Score Level Fusion Based Approach for Water Leak Detection in Infrared Images

Dr. Ashwath Rao¹, Mr. S.N. Bharath Bhushan¹
¹² Sahyadri College of Engineering and Management, Mangalore, Karnataka, India

Abstract: Identification of water region plays an important role in many of the industrial and agricultural applications. Detection of water and non-water region will be tedious if manual methods are adapted. To tackle this, this article presents a detailed image processing based method to detect water and non-water region using infrared Tau 2 640 camera. An algorithm is developed to identify the water and non-water regions in a remote area using Tau 2 640 camera mounted quad copter. A series of experiments is carried to detect the water regions. Results of the experiments present the effectiveness of the proposed algorithm.

Keywords: water regions, infrared, water detection, Tau 2 640

I. INTRODUCTION

With the development of technology for infrared (IR) sensors in last decades, many image processing applications based on IR images has emerged. IR image is generated by detecting radiation in the long-wave electromagnetic spectrum. The intensity value of a pixel in an IR image represents the emitted IR radiation intensity i.e., the temperature of an object. IR images can provide all weather information, which is not observed by the human with naked eye. Therefore, IR images are widely used in surveillance, industry, military and other fields. Infrared thermography is used in various fields, from clinical diagnostics to industrial preventive and in agriculture also in predictive evaluation[2-4]. In these cases, it is important to reveal oddities and irregularities in the distribution of the analyzed bodies' temperature as these are indicators of anomalous, and therefore undesired situations. For example, areas of higher temperature than the standard conditions may identify infections or muscle injuries in the medical field, or damaged isolators and overheated joint, signs of incipient failure, in the industrial field, or high temperature in the regions are the sign of absence of water level in that particular area. This research article is focuses towards developing algorithms for identifying water resources using Tau2 640 Flir infrared camera. Water is an essential element without which any living species goes extinct. This research work mainly focuses on providing an invention which helps in detecting/identifying the underground water resource present which can be mapped and tapped to the reservoir. This saved water can be fed to the people during summer season or to the farmers for the agriculture purpose during drought period. The quad copter technology thus used will cover the maximum area autonomously whereas yielding a real-time detection of the water bodies using the infra-Red cameras and the image classification algorithms.

II. LITERATURE SURVEY

This section presents some of the state of the art feature extraction techniques with relevant applications for infrared object recognition. Since this article focuses on the object recognition in the infrared images, our study is restricted to feature extraction of conventional object recognition approaches and few works on infrared images. The main aim of object recognition is to locate and identify instances of an object from the infrared images captured from Tau2 640 Flir camera with the help of features extracted from the images. In literature most of the works on feature extraction techniques are classified into two categories like edge-based type and patch based feature types. From the survey it is clear that some approaches use combination of edge-based type and patch based feature type [5-9].

A. Edge Based Approaches

This method uses the edge map of the image and identifies the objects in the image in terms of edges [5, 6, 10-11]. Considering edges as features is advantageous because of many reasons, as they are largely invariant to illumination conditions and variations in objects' colors and textures. They also represent boundaries of the object well and represent the data efficiently in the large spatial extent of the images [10]. The main two deviations in these techniques are: use of the complete contour (shape) of the object as the feature [12-17] and use of collection of contour fragments as the feature of the object [5, 6, 11, 18-24]. Hamsici [12] the whole shape of the contour of the edges to get a foothold in the recognition of a set of points of contact between them. Schindler [16] considered the super-pixels, such as segmentation based approaches. They are considered to be close to the contours of the surrounding areas from the very
beginning to get the contours of the closure. Ferrari[21] at the edges of the object detection offers the best of contemporary methods used in the most advanced edge detection method. After the closure of the contours of the edges to form a network connected across the small gap between them. [19] Ren is significantly more difficult because of the presence of background information in the natural images; the contours of the objects are used to complete a triangulation. All of these techniques require additional computation intensive treatment and are often sensitive to the choice of a variety of practical outlining parameters of note. The other problem with such a feature for testing and validation of images, is available to match the contours of even an incomplete image and therefore the entire contour of the degree is generally low [15].

B. Patch Based Approaches

The patch based feature extraction approach has been in use since more than two decades [25], and edge-based features are relatively new in comparison patch based technique. Moravec [25] considered local maxima of minimum intensity gradients, he called it as corners and selected a patch around these corners. This work is enhanced by Harris [26], which made the new detector less sensitive to noise, edges, and anisotropic nature of the corners proposed in [25]. In its regular form, such as the features of the object templates [27] in order to use the same size of a rectangular or square in local areas. Such features are effective for multi-scaling (the appearance of a variety of material). The following may not be suitable due to the size of the fixed patch. The size of the patch is small; it is big but may not cover the most important local feature. Such a feature is a short list of information may be lost. The size of the patch is large on the other hand, it may not be present simultaneously with other images or more than one separate covers. Another shortcoming of many small rectangular patches needs to be overcome in order to assess the attributes and the material. Both of these are computationally expensive and memory intensive. The images have a variety of features such as robustness, use of smaller or larger features, better and faster learning capabilities, and requiring less storage [28].

III. PROPOSED MODEL

The paragraph of the article presents the different steps involved in the proposed model. The first step in the proposed model consists of enhancing the infrared images. The main aim of enhancing the infrared images are, different with visible images captured IR camera, IR images are typically low contrast, contains blurred edges and lot of noise in it. One of the main reasons for low-contrast and blurred edges is that generally foreground and background have similar temperature. Low contrast and blurred edges will generate low quality infrared images. Also, the read out sensors of the IR cameras with low signal to noise ratio will generate low signal and high noise. This noise will further degrade the quality of the IR image. Analyzing such low quality images is a challenging task. It is desirable to adopt an effective IR image enhancement technique to generate an IR image with high contrast, clear details and less noise. To enhance an IR image, two problems need to be addressed. The first one is to enhance both global and local contrast of an image. Next problem is to suppress the noise in the IR image. Though there are few techniques like contrast adjustment based methods and multi scale decomposition based methods, they will only improve the contrast of the IR image but they will not eliminate the noise present in the image. But in this paper we present a new IR image enhancement technique, which will not only improves the global and local contrast of the IR image but also suppress the noise in the IR image. Generally, infrared image is composed of low frequency component and a sequence of high frequency components with multi-scale edge preserving filter. Then different strategies are proposed to deal with the LF and HF components.

A. Image Enhancement

In this section we briefly introduce an edge preserving smoothing filter, i.e., weighted least squares (WLS) filter. The filter can smoothes the image at the same time preserving the main edges. The WLS filter has been used in various image processing applications. The filter can make a good compromise between the blurring and the sharpening when compared with other filters. The WLS filter tries to seek an output image $I$ that is a smooth version of original image $S$ and is as similar as possible to original image $S$. The filtering image $I$ can be defined as:

$$I = \arg \min \left\{ ||I - S||^2 + \lambda (a_x ||D_x I||^2 + a_y ||D_y I||^2) \right\}$$

(1)

The data term $||I - S||^2$ is for generating output image as similar as possible to original image $S$, while the rest term i.e., the regularization term tries to generate a smooth version of the original image by minimizing the partial derivatives of the output image. The $a_x$ and $a_y$ are roughly equal $a_x = a_y = a$ and they give a degree of control over the affinities by non-linear scaling the gradients. $\lambda$ is the regularization parameter, which is for the balance between the two terms. If we increase the value of $\lambda$, we would obtain a smoother image $I$. According to eq (1), one can obtain the filtering image $I$.

$$I = G_\lambda(S) = (E + \lambda H)^{-1} S$$

(2)
Where \( E \) is identity matrix and \( H = D^T \alpha_{x} D_{x} + D^T \alpha_{y} D_{y} \)

### B. Proposed Image Enhancement System

The proposed framework is shown in Figure 1. This framework involves three main steps, which consist of image decomposition, component enhancement and image construction. Image decomposition step is to decompose the original image into a LF component and a sequence of HF components. Each component is enhanced according to its characteristic in component enhancement step. Finally, the enhancement IR image is constructed with the enhanced LF component and a sequence of HF components in image construction step.

1) **Image Decomposition**: Different components of an image have different characteristics. Making full use of the characteristics of the image components can effectively enhance the IR image. In this paper, we used the WLS filter to decompose the original IR image into the LF and HF components. As mentioned in previous section, a larger \( \lambda \) would result in a smoother filtering image when applying WLS filter. Thus, we can obtain a sequence of progressively smooth images by progressively creasing the parameter \( \lambda \). We can calculate the HF components from the differences of two smooth images. Finally, the IR image is decomposed into a LF component and a sequence of HF components. Specifically, for an original IR image \( S \), we can obtain \( C \) filtering images \( I_{i} \), \( i = 1, 2, ... , C \) with \( C \) different parameters \( \lambda_{i} \), \( i = 1, 2, ... , C \).

\[
I_{i} = G\lambda_{i}(S)
\]

where \( \lambda_{i+1} + 1 > \lambda_{i} \). The sequence of HF components i.e., detail images \( D_{i} \) are calculated as:

\[
D_{i} = I_{i} - I_{i+1}
\]

Herein, HF components actually are the differences of two filtering images. The smoothest filtering image \( I_{C} \) will be considered as the LF component of the original image. Figure 2 gives the framework of image decomposition using WLS filter.

2) **Component Processing**: In this part, we will introduce the procedure of processing LF and HF components. Firstly, non local means method is applied to the HF components to eliminate the noise. Then, a method based on local standard deviation is adopted to improve the local contrast of IR image. Finally, Plateau histogram equalization is employed to the LF component to enhance the global contrast. The schematic of component processing is illustrated in Figure 3.

3) **Non-Local means filter for HF components**: Non-local means, which was proposed by Buades [22], is a powerful tool for image denoising. Many applications use non local redundancy to suppress noise, eliminate artifacts in image processing. Different with conversional "local mean" filters(such as median-based filter, Gaussian smoothing filter and the neighborhood filters), which calculate the weighted mean value of a region( or patch) as output, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are, to the target pixel [22]. As a result, it can better keep the edge while eliminate noise. IR image contains a lot of noise due to the limitation of IR cameras. The LF component represents the general profile of the IR image, while the HF components are accompanied by strong noise, since noise would be considered as detail information in the decomposition process. In order to suppress noise and preserve the edges, nonlocal means filter rather than median-based filter is employed.

4) **Local Contrast Enhancement for HF components**: The high-frequency components represent the details of the IR image. The local contrast of IR image depends on the local standard deviation of the HF components at a local region. A region with high local standard deviation is with more details and vice versa. To improve the local contrast, we adopt a strategy, in which the detail gain is proportional to the local standard deviation. Each pixel in the enhanced HF component is calculated by:

\[
D_{i}(i,j) = \mu (i,j) + \delta (i,j) \times (D_{i}(i,j) - \mu (i,j))
\]

where \( \mu (i,j) \) and \( \delta (i,j) \) is the mean value and standard deviation of the intensity of a patch centered at \( (i,j) \) respectively.

5) **Image Reconstruction**: After we obtain the enhanced LF and HF components, the resultant image can be generated by integrating those enhanced components. Figure 4 shows the schematic of image construction. Once the image acquisition stage is completed, the input images are subjected for \( k \) means clustering by fixing the \( k \) value to 2. Since the main objective of the proposed model to find the water and non water region, \( k \) (different number of clusters) is fixed to 2. The features are extracted in order to differentiate between water and non water region. Classification of regions is based on set of features that are extracted the captured images.

\[
\text{Variance} = \frac{1}{mn-1} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (I(x,y) - \text{Mean})^2
\]

\[
\text{Mean} = \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} I(x,y)
\]
Standarddeviation = \sqrt{Variance} \quad (7)

Where \( m \) = number of rows and \( n \) = number of columns in the image.

Also with the above mentioned features like variance, mean and standard deviation, we have defined pixel intensity features like Horizontal features and Vertical features. MeanHorz is calculated as the average intensity of each row in the image.

\[
Variance_{Horz} = \frac{1}{m-1} \sum_{x=0}^{m-1} (Mean_{Horz} I - Mean) \quad (8)
\]

\[
Mean_{Horz} = \frac{1}{m} \sum_{x=0}^{m-1} Mean_{Horz} I \quad (9)
\]

\[
Standarddeviation_{Horz} = \sqrt{Variance_{Horz}^2} \quad (10)
\]

MeanVart is calculated as the average intensity of each row in the image.

\[
Variance_{Vart} = \frac{1}{n-1} \sum_{x=0}^{n-1} (Mean_{Vart} I - Mean) \quad (11)
\]

\[
Mean_{Vart} = \frac{1}{n} \sum_{x=0}^{n-1} Mean_{Vart} I \quad (12)
\]

Above mentioned features are extracted and a knowledge base is developed for the identification of water and non-water region. Once the construction of the knowledge base is completed, knearest neighbor classifier will be trained with the extracted features. All the different stages in the proposed model are diagrammatically shown in the following diagram fig. 3.

**Figure 3:** Block Diagram of the proposed model
IV. EXPERIMENTAL SETUP

This section describes the details of the experiments conducted to demonstrate the working of the proposed algorithm. We have conducted a series of experiment to demonstrate the effective of the proposed approach. The proposed algorithm is implemented in MATLAB 2012a. The sample of the captured image and processed output image is as shown in the following figure. To evaluate any algorithm, datasets are required to examine the efficiency of the proposed algorithm. In the proposed model, image acquisition process is carried out with the help of Tau 2 640 flir camera. Dataset is composed of around 500 different set of images and images are captured in different time intervals to identify the wetness in the ground. Following are the few dataset samples, taken in different time intervals.

![Sample images](image)

Figure 4: Few dataset samples, taken in different time intervals

Once the dataset is developed, the proposed algorithm is evaluated is two different sets of experiments by dividing the dataset in the ratio of 60% for training 40% for testing and vice versa. Details of the experiments are as shown in the following table. In the above mentioned issue, the proposed algorithm is tuned to detect the presence of water and non-water region. At the outset this problem looks like two class problem, which can be reduced to single class problem like whether the water contents are there are not in the given region. Which means the running time of the algorithm will be reduced from n to n/2 where n = complexity of the algorithm. To evaluate the proposed algorithm, the well-known metrics like precision, recall and f-measure are applied on the proposed algorithm. The details of these metrics are presented in the following diagram.

<table>
<thead>
<tr>
<th>Sl No.</th>
<th>Dataset</th>
<th>Precision</th>
<th>Recall</th>
<th>f-measure</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Tau 2 640 Flir Camera</td>
<td>1</td>
<td>0.875</td>
<td>0.9333</td>
</tr>
</tbody>
</table>

V. CONCLUSION

Currently machine learning is used in many applications which including computer vision [29-34], bioinformatics [35-41], brain-machine interfaces [42-47], medical diagnosis [48-53], natural language processing [54-59], recommender systems [60-64], sentiment analysis [65-68], software engineering [69-73], structural health monitoring [74-76], syntactic pattern recognition [77-82]. In this article, a method of identification of water and non-region using Flir Tau 2 640 infrared camera is presented in this paper. The proposed algorithm consists of image processing technique for identification of process. A detailed experiment is conducted to demonstrate the efficiency of Flir Tau 2 640 infrared camera. Results of the experiments reveals that Flir Tau 2 640 infrared camera can be used for detection of water and non-water regions in the ground.

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