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Obstacle-free path Localization for Mobile Robots using Wavelet Transform

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1. Introduction

Building a robust platform for navigation has long been a very interesting topic. The quest for a robust algorithm even using non-visual sensors is still in its infancy. This is due to the different constraint that is being used on the different algorithm. Maja [2] et al, uses a simple segmentation technique to isolate the ground from other fixtures. The said algorithm process raw data very fast, since it involves a simple computation. But due to its simplicity, it exhibits some failure modes. The $\mu - k\sigma$ [1] cannot isolate an area, which exhibit a very dark color on the floor. And if it intend to isolate the said area, a problem of getting a blank segmented regions, which is unsafe for robot navigation, will be produced.

The quest of finding a solution to this failure modes leads us to Wavelet transform that promised good result depending on the basis used. Wavelet transform is a mathematical tool for decomposing functions [5]. Due to its decomposition property, it leads us to think that this will somehow decompose the floor from other fixtures which is our main concern.

2. Theoretical Background

Wavelet Transform is a new transform technique that addresses the problems on image compression and feature detection [9]. The continous Wavelet transform was introduced by Grossman and Morlet [7]. It is being represented in equation 1.

$$W_f(a,b) = \int_{-\infty}^{\infty} f(x)\psi_{a,b}(x)dx \qquad (1)$$

where $f(x)$ is the signal to be analyzed and

$\psi_{a,b}$ is the basis function. The idea of using a basis function to decomposed a particular signal is not new, and thus, there are many of such functions exist [8]. There are many basis functions which can be used for a specific applications. Thus, it gives an advantage in Wavelet compared to other transform since the basis function is not fixed, unlike with Fourier Transform. But with these many basis functions only a few of it produce a decomposition that has interesting properties [?].

A hypothetical basis function is shown in Figure 1

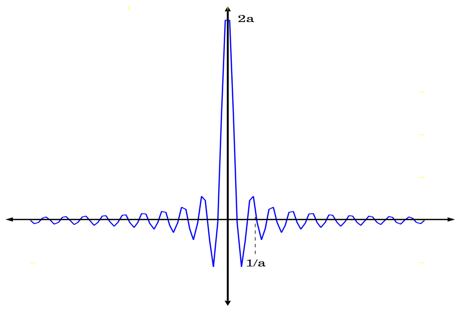

Fig. 1 Hypothetical mother wavelet

In equation 1, the transform is determined by taking the inner product of the input signal and the basis function. This value represents in some sense, taking the similarity between the input signal and one of the basis functions. If it is similar then it will produced a relatively large value, and if it isn't then it will produced a small value.

Wavelet Transform is reversible, thus an inverse equation is also present. But we are only concerned on the decomposition issue so we will not discuss here its inverse counterpart.

The basis functions is actually a linear combination of different scalings and translations and is normally called the mother wavelet. Thus, equation 2

$$\Psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \tag{2}$$

where $a > 0$ and b are real numbers. In this equation, the variable a represents the scale of a particular basis functions, while b is the translations.

Building your own basis is possible under the heading of Multiresolution Analysis [6]. There are different methods to build basis functions and one that is pointed out by Stollnitz [6] is the spline wavelets which was developed by Chui, et al. [3].

2.1 Basis functions

There are readily available basis functions. One of the easiest but poor choice [5] is the Haar Basis (See Figure 2).

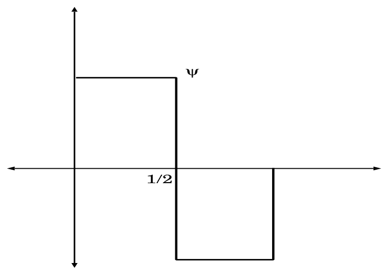

Fig. 2 Haar Basis.

Another basis from Daubechies also is shown in Figure 3.

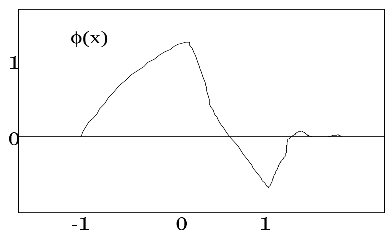

Fig. 3 Daubechies Basis

3. Mechanics

There are two types of Wavelet decomposition in Discrete form [5]. One uses the one dimensional solution which is termed as Standard Decomposition and the other is called the Non-standard decomposition. Standard decomposition uses the one-dimensional wavelet transform. In image processing application, the standard decomposition applies wavelet to each row of the image and after that applies the transform again in each column of the image. The nonstandard decomposition alternates between row and column operations. The latter is used in this research.

In nonstandard decomposition, the output image structure is found in Figure 4 below.

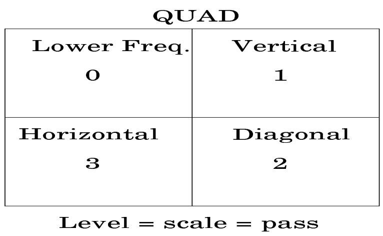

Fig. 4 Non-standard Decomposition

The Lower Frequency area which was shown above is actually the original image in half-size frame. This is the first pass of the transform, which means that it isn't complete. A sample image is shown in Figure 5.

Fig. 5 Wavelet Transform using Non-standard Decomposition

Figure 5 shows the following characteristic which were decomposed. The decomposed characteristic of the image is shown on the darker area of the same figure. To make the decomposed properties clearer, a negative equivalent is shown in Figure 6.

Fig. 6 Negative equivalent of the image above.

3.1 Data for segmentation process

After the application of the nonstandard decomposition of Wavelet transform to the image, the following quads are segregated, shown below,

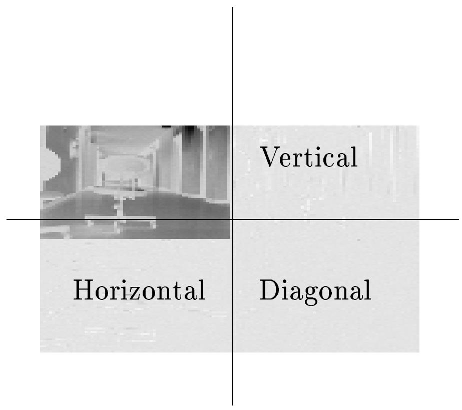

Fig. 7 Division of the transformed image.

The vertical and horizontal are each taken and combined together. Since the data of its quad represent the horizontal and vertical characteristic of the image, then combining them together will generate the possible edges in an image. See a hypothetical example below Figure 8. This shows that the images will be decomposed according to its vertical and horizontal characteristic.

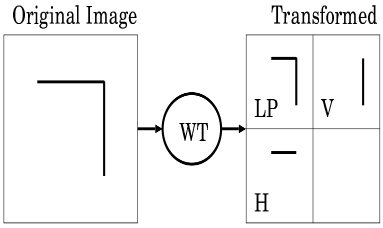

Fig. 8 Transformed image

Below is the combining process of the two data.

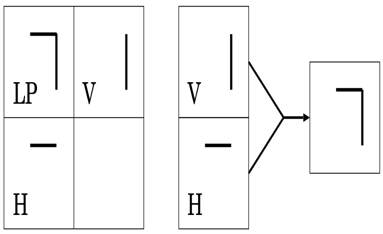

Fig. 9 Combining Process.

4. Three Scheme

Using the nonstandard scheme, the decomposed characteristic is shown in Figure 4. The quad 1, which represents the vertical characteristic, quad 2, the diagonal, and quad 3, the horizontal. Three scheme were introduced to segment the image using Wavelet Transform. The basis used for the Wavelet transform is the Haar Basis.

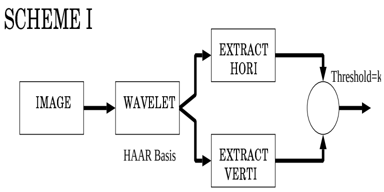

Fig. 10 Scheme A Segmentation.

Scheme I, is shown in Figure 10. This scheme takes an image, apply wavelet transform using Haar as its basis functions, extract the horizontal and vertical characteristic of the image, using the data in quad 1 and 3, fused them together using a threshold. This gives a segmented image as a product. The combining process can be found in Figure 11.

The following is the procedure in fusing the two data [vertical and horizontal]. The data taken from quad 1 is actually the whole image vertical characteristic, thus the location of the pixels corresponds on the same location as in the horizontal characteristic. Illustrated below is the said process,

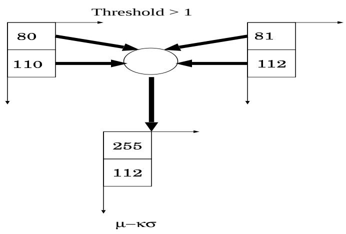

Fig. 11 Fusing two data for segmentation purposes.

For example, if we have the following data on the same location, and that our threshold is, $T = 2$. The absolute difference between the two data is taken first, and if it is greater than the threshold, what will be reflected is the value which is bigger than the two, [between 110 and 112]. And if it is less than or equal than the threshold then, a white space is reflected. The concept here is that, since we are dealing with the horizontal and vertical characteristic, thus, the vertical information is not found in the horizontal characteristic. Thus if we get the absolute difference between the two, we can readily found that if it generate a bigger value, it is either a vertical or horizontal in the image, thus using the bigger value from the two, but if it generates some value within the threshold, it is neither vertical or horizontal, which we defined as free space.

Below are the other schemes used, Scheme II and III. In here, we incorporate, the segmentation technique, the $\mu - k\sigma$ [1] that we develop before in getting the segmented image.

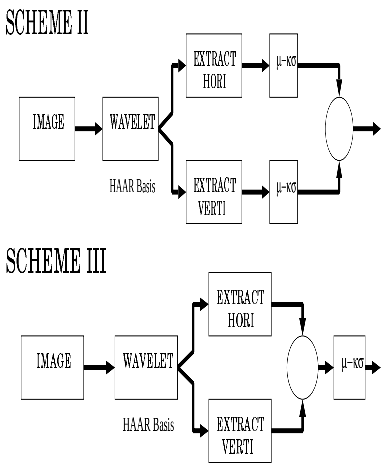

Fig. 12 Using $\mu - k\sigma$.

5. Processing Time

The processing time of the above schemes are shown below. Take note that the processing time of Scheme II and III are the same, while the processing time of Scheme A is different (See Figure 13).

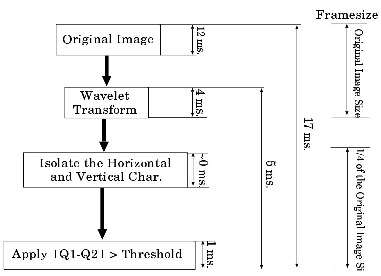

Fig. 13 Time Processing [Scheme I].

Figure 14 is the processing time of Scheme II and III. Notice that the processing time in the segmentation process is very fast. This is due to the fact that the frame size of the image has been reduced to a quarter of the original image.

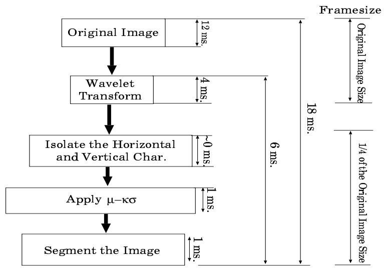

Fig. 14 Time Processing [Scheme II and III].

6. Sample Images

Below are the sample images using the three scheme above. Take note that the basis functions used here is the Haar Basis.

Notice that the threshold used for the said sample images is $T = 9$. The idea on the first scheme is to plug in some threshold value and see the output of the segmentation if it produces a good segmentation of the floor. And using Threshold, T=9, gives a good free space output compared to the rest, since it exhibits a less noise segmentation.

After the segmented frame output, the same procedure is used in the paper of Maja et al [1] to produce the free space plot.

7. Conclusion

It has been shown that Wavelet can decompose some characteristic of an image. Our main concern is decomposing the feature of the floor. This might be possible by using different basis. Though, the output of the test run does not really exhibit good segmentation as there are a lot of noises in its segmentation output. On Figure 16, a proposed point of improvements is shown. Build a new basis or use other existing basis will obviously improve the performance of the segmentation. This could be done by plugging the different h's values in the Wavelet box shown in Figure 16.

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10)

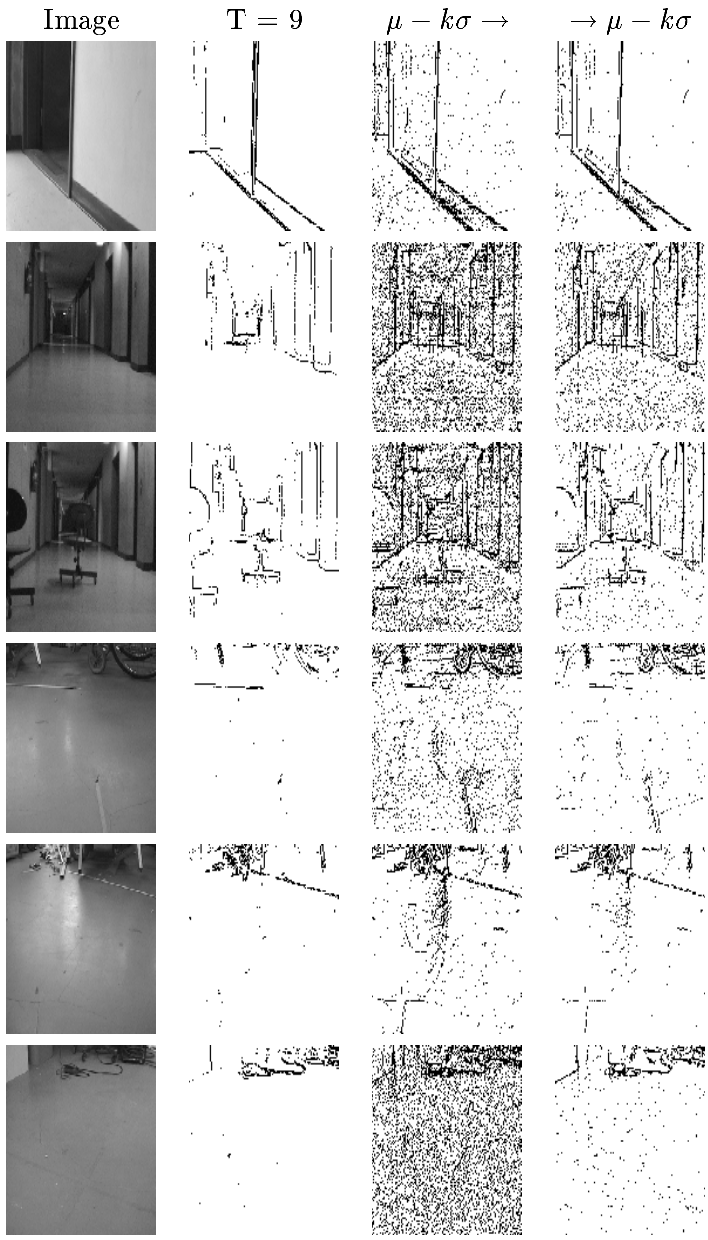

Fig. 15 Sample Images using Wavelet Transform.

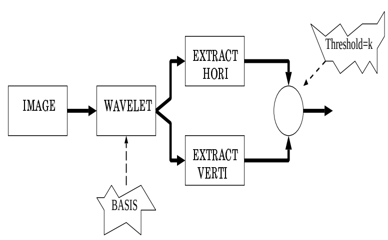

Fig. 16 The following scheme can be improved by changing the highlighted part.