FLOOD AND DROUGHT ASSESSMENT USING SUPPORT VECTOR MACHINE

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Abstract

The satellite image is preprocessed.The morphological method is used to segment the images. The mathematical morphology operations are employed to generate simulated droughts and floods of water bodies. Here, SVM Classifier is used to find the image type. Support Vector Machine (SVM) is utilized to identify levels of droughting and flooding in the input image.

In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbors in the input image. The rule used to process the pixels defines the operation as dilation or erosion.The image is then, tested with the SVM for water region identification of the river stage.

***Key words :** Image Processing, Support Vector Machine (SVM), and Morphological operation.*

I. Introduction

Droughts and floods are two major natural disasters which affect a wide range of environmental factors and activities related to agriculture, vegetation, human and wild life and local economies [7]. These two natural disasters are unavoidable, but it can provide an early warning and contribute to recovery and rebuilding efforts.

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Changes in river water levels govern a wide range of hydrologic, geomorphological and ecological processes [5] [6]. Measurements of water levels in the main channels of rivers, upland tributaries and floodplain lakes are necessary for understanding flooding hazards, methane production, sediment transport and nutrient exchange [1].In some cases, it is impractical to obtain accurate and consistent images.

Remote sensing techniques are widely used to collect information on the qualitative and quantitative status of natural resources in protracted areas [2] [18].

As a result, remote sensing of rivers, wetlands, and lakes is recognized as an additional useful source of water resource information [16].

Three possible approaches to estimating river discharge from satellite-based data can be summarized as follows:

- With the help of a hydraulic equation, or rating equation, estimate river discharge from the measurement of hydraulic variables from satellite and/or other remotely obtained information.
- Measure water level variation by using radar altimeter data or the interferometry radar technique and then convert it to river discharge on the basis of a rating curve between satellite-derived "water level" and ground-measured discharge.

- Correlate satellite-derived water surface areas with ground measurements of discharge, and then infer river discharge from satellite data on the basis of the water area–discharge rating curve [21].

Remote sensing techniques make it possible to obtain and distribute information rapidly over large areas by means of sensors operating in several spectral bands, mounted on aircraft or satellites. Remote sensing techniques are widely used to collect information on the qualitative and quantitative status of natural resources in protracted areas. Multispectral imagery has been used as the data source for water and land observational remote sensing from airborne and satellitesystems. [19].

In this paper, characterization of the influence zones of simulated droughts and floods of water bodies in a flood plain is performed. Drought and flood simulations are implemented by performing morphological erosion and dilation. Erosion and dilation are the basic morphological processing operations. Dilation enlarges the size of the particles by connecting neighbor particles and erosion removes isolated particles and small particles, shrinks other particles, discards peaks on the boundaries of objects and disconnects some particles.

In the testing phase, image is tested with the SVM for water region identification of the river stage and SVM is also utilized for the identification of the river stage. Support vectors are the data points that lie closest to the decision surface, i.e. on the margin.

II. Existing Method

A handful of researches are available and they are reviewed below.

Kalaivani et al. [16] have analyzed to determine the stage of water level. Three phases involved in this work were the training phase, analysis phase and the testing phase. In the training phase, two ANNs were trained. One network was for the identification of water regions and the other was for analyzing the status of the river. In the testing process, the input raw river image was denoised and morphological operation was carried out on the denoised image. Then, the river image was segmented into water regions with the aid of the ANN. Finally in the analysis phase, the stage of the river water was identified whether the river was in draught, normal or flood stage.

Hostache et al. [13] have provided distributed water levels from SAR images. Furthermore, in view of improving numerical flood prediction, a variational data assimilation method (4D-var) using such distributed water level has been developed. This method combined an optimal sense remote sensing data (distributed water levels extracted from spatial images) and a 2D shallow water model. They also derive water levels with a ±40 cm average vertical uncertainty from RADARSAT-1 image of a Mosel River flood event.

Shah et al. [14] have presented the methods like edge detection, thresholding, image erosion and other color and feature extraction algorithms to extract water content (river). The algorithms used here includes, K means clustering algorithm, Hill Climbing Algorithm, Color histogram and image thresholding. Here, the condition of river like normal, drought or flood is also predicted by visual inspection of the processed satellite image.

Powell et al.[15] have demonstrated an approach for mapping salt cedar along 50-km of the Bighorn River in

Montana using ASTER (Advanced Space borne Thermal Emission and Reflectance Radiometer) imagery and a Random Forests classification tree modeling approach. They modeled the continuous probability of salt cedar presence and evaluated optimal threshold levels in terms of omission and commission error. Reasonable classification accuracy was achieved for some management purposes.

Goswami [11] has discussed the Majuli Island has lost a considerable part of its total geographical area due to severe erosion caused by the Brahmaputra River and its tributaries. The island has also been witnessing gradual morphological changes, particularly, after the devastating Assam earthquake of 1950.

Seng Mah et al. [8] have discussed the hydraulic models that was successfully identified the weaknesses and areas for improvement with respect to flooding in the Sarawak River system, and can also be used to support decisions on flood management measures. They have demonstrated a theoretical flood management framework inferred from Sarawak River modeling outputs.

Rawat et al. [12] have analyzed the morphometric parameters of third order sub basins (TOSBs) special reference to natural hazard vulnerability assessment through integrated GIS database modeling on geo-informatics and morphometry-informatics modules. The Dabka River Basin (DRB) constitutes a part of the Kosi Basin in the Lesser Himalaya, India in district Nainital has been selected for the case illustration.

Adediji et al. [17] have investigated the assessment of the dynamics of major dams (Ede-Erinle and Eko-Ende reservoirs) in Osun State, Nigeria using Landsat-TM (1986) and Landsat-ETM+ (2002). The images have been processed, interpreted and classified using ILWIS 3.3 software. The results have shown a sharp decline in the surface area of the study reservoirs from 1986 to 2002 as indicated by the percent of reductions 37.49% and 45.42% for Ede-Erinle and Eko-Ende, respectively. In the light of the above, to prolong the lifespan of the study dams, necessity of carrying out the evacuation of the hydrophytes which had colonized the edges of the study reservoirs/dam has been identified. Also, to ascertain the current volume of water in the dams, bathymetric survey of the impounded reservoirs has been suggested.

ANNs have proven good classifiers but they require large number of samples for training, which is not always true in practice [2]. Support vector machines are based on statistical learning theory and they specialize for a smaller sample number. SVMs have better generalization than ANNs and guarantee the local and global optimal solution similar to that obtained by ANN[3]. In the recent years, SVMs have been found to be remarkably effective in many real world applications [4].

III. Proposed Method

In previous works [16] and [20], Back Propagation Network (BPN)and Radial Basis Feed Forward Network (RBFNN)used to identifythe stage of the river.In this work, Support Vector Machine [9] is usedand the proposed mechanism is detailed below.

The satellite image is used as input. Input image is obtained from the database and is preprocessed.

```
[File path]=uigetfile('*.bmp;*.jpg');

img=imread([path file]);
```

The above code is to read image from the database. Figure-1 shows the original satellite image.

Figure 1 : Original Image

A. Gaussian Filter

A Gaussian filter smoothes image by calculating weighted averages in a filter box. Gaussian filter modifies the input signal by convolution with a Gaussian function.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}}$$

Initially, the image is applied with filter in order to remove noise for the betterment of image.

```
h = fspecial('gaussian', [3 3], 0.5);

img = imfilter(img,h);
```

Above coding is applied to filter and remove noise of the image.

B. Lab Color Space Conversion

When noise is removed from the image, then the image is converted to LAB color space. The conversion of all the image pixels in same color space helps to obtain proper output and also to obtain keen information.The following set of code show the conversion of RGB color image into CIE Lab color space.

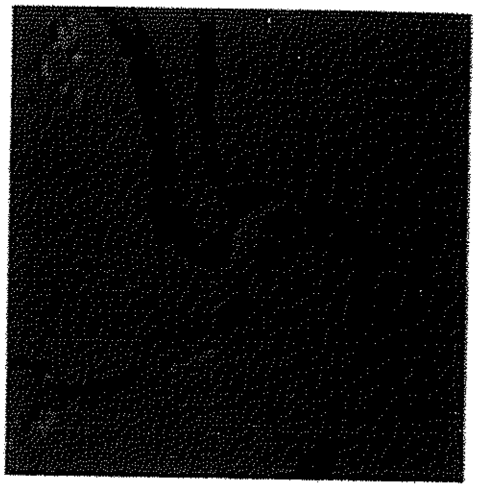

Figure 2 : LabColorSpace Image

```
cform = makecform('srgb2lab');

lab = applycform(img,cform);
```

Fig-2 shows that original image is converted into CIE LAB color space image to make all image pixels in same color space to obtain proper output.

The CIELAB color space image is used for process. The LAB color spaced image is applied with diffusion segmentation.Thefollowing set of equationsshow the formulas for the conversion of RGB color image into CIE Lab color space.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} X_r & X_g & X_b \\ Y_r & Y_g & Y_b \\ Z_r & Z_g & Z_b \end{bmatrix} * \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

C. Segmentation

Segmentation is used to distinguish objects from the background. The segmentation is based on measurements taken from the image and it may be grey level, color, texture, depth or motion. Here, non-linear diffusion segmentation mechanism is used. Anisotropic diffusion segmentation is used to obtain information of regions clearly, which incorporates both physical processes of diffusion and Laplacian.

D. Binarization

In this binarization process, the converted LAB color spaced image is given as input. Input image is converted into binary form.

The formula used to convert binarized image is

$$Im_{gray} = \frac{(L+a+b)Im_{seg}}{3}$$

Below shown the coding used to convert into binary image and result is shown as Fig-3.

```
bw1 = im2bw(SegImg);
```

Figure 3 : Binary Image

E. Thresholding to remove thesurplus regions

The remote sensing images capture the river area as well as land area. The thresholding operation eliminates land area as well as the small watered regions from the surplus region. Hence, the watered area is identified.

F. Smoothing of image through morphological operation

Morphological operation is utilized to extract and smoothes the image for obtaining clear view and structure of the image. Morphological operation is also used to identify the boundaries of the outcoming image.

A closing operation is used to enlarge the boundaries of foreground regions in the image and shrink background holes in such regions. The closing operation is expressed as:

$$Im_{br} \cdot st = (Im_{br} \oplus st) \ominus st$$

Figure 4 : Morphological Image

For this process, the imclose operation is used to close the image and here se is the structuring element and disc structure is used.

```
se = strel('disk',1);

imclosebw = imclose(bw,se);

figure,imshow(imclosebw);title('MorpologicalImage')
```

Fig-4 depicts the morphological operation applied to the binary image to smooth the image.

G. Suppression :

The elimination of surplus and residual watered regions from the output image is performed.The watered regions marked within the output image to identify the stage of the river shown in Fig-5.

Figure 5 : Final Segmented Image

IV. SVM CLASSFICATION

Support Vector Machine (SVM) Classifier is utilized for identifying the stage of the river. The Support Vector Machine (SVM) is a state-of-the-art classification method introduced in 1992 by Boser, Guyon, and Vapnik[10]. SVMs related to the generalized linear classifier's family. SVMs are also regarded as a special case of Tikhonov regularization. A peculiar property is that they have diminished the empirical classification error and increase the geometric

margin at the same time. Therefore, they are termed as maximum margin classifiers [4]. Support vectors are the data points that lie closest to the decision surface, i.e. on the margin.

The preprocessed image is classified using SVM Classifier, in order to identify the stage of the river. The training set and length of the watered region are the measuring elements here. Finally, the stage of the river water was identified using length of the watered regions as shown in Fig-6.

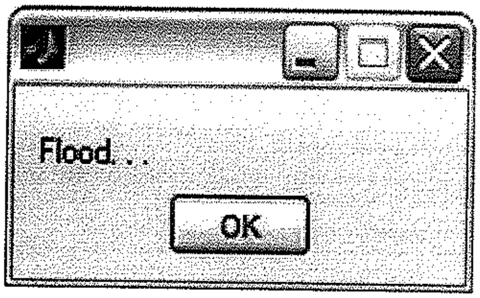

Figure 6 : Stage of Original River Image

V. RESULTS AND DISCUSSIONS

A. Comparison of classification performance between the SVM model, BPN model and RBFNN model

Table 1 shows the comparison of the performance of back propagation, radial basis function neural networks and support vector machine. It is clearly seen SVM has better accuracy when compared with the back propagation neural network and radial basis function neural networks.SVM gives higher accuracy and lower error rates.

Table 1 : Comparison of RBFNN, BPN and SVM

Method	TP	PP	FP	NP	Sensitivity	Accuracy	Specificity
SVM	100	100	0	100	100	100	100
BPN	100	92	7.41	100	100	96	92.5
RBF	100	100	0	100	100	97.5	98.5

TP-True Positive Rate

FP-False PositiveRate (1- Specificity)

PP-Positive Predictive Value

FP-Negative Predictive Value

B. Performance parameters calculated for SVM

The various parameters that are calculated and compared include true positive, true negative for all three stages drought, flood and normal, sensitivity, specificity, accuracy, false positive rate, positive predictive value, negative predictive value, false discovery rate and Mathew's correlation coefficient [16].Table-2shows theperformance parameters that are calculated for SVM.

Table 2 : Performance parameters calculated for SVM

Stage of river	TP	TN	FP	FN	Sensitivity	Accuracy	Specificity
Normal	2	4	0	0	100	100	100
Draught	2	3	1	0	100	83.33	75
Flood	1	4	0	1	50	83.33	100

VI. Conclusion

The input image was preprocessed. The above mentioned operations are applied to remove noise in the image. Then, the output image was segmented into water regions using SVM classifier. Finally, the stage of the river water was identified whether the river was indraught, normal or flood stage. The proposed methodology was evaluated with different river images obtained from websites.

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Author's Biography

Ms. V. Sudha, was born in Coimbatore on 31.05.1988. V. Sudha have completed M.Sc Software Systems in Kovai Kalaimagal College of Arts and Science in Bharathiar University Coimbatore,Tamil -Nadu on 2010 and M.Phil in Sri Krishna College of Arts and Science in Bharathiar University Coimbatore, TamilNadu on 2013.

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