

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images, face detection, and so on (Huang et al., 2020; Ravikumar & Arulmozhi, 2019). But its use is rarely found in sandy soil images (Chouhan & Kaul, 2018; Minaee et al., 2020; Morais et al., 2019; Shi-gang et al., 2018).

Watershed Transform is a method proposed by S. Beucher and F. Mayors in 1990 (Dar & Padha, 2019; Ravikumar & Arulmozhi, 2019). This method is based on the gradient morphology applied to the gray image, which is considered as the surface topography. Using a boundary approach to detect local and regional changes to look for similarity pixels to distinguish the foreground from the background (Philip et al., 2021; Sachin et al., 2018).

Watershed Transform can separate overlapping objects quickly and reliably for edge and region detection (Ravikumar & Arulmozhi, 2019). However, it is too segmented and sensitive to noise (Bharadwaj et al., 2021; Dar & Padha, 2019; Hassan et al., 2017; Ravikumar & Arulmozhi, 2019). It becomes slow and inefficient in topography with large terrain. Requires high memory and long processing time (Xiong & Zhang, 2019). Otsu Thresholding discovered by Nobuyuki Otsu in 1979 has been widely applied in image segmentation. By processing grayscale or RGB images by calculating the maximum variance between the foreground and background, it is proven to increase the effect of image segmentation (Fellenius, 2017; Huang et al., 2021; Xiong & Zhang, 2020).

Otsu Thresholding chose a boundary park to minimize the intraclass variance of the black and white pixel park, using the optimal gray value of the image and the park (Shukla, 2017). So that it can increase the operating speed and threshold, has noise immunity (Fellenius, 2017; Xiong & Zhang, 2020). It is suitable for lighting and surface detection, and saves time when detecting the foreground and background (Azizi et al., 2020; Dorgham, 2018). However, if the threshold is not correct, it can cause misclassification of objects and background areas, besides that it can become complex if the threshold level is increased (Fellenius, 2017). In the process of testing the image sometimes becomes a problem if the entered image is filled with noise. Noise can reduce image quality, make the original image distorted, and affect the preprocessing process so that the image processing process becomes slow (Mafi et al., 2019). There are various kinds of noise that can affect the input image, one of which is Gaussian noise, in addition to noise that occurs in general such as sensor images, optical defects, relative motion, shooting noise, salt and pepper noise, and so on (Mafi et al., 2019). For this reason, based on this background, the authors wanted to test and compare the Watershed Transform and Otsu Thresholding methods on sandy soil image segmentation to find out which method is most suitable based on one of the image segmentation quality criteria, namely gaussian noise.

2. Material and Methods

2.1. Research Materials

The research material used by the author is "Land Sand Imagery" which was taken by taking 30 pictures directly in the field, using the original Sony Alpha A6000 camera located in Tambak Holland and Namalatu, Ambon City, Maluku. Image size 1920x1080, JPEG format, and RGB scale, as shown in Figure 1.

Figure 1. Image of sandy soil

2.2. Research Tools

The research tool used in this study was an Asus Laptop with the following hardware and software specifications: Hardware specifications used to test the data, as shown in table 1.

The software used in this study are: Adobe Photoshop and Matlab. Adobe Photoshop is a graphic editor application developed by Adobe Inc for Windows and Mac operating systems. With various features and version development to facilitate image editing. This application is implemented to make it easier to edit images that will later be needed in the segmentation process. Meanwhile, Matlab is software that is used to perform numerical and symbolic calculations quickly and accurately, accompanied by sophisticated graphical and visualization features *(Romero-Tarazona et al., 2020)*. In this study the authors used Matlab R2014a software to support digital image visualization. The operating system used in this research is Windows 8.1 pro.

Table 1. Asus Laptop Hardware Specifications.

Computer Parts	Specifications
CPU	Intel®Core™ i5-3317U CPU @1.70GHz
GPU	NVIDIA GeForce GT 635M
RAM	4 GB

2.3. Research Steps

In this study the authors first conducted a literature study, then collected image data obtained by taking pictures directly in the field, from the image data obtained manual segmentation was carried out using Adobe Photoshop software, then algorithm analysis, system design, and systems were carried out. Implementation and evaluation, as shown in Figure 2.

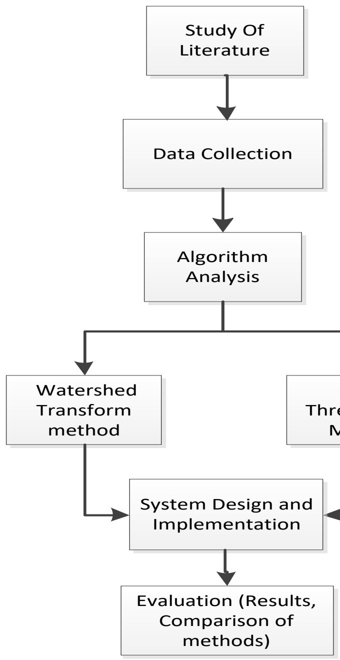

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Figure 2. Flow chart of research steps

Literature study is the stage where the writer collects various texts from various sources related to the research in question. The literature collected included information on civil building planning, sandy soil classification, segmentation, the Watershed Transform method, and the Otsu Thresholding method.

Data collection was carried out to obtain sandy soil image data obtained by taking pictures directly in the field. Image shooting using a Sony Alpha A6000 camera, located in Telaga Holland, Namalatu, Ambon City, Maluku, with an original image size of 1920x1080 pixels, JPEG format, and RGB scale. Coarse-grained sand soil images consist of gravel with a grain size that is still included in the sand group of 4.75 mm - 76.2 mm and sandy soil whose grain size ranges from 0.075 mm - 4.75 mm (Daryati et al., 2019).

The analysis of the two methods is the Watershed Transform method and the Otsu Thresholding method to determine the stages of segmentation with reference to the research of (Li, Zhang, et al., 2019) and (Bhagya et al., 2019). Following are the steps for implementing the watershed transform and otsu thresholding methods.

For the Watershed Transform, the input image in RGB form is converted to a grayscale image, then a histogram alignment is performed to increase the brightness and contrast of the image to make it easier to identify objects (Bhandari et al., 2018; Ye et al., 2018). After that displays a gradient image. Where the gradient image is more effective in displaying gray image changes in an area. Using a morphological gradient, because the magnitude of the gradient by applying sobel edge detection is sensitive to noise (Li, Luo, et al., 2019). To facilitate the segmentation process, it is necessary to carry out gradient reconstruction, to improve image quality with the opening by reconstruction function, namely erosion followed by image morphological reconstruction and close by reconstruction, namely dilatation and then continued with image morphological reconstruction. This process works to remove noise so that the image looks smoother.

From the results of image morphological reconstruction, the next process is to find the regional area of an image. Gradient images are modified by regional minima, which are also called markers(Li, Luo, et al., 2019). Define internal markers as foreground to help define catchment lines and external markers as background (Dorgham, 2018). Thresholding process to remove the background (background) from the image into a binary image (black and white). The black color indicates the background of the image. the goal is to separate objects or regions based on their pixel values (Fico et al., 2018). After that is done, a distance transformation process is needed to distance the edges of the object and the background so that they are not too close together. The next step is to find the watershed line, by first making the minimum area of the image with the imimposemin function, and the last step is widening it with the dilation process so that the object segmentation results can be seen clearly.

For the OTSU thresholding method, the input image in RGB form is first converted to a grayscale image, then displays an image histogram that will be used to determine the threshold. Choose a threshold that maximizes class variation. Then calculate the probabilities and mean values for values above and below the threshold. Add the two variants by weight, to calculate the within-class variance for foreground and background. By calculating the mean and variance, to find the threshold values of the foreground and background classes, namely the within-class mean variance as close as possible within classes and the variances between classes or as far as possible between classes. Minimizing within-class variance and maximizing inter-class variance can separate objects from the background. Repeat for different threshold values and compare within-class variances. Furthermore, the lowest threshold value in class variance is chosen as the final result.

Based on the results of the algorithm analysis, the system design and implementation stages were carried out, namely the first of the two algorithm methods, namely watershed and otsu thresholding, system design was carried out using a programming language then implemented using matlab to obtain sandy soil image segmentation results, in the form of sandy soil grain objects, which later can be used for further research processes, determining the size of soil particles and proceed to the soil classification process.

3. Results and Discussion

The process of testing the Watershed Transform method on sandy soil images, as shown in Figure 3. In the process of searching the watershed line is divided into three stages, namely image enhancement, morphological gradient and morphological reconstruction. Where in image enhancement, the input image in the form of a sandy soil image resulting from manual segmentation in RGB form is changed to an image with a gray scale, where the gray image is considered as a topographic relief in the segmentation of the watershed transformation. Assuming the grayscale value of a pixel is the height at a certain point (Xiong & Zhang, 2019). Changing the RGB image resulting from manual segmentation into an image with a gray scale, dividing the red, green and blue values evenly, so that a gray level value is obtained. After converting the image to gray scale, the next step is to improve image quality and image contrast by means of histogram equalization (Rao, 2020). After the image enhancement process, to display changes in the image area, a gradient search is carried out using a morphological gradient. From this process we can find the DAS line, but it still results in oversegmentation, because of the large amount of noise. To overcome this, it is necessary to reconstruct the gradient image morphology using opening, closing, dilation, and erosion. This process is to overcome oversegmentation and noise problems, as well as its reconstruction to eliminate extreme local areas, due to noise that approaches the minimum and/or maximum areas (Dorgham, 2018; Ramesh et al., 2021). In the opening process, it is intended to be able to remove smaller soil grain objects through erosion and smooth the boundaries of objects in the image without changing the area of the object due to dilation. Whereas after opening-closing, it can be seen that the small holes in the image are not completely closed, even though it is intended to improve the contours of the image so that it looks smoother by dilating and removing small holes in the image by erosion.

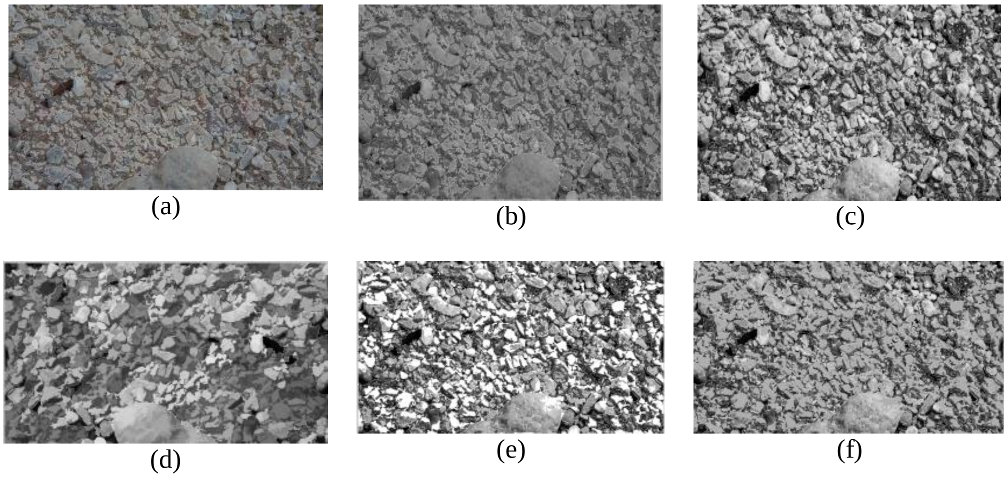


Figure 3. Sand Soil Image Testing Process: (a) manual rgb segmentation image; (b) Gray manual segmentation image; (c) Histogram alignment; (d) opening closing reconstruction drawings; (e) internal markers; (f) Watershed segmentation results

After performing the opening closing process, objects in the sandy soil image appear smoother, even though the texture of the holes in the soil grains is not completely closed. After being reconstructed, it can be seen that the noise on the object has disappeared a bit even though the outline of the object doesn't look too perfect. Opening with reconstruction is erosion with reconstruction of image morphology and closing with reconstruction is dilatation followed by reconstruction of image morphology, to get an image that looks smoother and eliminates noise. Furthermore, the gradient image is modified with a minimum area which is also called a marker (Li, Luo, et al., 2019). First of all look for internal and external markers as foreground and background markers to help determine the watershed line (Dorgham, 2018).

The process of repairing closed and shaded objects by closing and scraping. Then look for external markers, by calculating the DAS transformation from the distance transformation. After that, image modification is carried out with minimal coercion, to eliminate noise and local aberrations which cause oversegmentation problems, by modifying the regional areas on internal and external markers, and the last process is determining the watershed line.

The following is the application of the DAS transformation method to manually segmented sandy soil images, as shown in Figure 4.

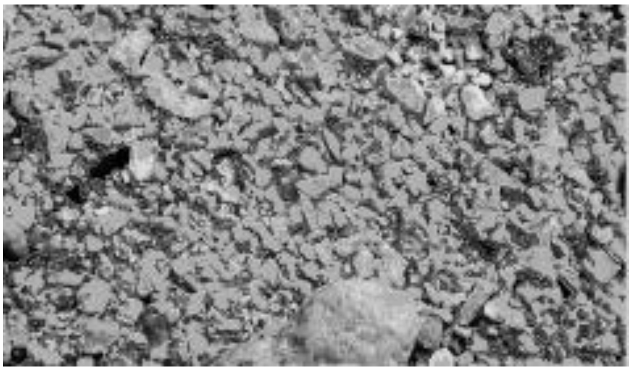
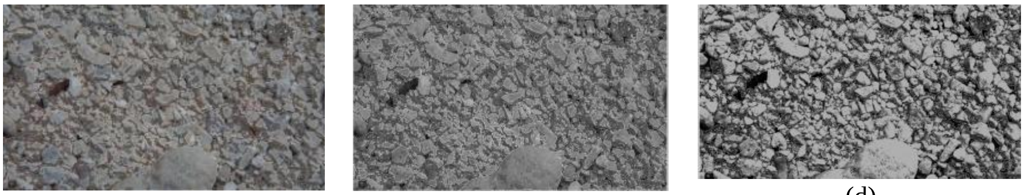


Figure 4. Image of manually segmented sandy soil

The process of testing the Otsu Thresholding method on sandy soil images, as shown in Figure 5.



(a) (b) (d)

Figure 5. Sand Soil Image Testing Process: (a) RGB manual segmentation image; (b) Gray manual segmentation image; (c) Thresholding Otsu segmentation changed to gray image form

The input of the sandy soil image resulting from manual segmentation is in the form of RGB, then converted into an image with a gray scale, by dividing the red, green and blue values evenly, so that a gray level value is obtained. From the sandy soil image on a gray scale or grayscale then look for the intensity histogram value.

The histogram shows the frequency distribution of image pixel intensity values. Where the pixel intensity of the gray image is in the range 0-255. The image histogram looks normal because it is spread evenly over all gray degrees with a gray intensity value range of 10 – 170, with a total of 2,073,600 pixels.

The main objective of the Otsu method is to find the appropriate threshold (T), by dividing it into two categories (classes), minimizing within-class variance (vw) and maximizing inter-class variance (vb). While Threshold itself aims to binary gray image to separate the foreground and background.

Determine the possible Threshold values from the intensity of 10-170 in the TP1 image, T = 94, which is obtained based on the search for the largest variance value of the total sigma intensity histogram and matched with the Matlab graythresh level function as shown in Table 2.

Table 2. Sand Soil Image Threshold Value

Thresholding	T=94
σwc^2	0.36
σbc^2	677.69

This shows that the within-class image variance distance is 0.36 and the maximum variance distance between classes that distinguishes background and foreground is 677.69. Following is the application of the Otsu Thresholding method to 30 sandy soil images resulting from manual segmentation, as shown in Figure 6.

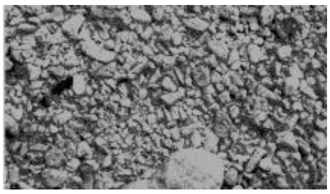


Figure 6. Image of sandy soil with Otsu Thresholding

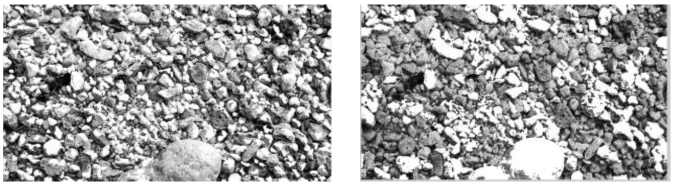
To test the image quality on the watershed transform method and the Otsu Thresholding method before and after being given noise, it is necessary to add noise to the original image and the results of image segmentation manually first. The original image which is distorted by noise is then tested using the watershed transform and otsu thresholding methods to obtain segmentation results from the two methods which are distorted by noise. Then the results will be compared with manually segmented images that are distorted by noise. Giving noise is based on the research of J. S. Owotogbe, et al, namely gaussian noise (Joshua et al., 2019).

Gaussian noise is noise that has a probability density function given (PDF) by a Gaussian curve. Often referred to as amplifying or additive noise and can also be referred to as white noise which has a normal distribution. This noise can appear during image acquisition (Joshua et al., 2019). The following is the addition of Gaussian noise to the results of manual image segmentation with a standard deviation of 10.20 and 30, as shown in Figure 7:

(a) (b) (c)

Figure 7. (a) Manual image segmentation with gaussian noise=10 ; (b) manual image segmentation with gaussian noise=20; (c) manual image segmentation with gaussian noise=30

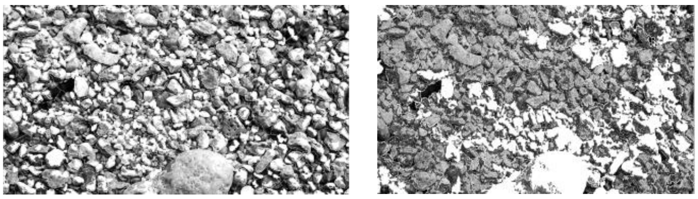
Giving a normal distribution standard deviation of 10,20,30 will give a deeo gaussian noise effect of 10, 20 and 30 in the range 0-255 and a value of 255 is the noise with the maximum level. For the Watershed Transform, it gives gaussian noise with a standard deviation value of normal distribution of 10, as shown in Figure 8:



(a) (b)

Figure 8. (a) Watershed segmentation; (b) Gaussian noise=30

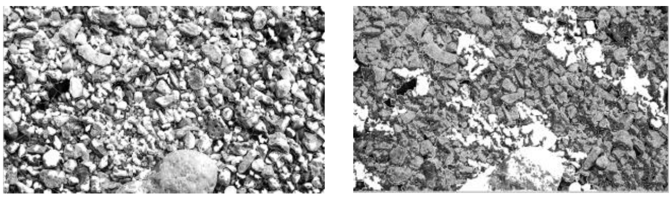
If we look at the results of image segmentation using the DAS transformation method shown at point (a), then compared to sandy soil images that experience gaussian noise with a standard deviation value of normal distribution (σ) = 10 at point (b), it can be seen that noise affects several markers. internal markings start to disappear and only mark some objects around the edges of the image, in addition the position of the waterline line also disappears and marks other internal marking areas. Next, gaussian noise is given with a standard deviation value of the normal distribution (σ) = 20, as shown in Figure 9.



(a) (b)

Figure 9. (a) Watershed Segmentation; (b) Gaussian noise distorted image (σ) = 20

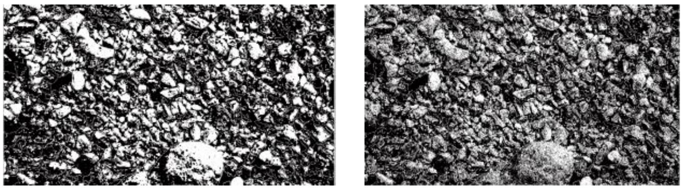
In sandy soil images that experience gaussian noise with a standard deviation of normal distribution values (σ) = 20 at point (b), it can be seen that the noise affects the results of watershed segmentation, namely some internal markers are missing and only markers. some objects in the center to the bottom edge of the image, besides that the position of the waterline line also disappears and marks other internal marking areas. The next process is giving Gaussian noise with a standard deviation value of the normal distribution (σ) = 30, as shown in Figure 10.



(a) (b)

Figure 10. (a) Segmentation of AND; (b) Gaussian noise = 30 distorted image

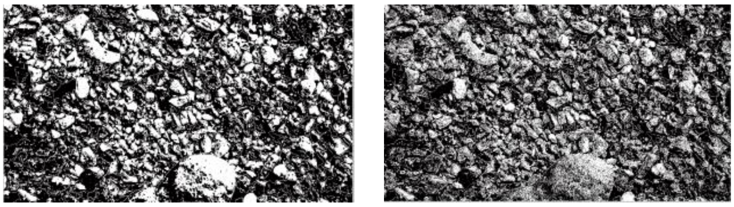
In the sandy soil image that experiences gaussian noise with a standard deviation value of normal distribution (σ) = 30 at point (b), it can be seen that the noise has more influence on the results of watershed segmentation, namely it removes more internal markers in the middle and edges of the image, besides that the position of the lines the water limit also disappears. For OTSU thresholding, the original image is treated with Gaussian noise with a normal distribution standard deviation (σ) = 10, as shown in Figure 11.



(a) (b)

Figure 11. a) Otsu thresholding binary segmentation; (b) Gaussian noise (σ) distorted image 10

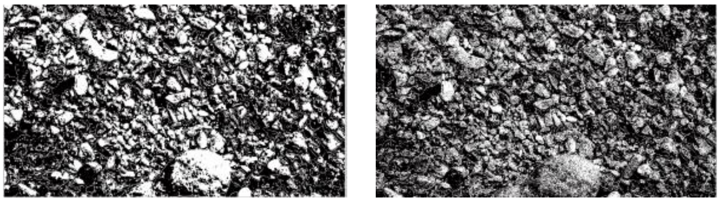
If we look at the results of image segmentation using the Otsu thresholding method in binary which is shown in point (a), then compared with the sandy soil images that experience gaussian noise with a standard deviation value of normal distribution (σ) = 10 at point (b) it can be seen that the noise spreads to all parts of the image and make the image appear black or dark, then noise tends to cover objects in the foreground, so that image objects appear unclear. Furthermore, gaussian noise with a standard deviation value of the normal distribution (σ) = 20, as shown in Figure 12.



(a) (b)

Figure 12. a) thresholding segmentation of Otsu; (b) Gaussian noise distorted image (σ) = 20

In Gaussian noise with standard deviation (σ) = 20 which affects sandy soil images, it can be seen that noise covers objects more evenly and makes objects or backgrounds black or appear dark, so that objects in the image become unclear. Whereas for the gaussian noise testing process with a standard deviation (σ) = 30, as shown in Figure 13.



(a) (b)

Figure 13. a) thresholding segmentation of Otsu; (b) Gaussian noise distorted image (σ) = 30

The effect of Gaussian noise with standard deviation (σ)=30 affects the image of sandy soil more than the effect of noise at (σ)=10 and 20, where noise covers objects more evenly and makes objects or backgrounds blacker or appear darker. dark, so that the small soil grains in the image are not clearly visible.

Based on the results of testing sandy soil images after being given gaussian noise with a standard deviation of the normal distribution of 10.20 and 30 as well as salt and paper noise with intensities of 10%, 20% and 30%. So to find the average squared error value in the sandy soil segmentation image it is calculated using the mean square error value with the assumption that the smaller the value or closer to 0, the more similar the segmented image is to the initial image(Aimin et al., 2018). Where is the nth pixel of the original image and is the nth pixel of the segmented image. The following is the MSE calculation for the watershed transform and otsu thresholding methods, with the results of manual image segmentation before noise distortion occurs as shown in Table 3.

From the calculation results in table 3, the mean square error (mse) is obtained, based on the difference between the results of manual segmentation of sandy soil images and the results of segmentation of sandy soil images using the watershed transform method, which is 3.08, while for the Otsu thresholding method it is 4.39. This shows that the error rate of the DAS method for segmenting sandy soil images is smaller, while the Otsu thresholding method has a higher error rate. So it can be concluded that the watershed transform method is better at segmenting sandy soil images when compared to the Otsu thresholding method. The calculation of the mse value in the watershed transform and otsu thresholding methods is based on the results of manual image segmentation that has been distorted by noise, as shown in Table 4.

Table 3. Das and Otsu Method Before Distorted Noise

Image to	Watershed Transform	Otsu Thresholding
1	3,22	4,43
2	4,68	6,28
3	4,88	6,64
4	3,85	5,28
5	3,33	4,64
..	...	...
30	1,5	2,59
Average	3,08	4.39

Table 4. Watershed and Otsu Methods After Distorted Noise

Image	Watershed Transform			Otsu Thresholding		
	Gaussian Noise			Gaussian Noise		
	10	20	30	10	20	30
1	2,62	2,75	2,91	4,08	4,25	4,58
2	3,95	4,25	4,13	5,86	6,08	6,46
3	4,22	4,49	4,94	6,22	6,44	6,84
4	2,68	2,83	3	4,84	5,04	5,38
5	2,32	2,41	2,5	4,23	4,43	4,74
...	...	...	...			
30	0,86	0,96	1,16	2.54	2.7	2.98
Average	2,30	2,46	2,67	4,10	4,29	4,62

For manually segmented images that are distorted by gaussian noise, when tested using the watershed transform method for various levels of standard deviation with normal distribution, respectively 10 equal to 2.30; 20 is 2.46, and 30 is 2.67, while for the Otsu thresholding method a row of 10 is 4.10; 20 at 4.29 and 30 at 4.62. It shows that the image quality in the watershed segmentation which is distorted by gaussian noise is still superior to the Otsu thresholding method. In addition, the higher the standard deviation level value given to the sandy soil image, the more it will affect the quality of the image.

To find out how long sandy soil images can be processed, the processing time is calculated when running the Watershed Transform and Otsu Thresholding methods, as shown in Table 5.

The total processing time for 30 sandy soil images obtained with the watershed transform method is 436.57 seconds with an average processing time of 14.56 seconds, this proves that to process sandy soil images the watershed method has a processing time that tends to be longer than the Otsu thresholding method has a total processing time of 30 sandy soil images, which only takes 103.36 seconds to process with an average test time of 3.45 seconds.

4. Conclusions and Suggestions

Based on testing sandy soil images using the watershed transform and otsu thresholding methods, there are several conclusions obtained as follows: The difference in the results of manual segmentation of sandy soil images with the results of segmentation of sandy soil images using the watershed transform method is 3.08 and the Otsu Thresholding method is 3.08 4.09.

This proves that the squared error value generated by the Watershed Transform method is smaller than the Otsu thresholding method. So that proves that the watershed transform method is superior to the Otsu thresholding method for segmenting sandy soil images. Testing the quality of both methods based on noise, namely gaussian noise with various standard deviation values of normal distribution and noise intensity of 10, 20 and 30, it was found that the watershed transform method is better at segmenting noise-distorted sand soil images than the Otsu thresholding method in terms of processing time. The OTSU Thresholding method is faster or superior than the Watershed Transform method.

Table 5. Processing Time for Sand Soil Image Segmentation

Image	Time (Second)	
	Watershed Transform	Otsu Thresholding
1	15,74	3,86
2	12,42	3,63
3	17,08	3,07
4	12,53	3,17
5	11,31	3,13
...		
30	14,15	2,97
	436,57	103,36
Average	14,56	3,45

As a suggestion for further research, it can be tested and compared using the Watershed Transform and Otsu Thresholding methods on different images. It can also be tested for image quality based on speckle noise, poison, salt and paper or Gaussian noise with standard deviation normal distribution values and different noise intensity levels.

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