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Implementation of Wavelet and Curvelet Transform for Image Fusion

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Abstract:
This paper introduces a wavelet transform, as well as a second generation curvelet transform, as a basis for the creation of image fusion techniques. We also present a wavelet transform, as well as an image fusion strategy that is founded on the wavelet transform. With the wavelet transform, it is not feasible to correctly represent edges and singularities. So the wavelet transform is used in conjunction with the second generation curvelet transform, and the image fusion process is completed as a result of this combination. This approach is used to a variety of experiments to demonstrate its value, including multi-focus picture fusion and complementary image fusion, in order to demonstrate its effectiveness. Despite the fact that there are a significant number of source pictures employed, the suggested approach manages to maintain critical information from each one of the source images.
It is utilised in this work to combine images and apply various wavelet treatments to them. It also makes use of the Second Generation Curvelet Transform, among other things..

I. INTRODUCTION

In image fusion, which is a sort of data fusion approach, images are used as the major research materials. This is regarded to be a form of data fusion since photographs are used as the primary study materials. It is classified as a technique when it integrates multiple photographs of a single scene acquired from separate image sensor data or when it integrates multiple photographs of a single scene obtained at different times from a single image sensor [1] that are captured at different times from the same image sensor. It was used as a multiresolution analysis image fusion strategy during the previous decade, based on a multiresolution analysis picture fusion technology based on Wavelet Transform, which had been more swiftly developed in the previous decade [2]. In signal processing applications, Wavelet Transforms are particularly valuable because of their outstanding time-frequency characteristics. [3] It has been demonstrated that the implementation of this method in image processing may be quite beneficial. Because of its one-dimensional nature, the product's one-dimensional characteristic cannot be simply transferred to two- or multi-dimensional applications without additional work. A one-dimensional wavelet bridges a separable wavelet, resulting in a wavelet with a restricted directivity [4]. The Curvelet Transform theory, which was developed by E. J. Candes and D. L. Donoho in 2000 [5] to overcome these limitations, was created with the goal of overcoming these difficulties. As an illustration, the Curvelet Transform was developed by integrating numerous components, including a specialised filtering mechanism and a multi-scale Ridgelet Transform, to achieve its final form. It has the potential to be a terrific match when used in conjunction with an image. The Curvelet Transform is accomplished using a more comprehensive digital realisation, which includes features such as sub-band splitting, smoothing blocks, normalising, Ridgelet analysis, and other refinements, as well as additional features such as sub-band splitting. In a study including the use of Curvelet's pyramid decomposition, it was observed that data redundancy was a significant source of worry [6]. E. J. Candes's Fast Curvelet Transform(FCT) was the Second Generation Curvelet Transform, and it was easier to understand than the preceding generation. It was first presented in 2005[7] and has since been updated. The FCT was implemented in MATLAB, and the C++ code was built to run on the computer. Because the technique was so straightforward, the user was able to understand it in a short period of time. Li Huihui's study on multi-focus picture fusion based on the Second Generation Curvelet Transform [8] was published in the journal Image Fusion [8], and it was done with the help of the Curvelet Transform. The research was done with the help of the Curvelet Transform. The Second Generation Curvelet Transform is found to be effective for fusing images in the following ways, according to the findings of this investigation: With the use of this technique, source photos may be mined for information, and the collected information can then be merged with fusion images to generate sharp images. It is now in its infancy as a technological endeavour.

It is necessary to use the WAVELETS II algorithm in order to construct image fusion approaches.

A high-level overview of the wavelet-based photo fusion approach is depicted in Figure 3.1, and more detailed information can be found in the text. We assume that all of the source photos will be correctly identified and registered, and that the variables I1 and I2 will indicate which source images will be merged. With the letter L, we may indicate the extent to which wavelet decomposition was used in the inquiry. The letter F represents the last fused image in the final fused picture, which is represented by the letter F. Pictures I1, I2, and I3 are initially decomposed using the Lth level wavelet transform, which is applied to each picture. Picture I4 represents the final fused picture, which is represented by the letter F. Each of the L resolution levels is represented by a rough approximation of the image at the coarsest resolution level, and each of the L resolution levels is represented by a rough approximation of the image at the highest resolution level. This transform also produces 3L horizontal, vertical, and diagonal detail sub-images at each of the L resolution levels. It is possible to combine images I1 and I2 because each individual image is made up of a pair of subimages from the other. These subimages are then blended together to generate the combined image. As part of this process, the final fused picture is rebuilt from the changing coefficients, which is done through the use of an inverse wavelet transform.

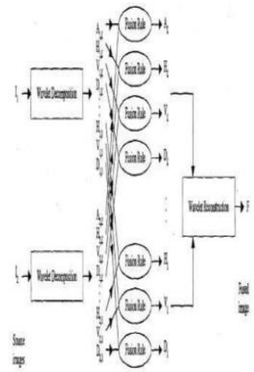

Fig.1 Wavelet based Image Fusion Procedure

III. Curvelet Transform

A version of the Ridgelet Transform, this transform was developed by Cands and Donoho in 2000. It is a symmetric transform that is derived from the Ridgelet Transform. Cands and Donoho were the first to create it, back in 2000. (from which it receives its name). Ridgelet Transform (which was a distinct function from standard Curvelet Transform) was not provided, but it did support expression forms of Curvelet basis in the frequency domain, so making it a full-fledged Curvelet Transform in all of its facets.

3.1 The Curvelet Transform is a data transformation technique that is utilised in Continuous Time.

Both of these modifications to the Continuous Curvelet Transform were substantial, and they were made in recent years to keep up with the times. Building the first Continuous Curvelet Transform took a long time since it necessitated a complex series of techniques, which included the ridgelet analysis of the radon transform of a picture, which was difficult to do. When the system was in operation, it moved at a glacial pace. It was decided to make an improvement to the algorithm in 2003, which took place in the year 2003. In addition to a considerable reduction in redundancy, the use of the Ridgelet Transform has been phased out, which has resulted in a significant boost in the speed of the transform as a result of the phase out of the transform. Curvelets are handled as tight frames in this novel technique, which represents a departure from past approaches to thinking about curvelets. When using tight frames to support an individual curvelet in the frequency domain, the result is frequency support in a parabolic-wedge region in the frequency domain. When using tight frames to support an individual curvelet in the frequency domain, the result is frequency support in a parabolic-wedge region in the frequency domain.

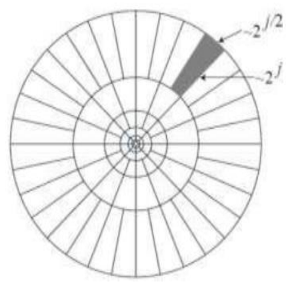

Fig. 2 Continuous Curvelet support in the frequency domain

A series of curvelets is said to have tight frames if and only if there is some value for A that results in the following:

$$A\|f\|_{L^2}^2 = \sum_{j,l,k} |\langle f, \gamma_{j,l,k}\rangle|^2 ; \forall f \in L^2 \qquad (4)$$

And each curvelet in the space domain has the following definition:

$$\gamma_{j,l,k} = 2^{\frac{3j}{4}} \gamma\left(D_j R_\theta x - k_\delta\right) \qquad (5)$$

The inverse of the curvelet transform is readily discovered by using the property of tight frames, which may be writte as

$$f = \sum_{j,l,k} \langle f, \gamma_{j,l,k}\rangle \gamma_{j,l,k} \qquad (6)$$

It will be covered in detail in this lecture how the discrete curvelet transform is wrapped around a function.

Based on the theoretical groundwork provided out in, this paper examines two independently implemented digital (or discrete) curvelet transform (DCT) algorithms that were developed independently of one another (where the continuous curvelet transform is constructed). If we consider the unequal Fourier Fourier Transform (also known as unequispaced Fourier Fourier Transform), we can see that the following statements are correct: Rather of sampling the fourier coefficients of an image in a normal fashion when computing the curvelet coefficients of an image, this technique samples the fourier coefficients in an irregular manner, resulting in a more accurate result.

The Wrapping transform, which makes use of a sequence of translations as well as a wraparound technique, is the second way that will be discussed in further detail later down this section. When compared to the other technique, although though both produce equivalent results, the

Wrapping Approach is more user-friendly and consumes less computing time than the other strategy. Consequently, the Unequispaced FFT methodology will be excluded from this inquiry, with the Wrapping DCT method serving as the major focus.Here is the definition of the Discrete Curvelet Transform in its simplest form:

$$c(j,l,k) = \int f(w)\tilde{U}_j(S_{\theta_l}^{-1} w)\exp[i\langle b, S_{\theta_l}^{-T} w\rangle]dw = \int \hat{f}(S_{\theta_l} w)\tilde{U}_j(w)\exp[i\langle b, w\rangle]dw$$

Because of this, the Wrapping Algorithm is more efficient than the other methods in terms of calculation time. It is the spatial grid that is used to translate curvelets at different sizes and angles that is the most noticeable difference between these two systems when comparing them side by side.

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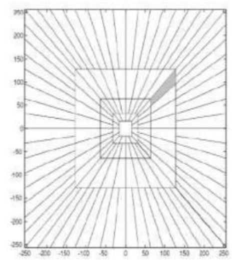

Fig. 3 Digital Corona of the Frequency Domain

IV. Image Fusion Algorithm Based On Wavelet And Curvelet Transform

After pre-processing, it is necessary to cut the same scale from the pending fused photos in accordance with the prescribed region, and then the images must be merged together as a result of the cut. Next, we use the Wavelet Transform to break pictures into sub-images of varying sizes, which we then combine using a mathematical formula to create a final image. Optical character recognition (OCR) Because of this, it should be essential to construct a local Curvelet Transform of each sub-image so that, as a consequence of the scale adjustment, the pictures of the sub-subblocks are different from the pictures of the other sub-images and vice versa. This procedure is essential in order to combine two photographs using the Curvelet Transform, and it should be completed in the following steps: 1. We can repair distortion and original images in such a manner that their probability distributions are equal to one another via the use of resampling and registration of original photographs. Because of the procedure stated above, a Wavelet coefficient with the same magnitude as the original component is produced as a result of using this method to generate a comparable component.

With the help of the Wavelet Transform, it is possible to divide original photos into appropriate levels, which is accomplished by segmenting them into smaller segments. In addition to one low-frequency approximate component acquired in each degree of difficulty, each degree of difficulty will have three high-frequency detail components, one low-frequency approximate component, one low-frequency approximate component, and one low-frequency approximate component, in addition to one low-frequency approximate component acquired in each degree of difficulty. Each level of difficulty will have one low-frequency approximation component that will be acquired at a low frequency

With this approach, the Curvelet Convert function is used to transform the low frequency approximation component and the high frequency detail component from two images that were captured independently with different cameras into one image with the low frequency approximation component and the high frequency detail component. The features of grey can only be changed once they have been detected using the neighbourhood interpolation approach. Once they have been determined, it is difficult to modify them.

The usage of local area variance, which is determined in accordance with a certain criterion for merging pictures together and may be computed, is required in order to study the low frequency component of the image. Known as regional activity, this type of high-frequency fusion may be observed in a specific area of the electromagnetic spectrum and is commonly observed. Some people refer to it as "regional activity," which is another term for it.

It is expected that as a result of the post-fusion inverse change of coefficients approach, the reconstructed images will have a look that is identical to the original photographs.

V. Image Fusion (also known as image fusion

5.1 Multi-Focus Image Fusion

In order to accomplish this result, we employ photographs that have a variety of focal points. An example of a photograph with the right level of sharpness is shown in Figure 4. On the left-hand side of the screen, in Figure 5, is an image that is in focus. Aiming to examine and contrast the influence of fusion on different areas of the system, this research employs several simultaneous implementations of three fusion methods. It is utilised in this study to employ all of the discrete wavelet transforms (DWT), the Second Generation Curvelet Transform (DFCT), and the Discrete Fast Curvelet Transform (DFCT) that have been suggested in this study; nevertheless, they are used in conjunction with one another. The Department of Workforce Technology (DWT) mandates that we use a range of fusion standards throughout the site, with each standard being suited to the specific needs of the customer. In order to reduce the complexity of the fusion standard, the average operator is used as a fusion standard for low-frequency sub-bands in the fusion standard in order to reduce the number of possible combinations.

Using the maximum absolute value of the fusion operator for each of the three high-frequency subbands, one may derive fusion standards for each of the three high-frequency subbands, beginning at the top of the highest scale and working one's way down. High-frequency subbands from various scales are fused together by employing the fusion operator with the biggest local area variation in the input signal. To determine which of the accessible fusion operators has the biggest local area variance, choose the fusion operator with the greatest local area variation among all of the available fusion operators. According to the results shown in fig.6, the effect of DWT appears to be much worse in comparison; as can be seen, the boundaries are noticeably fainter as a result of employing the technique. DFCT has the potential to have the most positive subjective impact of all of the available therapies. The combined picture is the most distinct, and the most precise information is kept to the maximum degree practically practicable throughout the process, resulting in the most distinct picture possible. The entropy of the fused picture, the correlation coefficient CC C, and the root mean square error Erms [8] are all employed to assess the overall quality of the fused image in this study.

Fig.4 Right focus image

Fig. 5. Left Focus Image

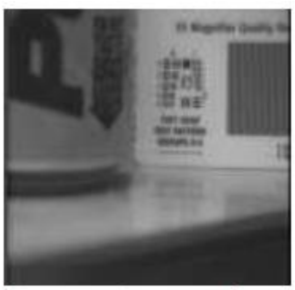

Fig. 6 Fused Image of DWT

5.2 Complementary Image Fusion

X-ray tomographic scanning pictures (CT scans) and magnetic resonance imaging (MRI scans) are both tomographic scanning images that are utilised in the area of medicine for the diagnosis and treatment of patients. Their individual qualities are distinct from one another. It can be observed in the example CT scan on the right that the brightness of an image is related to the density of tissue; the brightness of bones is higher than the brightness of soft tissue, and some soft tissue is not visible on the CT scan because of the density of tissue. MRI images, such as the one seen in Figure 8, are influenced by the quantity of hydrogen atoms present in the tissue; as a result, the brightness of soft tissue is greater than the brightness of bone, and bones are not visible. There is information in each of these photos that is complementary to the information included in the other shots. We use the same approaches that have been proved in medical images, as well as the same fusion criteria that have been developed, for the fusion process. fusion process

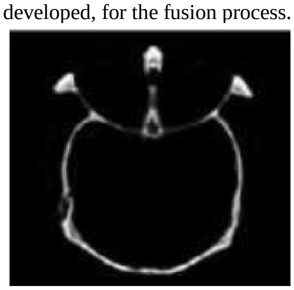

Fig.7 CT image

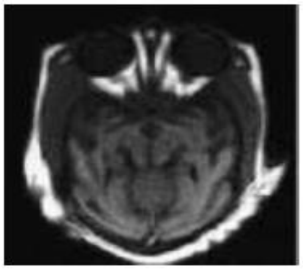

Fig. 8 MRI Image

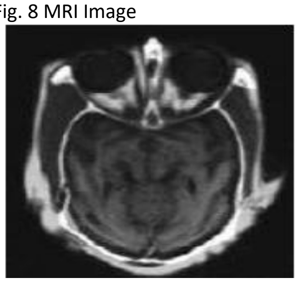

Fig. 9 Fused Image of DWT

VI. Conclusion

By combining the Wavelet Transform and the Second Generation Curvelet Transform, this research proposes that an image fusion technique may be developed that is both speedy and accurate. In the Wavelet Transform, the Second Generation Curvelet Transform provides improved direction recognition skills for the edge feature of awaited descriptive pictures. The Second Generation Curvelet Transform also provides multi-resolution analysis capabilities in the Wavelet Transform. When it comes to describing the edge direction of pictures and when it comes to analysing the features of images, this approach is more accurate. After doing extensive research on fusion standards and presenting complementary fusion projects, the study comes to the conclusion that the Wavelet and the Second Generation Curvelet Transforms are acceptable for usage in fusion photos, according to the findings. Using these fusion algorithms in simulated studies that make use of multi-focus and complementary fusion pictures will be the next step in the research process. The fusion strategy suggested in this research achieves superior fusion results in the field of vision when compared to any other method that has been proposed earlier..

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