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UNDER WATER IMAGE ENHANCEMENT VIA MINIMAL COLOR LOSS

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Abstract:
Underwater images typically suffer from color deviations and low visibility due to the wavelength-dependent light absorption and scattering. To deal with these degradation issues, we propose an efficient and robust underwater image enhancement method, called MLLE. Specifically, we first locally adjust the color and details of an input image according to a minimum color loss principle and a maximum attenuation map-guided fusion strategy. Afterward, we employ the integral and squared integral maps to compute the mean and variance of local image blocks, which are used to adaptively adjust the contrast of the input image. Meanwhile, a color balance strategy is introduced to balance the color differences between channel a and channel b in the CIELAB color space. Our enhanced results are characterized by vivid color, improved contrast, and enhanced details. Extensive experiments on three underwater image enhancement datasets demonstrate that our method outperforms the state-of-the-art methods. Our method is also appealing in its fast processing speed within 1s for processing an image of size 1024×1024×3 on a single CPU. Experiments further suggest that our method can effectively improve the performance of underwater image segmentation, key point detection, and saliency detection

I.INTRODUCTION

Digital image is defined as "An image is not an image without any object in it". Human visual system has ability to perceive the objects in digital image using edges in efficient manner. Halo artifacts introduces blur in digital image which makes perception of content difficult. Various filtering techniques have designed in literature to preserve the global and local statistics but none can meet the desired requirements and various algorithms yields high complexity which fails them to achieve practical reliability. Digital image processing domain has different research fields and all these research fields have applications ranging from low level to high level. Edge preservation in all these research fields attains attention and implementation of smoothing filters has ability to filter noise content by preserving the edge information. Smoothing algorithms can be classified into two types namely global filters such as bilateral filter , tri-lateral filters , and finally guided image filter .

Global filters attain images with good quality but these filters are highly expensive. Local filters are considered as alternative to global filters which are simple and cost effective but fail to conserve the sharp edges information like global filters. When local filters are forcefully adopts to smooth edges it results halo artifacts. Halo artifacts produced by bi-lateral filter and guided image filter are fixed in equipped way using similarity parameter in terms of range and spatial. Bi-lateral filtering mechanism is considered as adaptive filter and this adaptive mechanism helps to handle the halo artifacts and on negative side it destroys the 3D convolutional form .

An interesting algorithm named weighted guided image filtering scheme is proposed in this paper by combining the edge-based weighting scheme along with guided image filtering. Calculation of edge based weighting scheme is calculated by using 3×3 local variance in a guidance image. This local variance scheme of one individual pixel is normalized by all pixels local variance in guidance image. The acquired normalized weights of all pixels are then adaptively adapted to WGIF. WGIF helps to avoid halo artifacts in accurate manner for excellent visual quality. The intricacy of WGIF is same as GIF. The proposed weighted guide image filtering (WGIF) is applied for multiple purposes as single image mist removal, single image detail enhancement and different exposed images fusion.

In human visual perception, edges provide an effective and expressive stimulation which is important for neural interpretation of a scene. In the fields of image processing and in many computational photography employ smoothing techniques which could preserve edges better. In smoothing process an image to be filtered is typically decomposed into two layers: a base layer composed by homogeneous regions with sharp edges and a detail layer formed by either noise, e.g., a random pattern with zero mean, or texture, e.g, a repeated pattern with usual arrangement. There are two types of edge-preserving image smoothing techniques: global filters such as the weighted least squares (WLS) [8] filter and local filters such as bilateral filter (BF) [3], trilateral filter, and their accelerated versions [4], as well as guided image filter (GIF) [11].Though the global optimization based filters frequently yield excellent quality, they have high computational cost. Comparing with the global optimization based filters [1], [2], [8] and [9], the local filters are generally simpler. However, the local filters cannot conserve sharp edges like the global optimization based filters. Halo artifacts were usually produced by the local filters when they were adopted to smooth edges. Major reason that the BF/GIF produces halo artifacts was both spatial similarity parameter and range similarity parameter in the BF [3] were fixed. But both the spatial similarity and the range similarity parameters of the BF could be adaptive to the content of the image to be filtered. Unfortunately as pointed out in [6], problem with adaptation of the parameters will destroy the 3D convolution form in [5]. We introduce in present paper, an edge-aware weighting technique and incorporated into the GIF to form a weighted GIF (WGIF). Local variance in 3×3 window of pixel in a guidance image is applied to calculate the edge-aware weighting. The local variance of a pixel is normalized by the local variance of all pixels in guidance image. The normalized weighting is then adopted to design the WGIF. As a result, halo artifacts can be avoided by using the WGIF. Similar to the GIF in [12], the WGIF also avoids gradient reversal. In addition, the intricacy of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF [14]. These features allow many applications of the WGIF for single image detail enhancement, single image mist removal, and fusion of differently exposed images.

II. LITERATURE SURVEY

2.1 Topic: A nonnegative factor model with optimal utilization of error estimates of data values.

Author: P. Paatero and U. Tapper

The fundamental principle of source/receptor relationships is that mass conservation can be assumed and a mass balance analysis can be used to identify and apportion sources of airborne particulate matter in the atmosphere. This methodology has generally been referred to within the air pollution research community as receptor modelling [Hopke, 1985; 1991]. The approach to obtaining a data set for receptor modelling is to determine a large number of chemical constituents such as elemental concentrations in a number of samples. Alternatively, automated electron microscopy can be used to characterize the composition and shape of particles in a series of particle samples.

2.2 Topic: "Underwater image processing: state of the art of restoration and image enhancement methods.

Author: R. Schettini and S. Corchs

The authors provide an overview of state-of-the-art image enhancement and restoration techniques for underwater images. Underwater imaging is one of the challenging tasks in the field of image processing and computer vision. Usually, underwater images suffer from non-uniform lighting, low contrast, diminished colour, and blurring due to attenuation and scattering of light in the underwater environment. It is necessary to pre-process these images before applying computer vision techniques.

Over the last few decades, many researchers have developed various image enhancement and restoration algorithms for enhancing the quality of images captured in underwater environments. The authors introduce a brief survey on image enhancement and restoration algorithms for underwater images. At the end of the chapter, we present an overview of our approach, which is well accepted by the image processing community to enhance the quality of underwater images. Our technique consists of filtering techniques such as homomorphic filtering, wavelet-based image denoising, bilateral filtering, and contrast equalization, which are applied sequentially. The proposed method increases better image visualization of objects which are captured in underwater environment compared to other existing methods.

2.3 Topic: "Underwater image super-resolution by descattering and fusion.

Author: H. Lu, Y. Li, S. Nakashima, H. Kim, and S. Serikawa

Underwater images are degraded due to scatters and absorption, resulting in low contrast and colour distortion. In this paper, a novel self-similarity-based method for descattering and super resolution (SR) of underwater images is proposed. The traditional approach of pre-processing the image using a descattering algorithm, followed by application of an SR method, has the limitation that most of the high-frequency information is lost during descattering. Consequently, we propose a novel high turbidity underwater image SR algorithm. We first obtain a high resolution (HR) image of scattered and bespattered images by using a self-similarity-based SR algorithm. Next, we apply a convex fusion rule for recovering the final HR image. The super-resolved images have a reasonable noise level after descattering and demonstrate visually more pleasing results than conventional approaches. Furthermore, numerical metrics demonstrate that the proposed algorithm shows a consistent improvement and that edges are significantly enhanced.

2.4 Topic: "Colour constancy using natural image statistics and scene semantics.

Author: A. Gijsenij and T. Gevers

Existing colour constancy methods are all based on specific assumptions such as the spatial and spectral characteristics of images. As a consequence, no algorithm can be considered as universal. However, with the large variety of available methods, the question is how to select the method that performs best for a specific image. To achieve selection and combining of colour constancy algorithms, in this paper natural image statistics are used to identify the most important characteristics of colour images. To capture the image characteristics, the Weibull parameterization (e.g., grain size and contrast) is used. It is shown that the Weibull parameterization is related to the image attributes to which the used colour constancy methods are sensitive. AMoG-classifier is used to learn the correlation and weighting between the Weibull-parameters and the image attributes (number of edges, amount of texture, and SNR). The output of the classifier is the selection of the best performing colour constancy method for a certain image. On a data set consisting of more than 11,000 images, an increase in colour constancy performance up to 20 percent (median angular error) can be obtained compared to the best-performing single algorithm. Further, it is shown that for certain scene categories, one specific colour constancy algorithm can be used instead of the classifier considering several algorithms.

III.EXISTING SYSTEM

Image processing is the manipulation of an image in order to improve its quality, enhances its ability to convey visual information and make it look better. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Underwater vision plays an important role in the missions of marine investigations and underwater robotic explorations. However, the images captured underwater are usually degraded by the absorption and scattering effects which occur during the light propagation Underwater images acquired in this situation frequently suffer from haze, low contrast and color distortion, especially in the marine environment (as shown in Fig. 1). These degraded image quality threatens the underwater object recognition task [3]. Therefore, enhancing the degraded underwater images becomes significant to a variety of vision-based applications in the underwater scenes

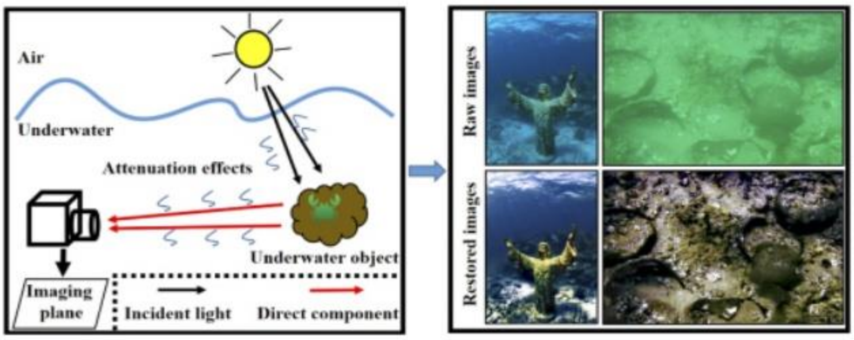

Fig: The underwater imaging model (left) and the results of the proposed underwater image enhancement method

Underwater image enhancement techniques are usually regarded as a pre-processing operation for other underwater tasks, e.g. real-time navigation [4] and deep-sea organisms tracking [5]. Many researchers dedicate to develop underwater image enhancement approaches to restore the images captured in seawater. Color distortion and haze removal are two main objectives of underwater image enhancement task. The preceding discussion leads to the following representation for a digitized image function.The right side of this equation is a digital image by definition. Each element of this array is called an image element, picture element, pixel or pel. Where f (1, 1) = f (0, 0) .The notation f (p, q) denotes the element located in row p and the column q.

The last stage involves recognition and interpretation. Recognition is the process that assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects.Knowledge about a problem domain is coded into image processing system in the form of a knowledge database. This knowledge may be as simple as detailing regions of an image when the information of interests is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated to list of all major possible defects in a materials inspection problem or an image data base containing high resolution satellite images of a region in connection with change deletion application. In addition to guiding the operation of each processing module, the knowledge base also controls the interaction between modules.

A histogram transformation is a pixel by pixel intensity transformation. A convenient representation of contrast of an image plots the number of pixels at each intensity value. As low contrast images have narrow distributions and high contrast images have broad distributions.

2.1 Histogram Based Methods

Histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

2.2Image Histogram

An image histogram is a type of histogram that acts as a graphical representation of tonal distribution describes the distribution of various bright and dark tones with in an image. During the scanning or image editing stage tones can be redistributed lightening a dark image (or) darkening a bright image. This histogram plots the no of pixels for each tonal value. By looking at the histogram for a specific image a person will be able to judge the entire tonal distribution.

Image histograms are present on many modern digital cameras. The horizontal axis of the graph represents the tonal variations and the vertical axis represents the no of pixels in that particular tone.

2.3 Normalized histogram

In this normalized histogram, normalized by dividing each value by the tonal no of the pixels in the image and it is denoted by the product MN where M and N are the row and column dimensions of the image.

Here p (r_k) represents the probability of occurrence of gray levelrk.

Some of all the components of a normalized histogram is 1. Histogram manipulation can be used for image enhancement the information which is inherent in histogram is also useful in other image processing applications like image compression and image segmentation.

2.4 Histogram Equalization

The probability of occurrence of intensity level rk in a digital image Histogram equalization is a technique for adjusting image intensities to enhance contrast. Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase.

p(r, k) = nk/ MN ...**(Eq.7)**

Where k=0, 1, 2 ...L-1

MN = Total number of pixels in the image

nk = number of pixels that have intensity

Normally, the histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit gray-scale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those gray-scale values. Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased. Through this adjustment, the intensities can be better distributed on the histogram.

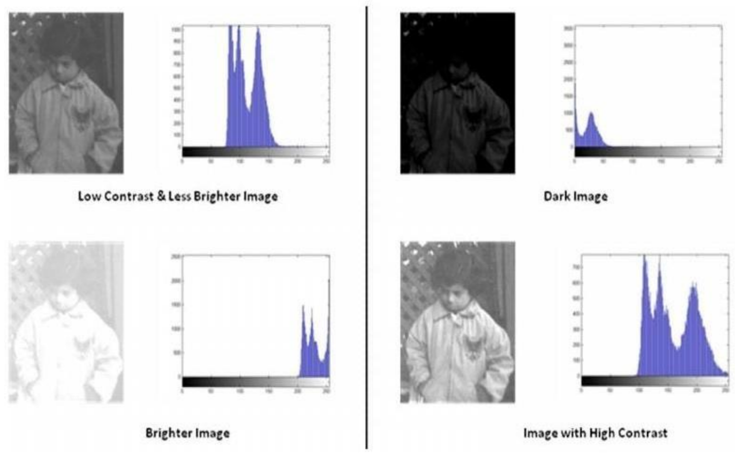

Figure: Different Types of Histogram Images with Different Contrasts

2.5 Adaptive Histogram Equalization

In Adaptive Histogram Equalization the image is divided into several rectangular domains, compute an equalizing histogram and modify levels so that they match across boundaries. Adaptive Histogram Equalization (AHE) computes the histogram of a local window centered at a given pixel to determine the mapping for that pixel, which provides a local contrast enhancement, Therefore regions occupying different gray scale ranges can be enhanced simultaneously.

III. PROPOSED SYSTEM

IN recent years, image fusion technology becomes more and more important, which has been widely used in many fields such as multi-focus image medical image infrared-visible image and remote sensing image The purpose of image fusion is to combine images containing the same scene from different sensors to generate a more comprehensive and accurate image including all useful information of these source images.

The current image fusion methods are divided into two categories. One is to directly fuse source images in spatial domain. However, this kind of methods is not good in dealing with edge. The other one is to integrate source images in transform domain. This type of approaches could remove the block effect and get more consistent fusion result. Image fusion methods based on MSD draw researcher's attention in recent years. For example, Discrete wavelet transform based method[8, 9], stationary wavelet transform based method[10], double-tree complex wavelet transform based method[11], curvelet transform based method[7], contour let transform based method[12], non-sub sampled contourlet transform based method

DWT, as a popular MSD tool, is first proposed, It provides a richer scale space analysis for image compared to other MSD tools because it can decompose image into magnitude and phase information. The magnitude of DWT is near shift invariant so it have better texture representation than wavelet and complex wavelet, and the phase of DWT contains richer geometric information.

IV IMAGE FUSION

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images. In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. But, the standard image fusion techniques can distort the spectral information of the multispectral data, while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will be usually, two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on DWT, uniform rational filter bank, and laplacian pyramid.

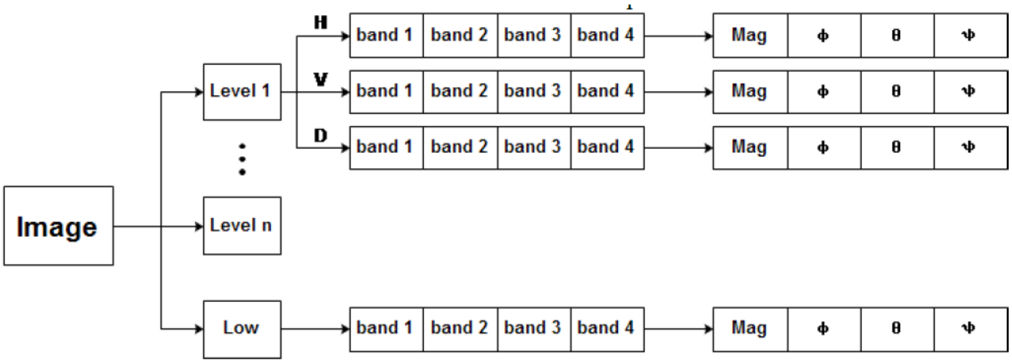

Fig. The DWT decomposition structure of image.

4.1 Discrete wavewle transform

The foundations of the DWT go back to 1976 when Croiser, Esteban, and Galand devised a technique to decompose discrete time images. Crochiere, Weber, and Flanagan did a similar work on coding of speech images in the same year. They named their analysis scheme as **sub band coding**. In 1983, Burt defined a technique very similar to sub band coding and named it **pyramidal coding** which is also known as multi resolution analysis. Later in 1989, Vetterli and Le Gall made some improvements to the sub band coding scheme, removing the existing redundancy in the pyramidal coding scheme. Sub band coding is explained below. A detailed coverage of the Discrete wavelet transform and theory of multi resolution analysis can be found in a number of articles and books that are available on this topic, and it is beyond the scope of this tutorial.

4.2 –D Discrete wavelet construction

The DWT of image f(x, y) can be defined as:

$$f(x,y) = A_n^q f(x,y)$$

$$+ \sum_{s=1}^{n} [D_{s,1}^q f(x,y) + D_{s,2}^q f(x,y) + D_{s,3}^q f(x,y)]$$

Where A and D coefficients and are approximation and difference directional components respectively, which also be called as the low frequency sub bands and high frequency sub bands of image. The analytic extension is constructed by real wavelet and its 2-D Hilbert transform: After image is decomposed by DWT, we can obtain a low frequency part and n groups of high frequency parts. The DWT decomposition structure of image is shown in Fig. 1. "Low" represents the low frequency part which composed by four low frequency sub bands, that is, band 1 to band 4. At each level, the high frequency information is presented in 3 directions (horizontal (H), vertical (V) and diagonal (D)), and there are four sub bands (band 1, band 2, band 3, band 4) in each direction. These four sub bands can be transformed into one magnitude and three phases.

4.3 The Sub band Coding and The Multi resolution Analysis

The main idea is the same as it is in the DWT. A time-scale representation of a digital image is obtained using digital filtering techniques. Recall that the DWT is a correlation between a wavelet at different scales and the image with the scale (or the frequency) being used as a measure of similarity. The continuous wavelet transform was computed by changing the scale of the analysis window, shifting the window in time, multiplying by the image, and integrating over all times. In the discrete case, filters of different cut off frequencies are used to analyze the image at different scales. The image is passed through a series of high pass filters to analyze the high frequencies, and it is passed through a series of low pass filters to analyze the low frequencies.

The resolution of the image, which is a measure of the amount of detail information in the image, is changed by the filtering operations, and the scale is changed by up sampling and down sampling (sub sampling) operations. Sub sampling a image corresponds to reducing the sampling rate, or removing some of the samples of the image. For example, sub sampling by two refers to dropping every other sample of the image. Sub sampling by a factor *n* reduces the number of samples in the image *n* times.

Up sampling a image corresponds to increasing the sampling rate of a image by adding new samples to the image. For example, up sampling by two refers to adding a new sample, usually a zero or an interpolated value, between every two samples of the image. Up sampling a image by a factor of *n* increases the number of samples in the image by a factor of *n*.

Although it is not the only possible choice, DWT coefficients are usually sampled from the CWT on a dyadic grid, i.e., $s_0 = 2$ and $\tau_0 = 1$, yielding $s=2^j$ and $\tau = k*2^j$, as described in Part 3. Since the image is a discrete time function, the terms function and sequence will be used interchangeably in the following discussion. This sequence will be denoted by x[n], where n is an integer.

The procedure starts with passing this image (sequence) through a half band digital low pass filter with impulse response h[n]. Filtering a image corresponds to the mathematical operation of convolution of the image with the impulse response of the filter. The convolution operation in discrete time is defined as follows:

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k]$$

A half band low pass filter removes all frequencies that are above half of the highest frequency in the image. For example, if a image has a maximum of 1000 Hz component, then half band low pass filtering removes all the frequencies above 500 Hz.

The scale of the image is now doubled. Note that the low pass filtering removes the high frequency information, but leaves the scale unchanged. Only the sub sampling process changes the scale. Resolution, on the other hand, is related to the amount of information in the image, and therefore, it is affected by the filtering operations. Half band low pass filtering removes half of the frequencies, which can be interpreted as losing half of the information. Therefore, the resolution is halved after the filtering operation. Note, however, the sub sampling operation after filtering does not affect the resolution, since removing half of the spectral components from the image makes half the number of samples redundant anyway. Half the samples can be discarded without any loss of information. In summary, the low pass filtering halves the resolution, but leaves the scale unchanged. The image is then sub sampled by 2 since half of the number of samples are redundant. This doubles the scale.

This procedure can mathematically be expressed as

$$y[n] = \sum_{k=-\infty}^{\infty} h[k] \cdot x[2n-k]$$

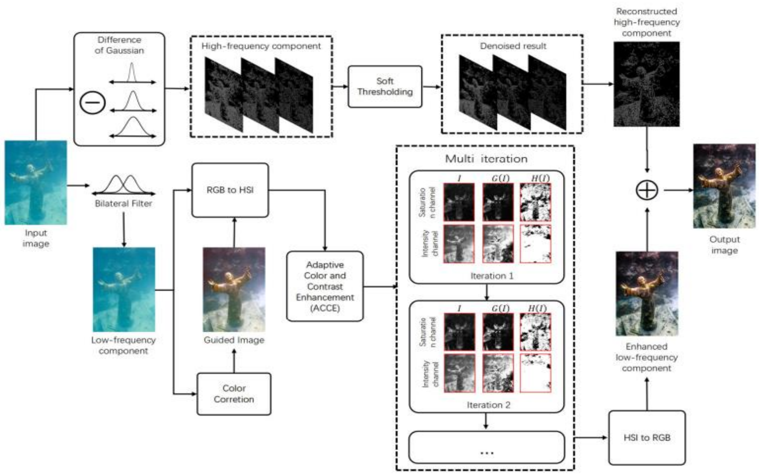

FIG: The framework of the proposed method.

The pipeline of our proposed underwater single image enhancement method is illustrated in Fig. 2. The degraded underwater image I_T suffers from haze and color distortion. We aim to recover a sharp image □ˆJ^, which looks like the image as clear as the one captured in the air. The proposed enhancement algorithm consists of four major steps:

(1) Background light estimation: the severely degraded image is divided into four sub-regions and the corresponding sub-region scores are calculated and compared. The process is carried out in an iterative manner till the sub-region with the best score is less than a predefined threshold, and then the final sub-region patch is reserved;

(2) Color recognition: by referring to the RGB color cross-reference table, our color recognition model is able to determine whether the image patch is blue or green tone;

(3) Adaptive color compensation: once the image background hue is determined, adaptive color compensation is applied to the degraded underwater image to remove the blue-green tones;

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V. RESULTS

Experimental Flow

We can institute the experimental flow correspond the fusion algorithm designed in this paper, the corresponding flow shown in Figure 4:

The whole experiment is divided into three parts: the first step is pre-process the remote sensing images, including the band combinations, registration, etc.; followed by is image fusion of remote sensing, create high-quality map sources; last get the road layers by road extraction.

VI. CONCLUSION

In this paper, a novel image fusion method Using DWT and multiple features is proposed. Compared to traditional MSD tools, the DWT can provide abundant magnitude and phase information, which meet approximate translation invariance and limited redundancy. Different from the traditional fusion methods using a single feature as the activity level measure, we combine the magnitude, phase and spatial variance of low frequency coefficient into a comprehensive feature as the activity level measure of low frequency coefficient and combine the contrast and energy of high frequency coefficient into the other comprehensive feature as the activity level measure of high frequency coefficient. These two multi-features are reliable and robust, which are available for image fusion. Finally, the experimental results demonstrate the proposed method is effective in all kinds of image fusion.

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