Processing of Hyperspectral Data using Wavelet Transform

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Abstract— Remote sensor technology has encouraged series of research work in the area of signal and image processing. This is because the application of remote sensor has made it possible to obtain different types of signals and images from different places all over the world. In most cases, data obtained from hyperspectral images are found to be too voluminous and noisy. This, to a certain extent affects the accuracy of the result obtained when such signals or images are further processed for some applications. Previous research works have not sufficiently addressed this fundamental problem. Therefore, this research work is out to make use of Wavelet Transform for processing signals obtained from hyperspectral images with a view to denoise and reduce the data dimensionality without losing part of its content. Having undergone the process of denoising, the quality of the image or signal is drastically improved in terms of its clarity and size. This produces a better result when such signal is used for some applications. The system was implemented using MatLab wavelet tool. Hence, the result obtained is found to be better than the previous ones. The result also produced an hyperspectral spectrum/signal that has been thoroughly denoised and dimensionally reduced to an acceptable size within a very short computational time.

Keywords— Hyperspectral image, MatLab, Wavelet

1. Introduction

Hyperspectral images provide ample spectral information to identify and distinguish between spectrally similar (but unique) materials. Consequently, they provide the potential for more accurate and detailed information extraction than is possible with other types of remotely sensed data (Peg, 2004). Hyperspectral image is a 3- dimensional data which consist of 1-dimensional spectral information and 2- dimensional spatial information. With the introduction of new technology called hyperspectral remote sensing technology, it has become possible to describe comprehensively different types of earth object in the field of Agriculture, surveying, environmental monitoring, geology, military etc. Although, over the last decade, the development of imaging spectrometer is rapid, hyperspectral remote sensing image is still affected by many complex factors during processing of acquisition and transmission which eventually provide a mass noise (Dong Xu et al., 2013). The data that are contaminated with noise can cause a failure to extract valuable information and hamper further interpretation. With the presence of noise in the image, extraction of all useful information becomes difficult and noise again can lead to artifacts and loss of spatial resolution.

Furthermore, noise also affects the target detection, classification and segmentation. So the issue of "noise" deserves a serious attention. Denoising signal make the image to become more accurate for practical applications. Also, hyperspectral data are always voluminous in nature and therefore require a large storage space. This is highly uneconomical and poses a serious threat to the computational process. Therefore, dimension reduction of hyperspectral data should be given utmost attention. Since wavelet has a good time frequency location property and multi-resolution analysis property, it is widely and successfully applied in several fields. This research work therefore made use of halving algorithm and wavelet transform for processing of hyperspectral data image.

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The method will be applied to denoise the hyperspectral image and hence carry out dimensional reduction of the image without loss of data or information. The system was implemented using MatLab tool box

1.1 Hyperspectral Image

Hyperspectral image can be defined as images whose pixels contain a fine sampling of the light spectra. Therefore each pixel is a high dimensional vector, whose components are the received radiance values inside a fine wavelength band of the spectra. Most of the hyperspectral sensors cover the visible light spectrum and the near infrared (NIR) spectrum (Olanloye, 2013). Fig. 1 shows the structure of a hyperspectral image.

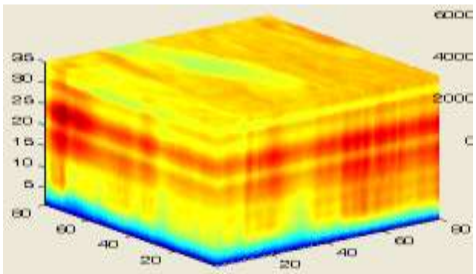

Fig.1: Structure of Hyperspectral image (Olanloye, 2013)

The data consist of m x n pixel and k bandwidth.

$$hyperdata = input\ (m, n, k)$$

Visualization of the ingested data in form of hypercube (for the whole datasets), sliced image of each bandwidth for all pixels, and graph plot of the spectrum for each pixel was provided as follows:

$$hypercube => drawcube(hyperdata, m, n, k)$$
$$images => drawimage\ (hyperdata, m, n, k_s)$$

$where\ k_s = 1..\ k_s$ provide interface for selecting a particular k_s bandwidth for viewing.

$$spectrums => plotgraph(hyperdata, m_i, n_j)$$

$where\ 1 < m_i < m$ and $1 < n_j < n$ provide an interface for selecting a particular m_i and n_j pixels for viewing.

Equation (1) shows the spectrum of pixel at i,j coordinates of the data cube which consists of $Z_k(k = 1..n)$ data points, where n is the number of bands.

$$X_i = Z_k(i = k, k = 1 \dots . n/2)$$

$$(1) \quad X_i = Z_k(i = k + \frac{n}{2}, \; k = n/2 + 1 \dots . n$$

Looking at the image from computational point of view as shown in Fig.2, it could be analyzed using a 3D plane consisting of 3 different axes. The first two dimensions represent the spatial coordinates while the third dimension represents the radiance spectra of the sample pixel.

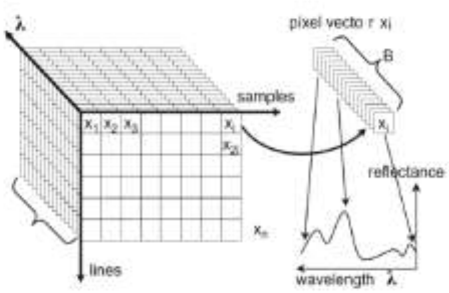

Fig. 2: Hyperspectral image from Computational Point of View

2. Literature Review

Sivaranjani and Suruthi (2014) published a research work titled denoising hyperspectral images using multijoint method of filter estimation. The author developed a multi linear algebra mode with parallel factor analysis for the decomposition process. Tao and Salah (2013) presented tensor decomposition as the method of denoising hyperspectral images. A real world HYDICE hyperspectral data was used in the experiment to access these 3 sensor based denoising methods and the performance of each methods were analyzed in two aspects: - signal to signal ratio and improvement of subsequent target of detection result.

Dong et al. (2013) also presented a research work on analysis and denoising of hyperspectral remote sensing image in the curvelet domain. In this work, each band of hyperspectral remote sensing image is transformed into the curvelet domain and the sets of the sub band images are obtained from different wavelength of hyperspectral remote sensing image. The algorithm was able to denoise the common spatty noise and the trip noise. Claudionor et al. (2008) presented a research work on reduction of dimensionality of hyperspectral data for the classification of Agricultural scene. The author was able to do this using genetic algorithm as the instrument.

Villa et al (2009) used independent component analysis to analyze hyperspectral images. Pavan (2013) in the published M.Sc. thesis used support vector machine for dimensionality reduction and classification of hyperspectral data. Antonio et al. (2005) was able to carry out dimensionality reduction and classification of hyperspectral image data using sequences of extended morphological transformations. Helmi et al. (2012) also published a research article which reviewed various techniques for hyperspectral remote sensing and its useful application in urban areas. Lele et al. (2007) published an article titled dimensional reduction in hyperspectral image by danger theory based artificial immune system.

Going through the literature, it is true that various methods have been used to denoise and reduce the dimension of hyperspectral signal. This research work made an attempt to use wavelet transform algorithm to denoise hyperspectral signal and to reduce the size to an acceptable level. The methodology used, compared to the existing ones, drastically reduced the size, computational process and time when the signal is to be further processed.

3. Methodology and Implementation

A new algorithm was developed to reduce the dimension to half of its initial dimension. Without loss of data, the process continues until the minimum dimension is obtained.

3.1 Algorithm

Step1: The given data series is cut into halves of equal sizes.
Step2: Selected those in the first half as horizontal coordinate
Step3: Select those in the second half as vertical coordinate
Step4: Plot each of the point on the horizontal coordinate against each of the point on the vertical axis
Step5: Create series of point image to form the characterisation map.
Step6: **If** the size is the minimum **then GOTO** step7 **Else GOTO** step1
Step7: Decompose the signal
Step8: Set the threshold
Step9: Reconstruct the signal
Step10: Stop

3.2 Denoising

The noisy signal is as shown in Fig.3 below

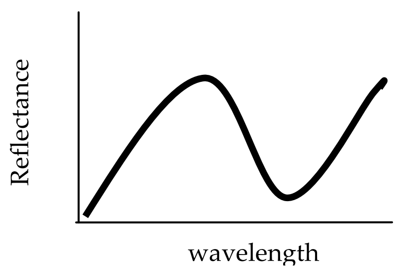

Fig. 3: Noisy hyperspectral signal

The basic de-noising procedure consists of three steps:

1) *Decompose the signal:* Choose the decomposition level. The decomposition level chosen for this research is 5 level of details and 5 levels of approximation. Fig. 4 indicates the detail level D1 to D5 and the Approximation level A1 to A5.

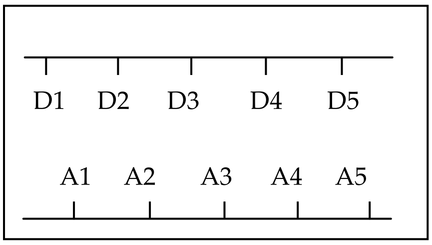

Fig. 4: Detail and Approximation level of the Signal

2) *Set the threshold:* The threshold for the detail coefficients is set at a specific level. Hence, D4=0 is set as the threshold level and all other level below the chosen level were set to zero. The selected range of coefficient after thresholding is shown in Fig. 5 below.

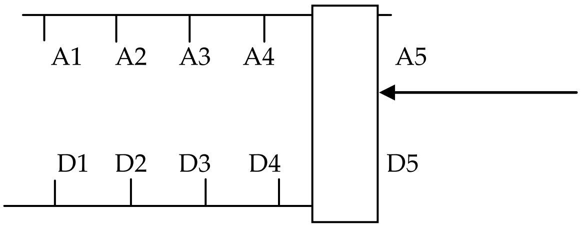

Fig. 5: Selected range of coefficient

3) *Reconstruction of the signal:* Reconstruct the signal from all the coefficients that fall within the selected threshold. Hence, for the reconstruction, 5th approximation and 5th detail were used ignoring all other levels. The reconstruction process produced a denoised signal as depicted in Fig. 6

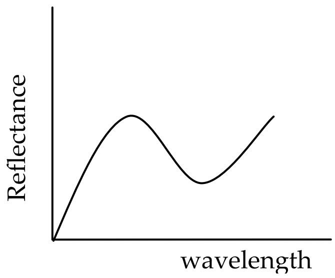

Fig. 6: Reconstructed denoise signal

MATLAB wavelet toolbox was used for the purpose of implementation. Different mother wavelet such as Haar, Daubechies, Mexican Hat, Meyer, Dmey, Reverse Biorthogonal 5.5 (rbio5.5) and Biorthogonal 1.3 (bior1.3) were tested but Dmey and Haar were found to be more stable and appropriate. The results were displayed in fig 7-14. The signal was decomposed at a particular threshold level. For the decomposition, the level of details to which the signal details should be analyzed was considered. Hence, level 1, 2, 3, 4, 5 i.e. (D1-D5) were selected. The signal was also reconstructed at 5th level of detail to obtain the denoise signal

4. Results and Discussions

Looking at the result obtained, Fig. 7, the first diagram shows the original detail coefficient where d1, d2, d3, d4 and d5 indicate the detail of the signal.

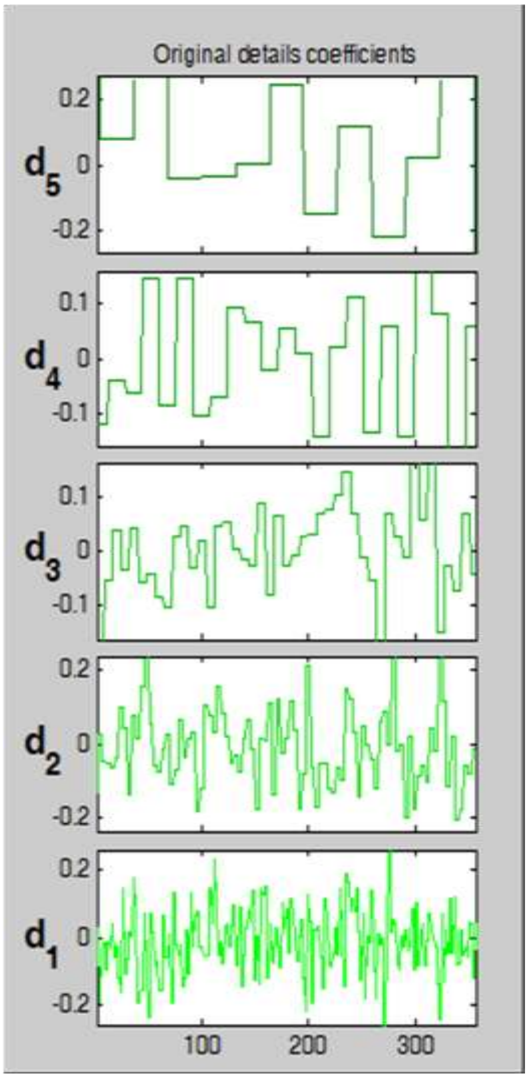

Fig. 7: Original detail coefficients

In Fig. 8, the original coefficients are plotted against the level numbers. At level1, there are 357 data points represented by 0.5 of the number of data points (about178 data points). Similarly, at level2, we have (0.5) of 178 which is (about 89 data points). At level 5, the data point has been reduced to the possible minimum level. There is a lot of noise in the signal which is indicated by different colors in the diagram. In the lower part of the diagram in Fig. 8, the coefficient was threshold thereby removing all the noise hence the diagram shows no colour.

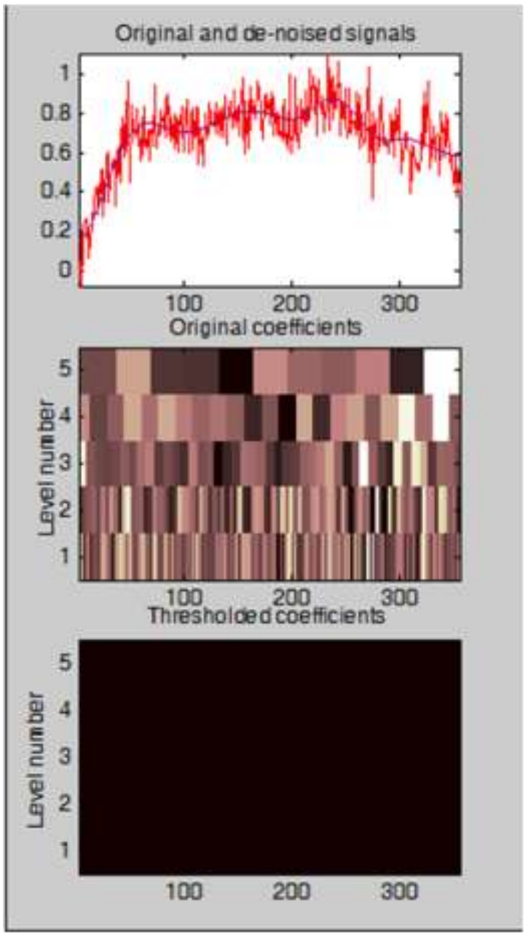

Fig.8: Original coefficients / level number

Also, in Fig. 9, the denoise signal obtained was shown in black colour with the removed noise superimposed on it.

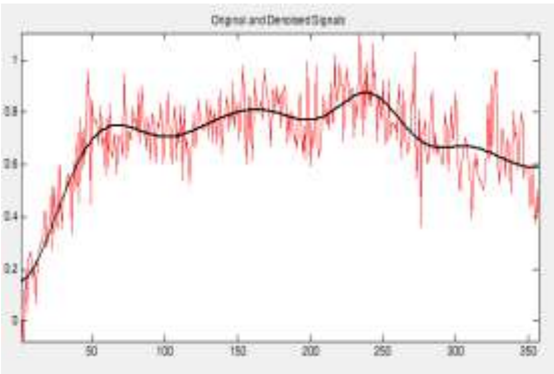

Fig.9: Original and denoised signal

The residual of the denoising process is shown in Fig. 10 which depicts/ shows the extracted noise and its signal properties. This process was carried out with various parent wavelets and the best two results obtained (Dmey and Haar) were shown in figure 7, 8, 9, 10 11, 12, 13, 14 respectively. The results of Dmey were shown in figure 7, 8, 9 and 10 while the result obtained when Haar was used are shown in figure 11, 12, 13 and14.

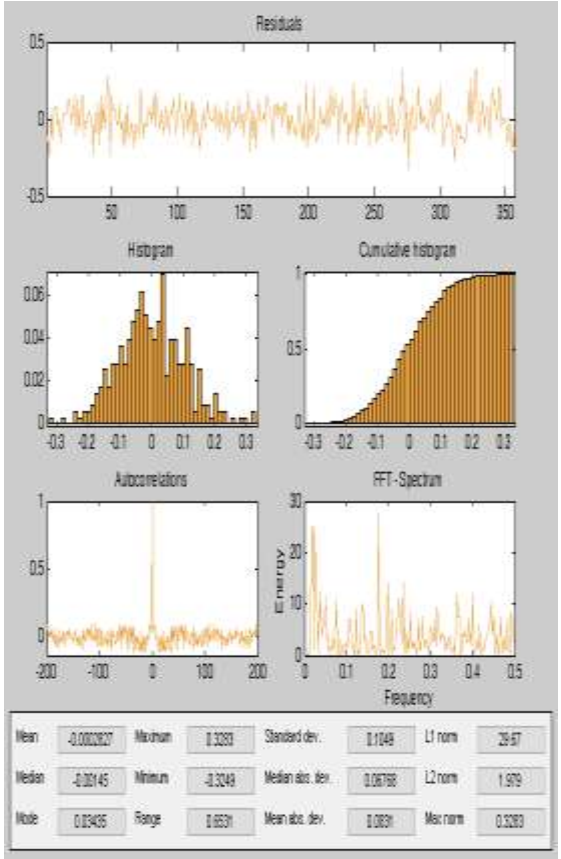

Fig.10: The denoising residual of the first signal

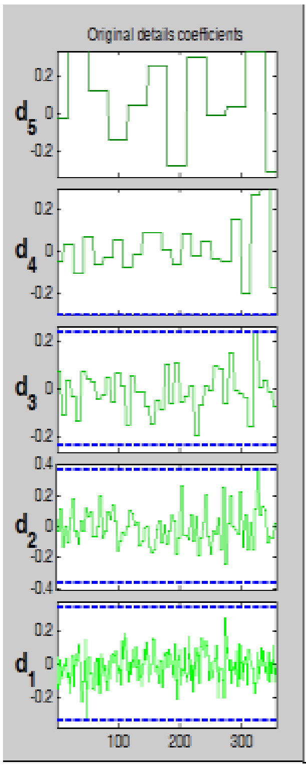

Fig.11: Original detail coefficient

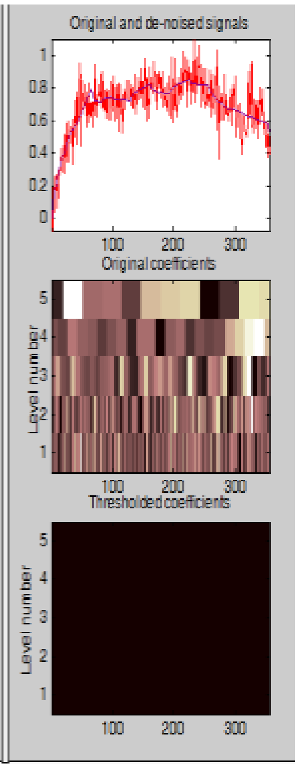

Fig.12: Original and denoise signal

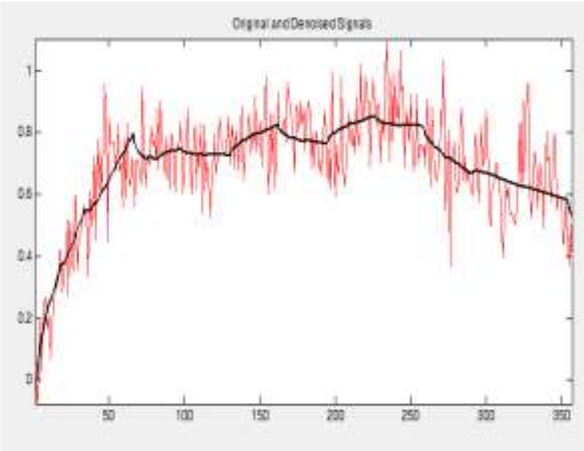

Fig.13: Original and denoise signal

5. System Evaluation

In this research work, different mother wavelets were tested and the result of the best seven compared with each other. The result obtained is displayed in Table 1.

Table 1: Comparison of STD and MSE of various mother wavelet methods

Mother Wavelet Methods	STD	MSE
Dmey	0.1049	0.0110
Haar	0.1063	0.0113
Meyer	0.3404	0.1159
Daubechies	0.2503	0.0626
Mexican Hat	0.3140	0.0986
Biorthogonal 1.3 (bior1.3)	0.3916	0.1534
Reverse Biorthogonal 5.5 (rbio5.5)	0.3901	0.1522

The standard deviation (STD) and the mean square error (MSE) for the various parent wavelet reveals that Dmey has the least STD and MSE (0.1049 and 0.0110) respectively. This is followed by Haar with STD of 0.1063 and MSE of 0.0113.The lower the value of STD and MSE the more the amount of noise removed from each band image and the more clearer the image. Therefore, from the result, we were able to establish that Dmey is the best for denoising hyperspectral images. The denoise signal occupies least amount of space since it is free of noise .If it is to be processed further for further applications, it occupies less space, the computational process and time is reduced. Again, to compare the new method with the existing ones, we compared most of the existing ones in term of MSE and pick the best two. This is shown in Tables 2 and 3.

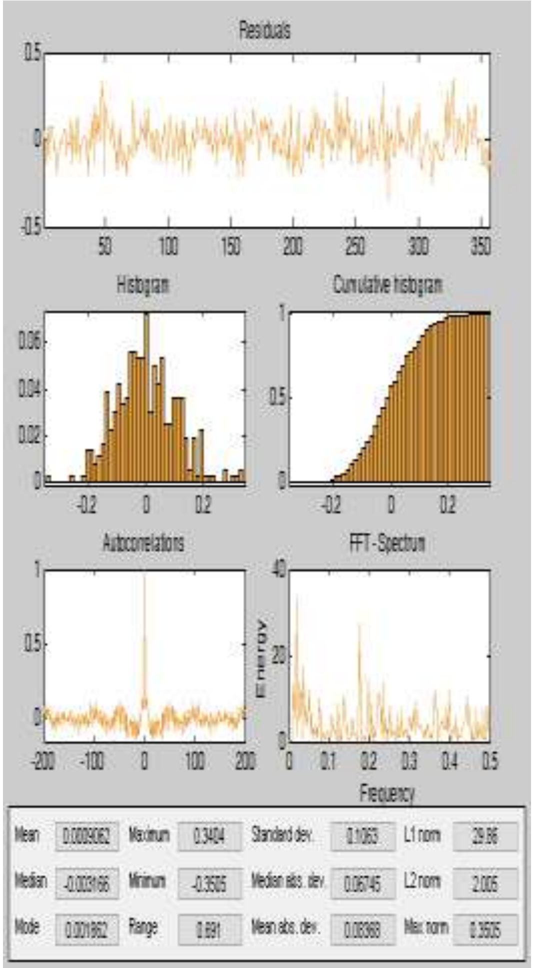

Fig.14: The denoising residual of the second signal

Table 2: Comparison of four different methods

Method	WT	SG	MA	MF
MSE	0.14	0.20	0.16	0.18

Source: Hao Yang, et al (2016)

Wavelet Transform (WT), Saritzky Golay (SG), Moving Average Method (MA), Media Filter Method (MF)

The methods used in Table 2 are Wavelet Transform (WT), Saritzky Golay (SG), Moving Average Method (MA), Media Filter Method (MF).

Table 3: Comparison of six different methods

Method	DA	DV	AT	HS	SC	MM
MSE	2.07	5.43	4.47	6.08	6.09	4.53

Source: Adam C. Zelinski and Vivek KGoyal. (2006)

Donoho's Visushrink Universal Treshold (DA), Atkinson's Threshold (AT), Heursure (HS), Sgtwolog (SC), Minimaxi (MM)

The methods used in Table 3 are Donoho's Visushrink Universal Treshold (DA), Atkinson's Treshold (AT), Heursure (HS), Sgtwolog (SC), Minimaxi (MM). Comparing Tables 1, 2 and 3, it is obvious that Dmey has the least MSE and therefore appears to be the best method for denoising hyperspectral data.

6. Conclusion

The research work has proposed a good method to denoise and reduce the size of hyperspectral data. Using this approach, the size of the data has been drastically reduced after denoising. Hence, when the data is to be further processed, the space required for storage, the computational process and the computational time are appropriately reduced. Therefore, better result will be obtained when such data is used for various applications.

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