SNOW COVER MONITORING USING IMAGES

Manjulavani. M, Jubin Mithra. B. K, Keerthika. D, Kanimozhi. S and Asst.Prof.MRS.Thirilogasundari. V
Department of ECE,
Valliammai Engineering college, SRM Nagar, Kattangulathur, Tamil Nadu, India

***Abstract*— Snow cover extension is one of the most important parameters for analyzing weather changes, availability of water resources and also providing guidelines for tourists. In this project, we study the problem of estimating snow cover in mountainous regions from user generated and outdoor webcam photographs. In the existing system, the SVM Classifier is used to estimate the only finite number of samples.**

In proposed system, Naive Bayes Classifier is used to identify mountain peaks, filtering out images taken in bad weather conditions, and handling varying illumination conditions using morphological processing, boundary detection and SIFT features. Images collected at regular intervals are used as input to observe the snow covered areas and human intrusion are monitored at the base station. The collected information's are forwarded to the monitoring headquarters through IOT. We created a manually labeled data set to assess the accuracy of the image snow covered area estimation, achieving 95% precision.

***Keywords*— IOT modem, Microcontroller, Morphological processing, PIR sensor, SIFT features.**

Introduction

Environmental monitoring requires avoiding the undesirable problems in the surrounding. The use of snow cover monitoring in mountain regions helps to identify weather changes and snow sliding hazards. This information is collected, by processing the snow covered mountain images available in online and surveillance camera. The images are processed by naive Bayes classification. It is easy to identify the snow covered area by human eyes. But it is complex when computing in the system based. In this paper, we are rectifying the complexity of identifying the snow covered area. We focus on monitoring peak, snow cover and human detection in the mountainous regions.

The objective of this paper is not to replace the existing process. Conversely, we argue that it is an additional method to identify these parameters and provide information for researchers and analysers. We are not using the satellite and remote sensing images, because Of the dense clouds, making the clear pictures of the mountain images is not possible. It gives the clear images in dynamic times, not in a regular manner. So we are taking images using the webcam. While capturing the images using satellite, it will not be helpful for the mountain climbers to detect the mountain peak from ground.

The main contribution of this paper is to provide detailed information about the snow cover in the mountainous us region and also used for military related applications.

I .Description of existing system –

To estimate the snow cover, first, they used SVM Classifier algorithm in the mat lab processing. There are 2 types of SVM classifier such as linear and non-linear SVM classifier. In the linear SVM classifier Hyperplane techniques is used to separate the image pixels. But in non –linear SVM classifier kernel functions are used to process the image pixels. There are 3 basic types of kernel functions namely Polynomial kernel functions, Non –polynomial kernel functions, Basic radial functions. But the main drawback of SVM classifier is that it only process the finite number of samples. We can't able to identify the type of kernel function used for some application. But this problem can be overcome by using Naive Bayes classifier algorithm.

II. PROPOSED SYSTEM-

In proposed system, we are using Naive Bayes classification for processing the image. Naive Bayes classifiers are based on applying Bayes' theorem with strong (naive) independence assumptions between the features. Naive Bayes is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set.

All naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. We prefer this system because naive bayes is easy to write and this classifier model is faster than SVM. The model can be modified with new training data without having to rebuild the model. Naive Bayes is fast because all it needs are the prior probability values that can be stored ahead of time, the same probability values are reused while calculating the posterior probability. The Naïve Bayes equation is,

$$P(c|X)=P(X|c)P(c)/P(X)$$

Where **P(c|X)** **->** posterior probability
P(X|c) **->**likelihood function
P(X) **->** predictor prior probability

$$P(c|X)=P(X1|c)\, P(X2|c)\ldots\ldots P(Xn|c)\, P(c)$$

session	high
Morning	yes
Afternoon	no
Night	yes
Evening	yes
Afternoon	yes
Morning	no
Night	yes
Evening	yes

Frequency Table		
Session	No	Yes
Morning	1	1
Afternoon	1	1
Evening	0	2
Night	0	2
Grand Total	2	6

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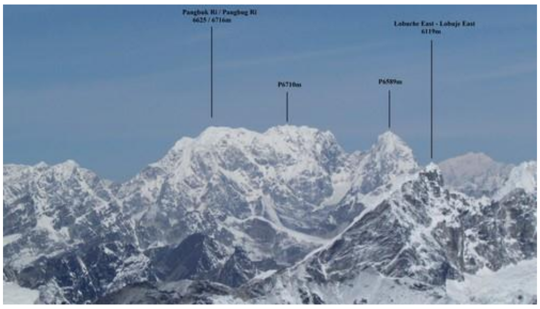
A. MOUNTAIN PEAK DETECTION

First, Mountain peak is detected by using photo-to-terrain alignment. This method was addressed by baboudet. But this method can't be used for large data set. Only 28 photographs can be used to detect the mountain peak.

Baatz approached a new technique to estimate the geographical position by using geo-tags. But using geo- tags was not effective. So the peak is detected using content-based- analysis.

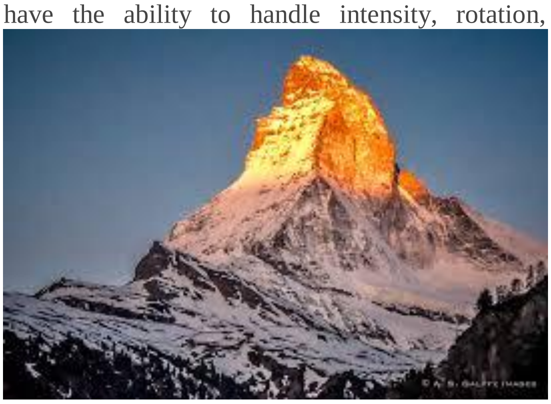
Later, Liu and Su used a new technique called as sky –to-terrain segmentation. In this segmentation, 2 images are considered which is having the same peak and the images are segmented in terms of skyline. But in the proposed system a new technique bounding box method is used. By using this method we provide a quantitative evaluation of a large data set, needed to cope with photos taken in the diverse weather condition, in presence of some objects such as trees, mountain slopes etc.



Likelihood Table				
Session	No	Yes		
Morning	1	1	=2/8	0.25
Afternoon	1	1	=2/8	0.25
Evening	0	2	=2/8	0.25
Night	0	2	=2/8	0.25
All	2	6		
	=2/8	=6/8		
	0.25	0.75		

B. SNOW COVER ANALYSIS

First, the image should be converted to gray scale images. We are processing the image based on the pixels and intensity of the images. After the identification of mountain peak, the images are processed for feature extraction for the classification of the image. Feature extraction- From the images, we compute the fixed dimensional features which are having the contents of the image. The classification of images is based on the feature descriptor. A good descriptor should have the ability to handle intensity, rotation, scale and



affirmed variations to some extent. Each image is abstracted by several local patches. Sift feature-SIFT key points of objects are first extracted from a set of reference images and stored in a database. An object is recognised in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based Euclidean distance of their feature vectors. The BOVW (Bag-of-Visual-Word) model is to convert vector-represented patches to "code words", which also produces a "code book". A code word can be considered as a representative of several similar patches. Forewords are then defined as the centres of the learned clusters. The number of the clusters is the codebook size. SIFT converts each patch to 128-dimensional vector. After this step, each image is a collection of vectors of the same dimension (128 for SIFT) DOG- Scale-space extreme is used for performing the DOG of an image. The difference of Gaussian pyramids is obtained by smoothing the image frequently by convolving it with the Gaussian operator.

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

We get an image,

$$g_1(x,y) = G_{\sigma_1}(x,y) * f(x,y)$$

Second time smoothing image as,

$$g_2(x,y) = G_{\sigma_2}(x,y) * f(x,y)$$

The difference of two images considered as difference of Gaussian,

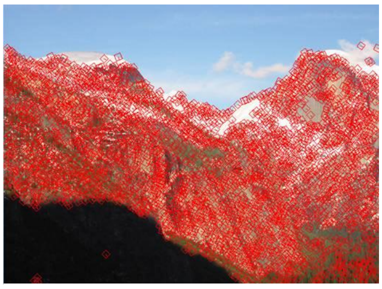
$$g_1(x,y) - g_2(x,y) = G_{\sigma_1} * f(x,y) - G_{\sigma_2} * f(x,y) = (G_{\sigma_1} - G_{\sigma_2}) * f(x,y) = DoG * f(x,y)$$

The Laplacian of Gaussian is

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y)$$

Where σ represents the width. The DoG is actually a band-pass filter, which removes high-frequency components representing noise, and also some low-frequency components representing the homogeneous areas in the image.

KEY POINT LOCALIZATION-The key points are low contrast pixels of an image. The key points are strongly independent with each other in Naïve Bayes classification. The features of images are stored in the database. The database is compared with the key points to classify the objects in an image.



HOG FEATURES-Histogram of Oriented Edges (HOG) descriptors were densely extracted, computing a histogram of oriented gradients in each 8 × 8 pixels cell and normalizing the result using a block-wise pattern. The first step of calculation in many feature detectors in image reprocessing is to ensure normalized color and gamma values. The technique counts occurrences of gradient orientation in localized portions of an image. It is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. SSIM-SSIM is used for measuring the similarity between two images. It is similar to that of BOVW model in SIFT feature.

C. SNOW COVER IDENTIFICATION

Once the image is appeared for estimation of snow cover with clear vision, then the image is classified into two parts are Snow covered and non-covered area. The classification not only depends on the single pixel intensity but also depends on context of the image. All the operations mentioned above are processed. Then the image is processed by morphological operation. It is used to avoid the imperfections of the binary image. Morphological opening and closing were processed to identify the snow covered area.

The dilation of A by B is defined by:

$$A \oplus B = \bigcup_{b \in B} A_b,$$

Where A_b is the translation of A by b. The erosion of the binary image A by the structuring element B is defined by:

$$A \ominus B = \{z \in E | B_z \subseteq A\},$$

Opening is the dilation of the erosion of a set A by a structuring element B:

$$A \circ B = (A \ominus B) \oplus B,$$

where $\ominus$ and $\oplus$ denote erosion and dilation, respectively.

Closing is the erosion of the dilation of a set A by a structuring element B:

$$A \bullet B = (A \oplus B) \ominus B,$$

where $\oplus$ and $\ominus$ denote the dilation and erosion, respectively.

The pipeline mentioned in this work produces the snow covered area by outlining the area from the input images. The snow covered area pixels became '1' and other areas are '0'.

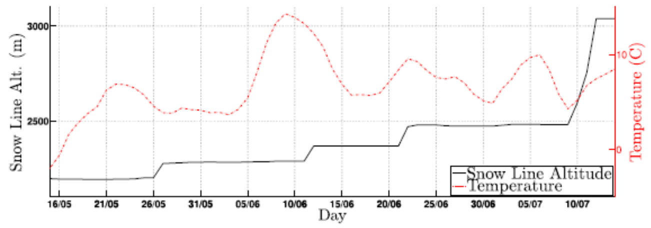
D. HUMAN DETECTION

Human interruption is the major problem in the India border. For helping our militarists, we introduced a new technique by using PIR sensor. PIR sensor is kept along with the camera. PIR sensor is controlled by using the ATMEGA8 microcontroller. PIR Sensor is used to detect the motion of humans within 12m from the sensor. If the movements of the humans are detected, PIR sensor will provide the buzzer alarm to the nearby base station. If the human is detected in mountain region, after the alert of the buzzer, the information is forward to the monitoring web page through IOT. The information consists of snow cover index and human detection is forwarded to the controller. The controller forwards the information to the web browser through IOT modem. It is helpful for mountain climbers, military wars and research analysers.

E. RESULT ANALYSIS

The estimation of snow cover index from web cam images are allowed to have a reliable source of data for the study of the consistency with respect to another measurement such as air temperature. We report results for fixed threshold of Naive Bayes Classifier, SVM, Snow-no snow classifier, GMM classifier. Fixed threshold method has more efficient than other classifiers.

	without Median without DMI	without Median with DMI	with Median with DMI
Random Forest	79.7	**93.5** (+13.8)	**91.6** (+11.9)
SVM	**81.8**	92.6 (+10.8)	**91.6** (+9.8)
Linear Regression	78.3	89.7 (+11.4)	88.8 (+10.5)
GMM3	73.7	79.2 (+5.5)	82.7 (+9.0)
GMM2	79.9	80.2 (+0.3)	83.3 (+3.4)
RGBNDSI	72.9	87.1 (+14.2)	87.0 (+14.1)
Snow-noSnow	68.6	81.7 (+13.1)	80.5 (+11.9)
Fixed Threshold	76.0	88.4 (+12.4)	87.6 (+11.6)



The trend of the snow level altitude, along with temperature registered by a nearby base station. It can be observed that the snow melting process was characterized by four occurrences when the snow level altitude increased abruptly. This behavior is correlated with the four temperature peaks observed by the meteorological station.

III. CONCLUSION

In this paper we addressed the challenge of snow cover monitoring from the public ally available images, we used methods like boundary detection, morphological processing for the mountain peak detection and snow covered in mountain areas. Additionally, we also extracted the features of same image at different views by using SIFT feature. Finally, we have also done human detection and transmitted the monitored data's from the base station to the head control using IOT. The future work will investigate the availability of information from the proposed system. A notable example is calculation of depth of the snow covered from the ground; we envision that this system will be more useful to mountain climbers to safeguard them from snow sliding hazards.

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