An Internal Waves Detection Method Based on PCANet for Images Captured from UAV

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Abstract. As internal wave is a universal geophysical phenomenon in stratified fluids, study of internal wave features in the coastal ocean is one of the most important tasks in physical oceanography. Traditionally, various internal wave detection methods, such as acoustic, optical, electrical based techniques and SAR based technique have been proposed. However, those methods need expensive measuring devices and often face the difficulties of the installation when deployed in the ocean. With the development of machine learning recently, internal wave detection based on computer vision and machine learning becomes a hot topic. In this paper, a framework for internal waves detection based on PCANet which is a feature learning deep network is proposed. First, we collect simulated internal wave images and non-internal wave images, then we give a label to each image to indicate whether it includes internal waves or not. Finally, we train a discrimination model with PCANet and predict new images at the test stage. Experiment results demonstrated the feasibility of the technique for internal wave detection.

1 Introduction

As a significant ocean interior wave phenomenon, internal wave is widespread in the ocean [1]. Internal wave and its side effects have been studied in various aspects since it can significantly affect oceanic current measurements, undersea navigation and antisubmarine warfare operation [2]. It could also affect offshore oil exploration and development. Internal wave is a tough research field in marine areas due to the complexity of its generation mechanisms and the randomness of its space-time characteristic [3].

Traditional internal wave detection methods usually obtain data from the synthetic aperture radar. Internal wave can be mapped on the SAR image due to the sensitivity of SAR data that changes with the small-scale surface roughness [4–6]. It provides users data over a wide range of area. However, practically it is impossible to repeatedly observe the same wave packet over a short period of time.

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In this paper, we introduce a new method based on machine learning for internal wave detection. A simple and effective deep learning network PCANet is conducted to train a single frame internal wave detection model. There are five sections in this paper. After the introduction section, the near surface internal waves was introduced in Sect. 2. In Sect. 3, features of learning algorithm with PCANet. In Sect. 4, performance of the model was evaluated by an original dataset collected in the lab. Final conclusions were addressed in Sect. 5.

2 Near-Surface Internal Waves

Internal wave is widely observed in the ocean, particularly in the relatively shallow waters such as Yellow Sea [7]. Internal wave occurs within subsurface layers of marine waters that are stratified due to temperature and salinity variations. Disturbance created within the ocean give rise to these waves, which represent a significant mechanism for transport of momentum and energy within the ocean [8].

Internal wave plays a significant role in maintaining the ocean circulation and global climate. Moreover, internal wave has certain impacts on human activities, such as platform drillings in industry and submarine voyages in military field [9]. Sea water would have strong inertia wave and stress force induced by the massive energy of internal wave, thus could influence human being activities significantly.

3 Internal Wave Features Extraction with PCANet

PCANet is a relatively simple deep learning network, which is easy to train and can be applied in different tasks in computer vision such as face classification and optical character recognition. The basic architecture of PCANet shown in Fig. 1. The training of PCANet has three stages: the first two stages based on PCA and in the last stage, hashing (in order to produce nonlinear output) and histogram used to demonstrate the results [10].

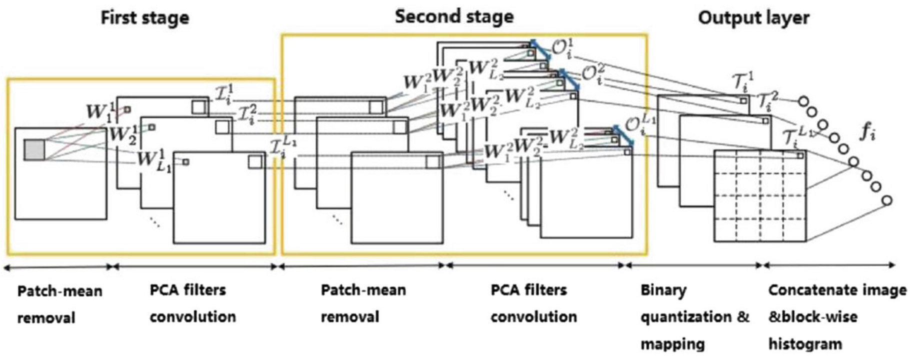


Fig. 1. The structure of the two-stage PCANet

Consider an image with $m \times n$ pixels in size – there are N images in the training set. In each image, a patch of size $k_1 \times k_2$ around each pixel was taken. All the patches were collected, vectored and combined into a matrix of $k_1 \times k_2$ rows and $(m - k_1 + 1) \times (n - k_2 + 1)$ columns.

For example, the i th image I_i, a matrix X_i was obtained, thus the patch mean from each patch was subtracted and get:

$$X = [X_1, X_2, \ldots,] \in R^{k_1 k_2 \times N_c} \tag{1}$$

where c indicates the number of rows of X_i. Then, the eigenvectors of XX^T was obtained, and the ones corresponding to the L_1 maximum eigenvalues as the PCA filters was saved, which can be expressed as:

$$W_l^1 = q_1\left(XX^T\right) \in R^{K_1 K_2}, l = 1, 2, \ldots, L_1 \tag{2}$$

The leading principal eigenvectors capture the main variation of all the men-removed training patches. The first stage was finished at this stage.

At the second stage, a similar process with stage 1 was applied. The input images I_i^l of stage 2 should be:

$$I_i^l = I_i * W_l^1, i = 1, 2, \ldots, N \tag{3}$$

the boundary of I_i is zero-padded so that I_i^l have the same size of I_i, all the patches of I_i^l was collected, and patch mean from each patch was subtracted thus get:

$$Y^l = \left[Y_1^l, Y_2^l, \ldots, Y_N^l\right] \in R^{k_1 k_2 \times N_c}, l = 1, 2, \ldots, L_1 \tag{4}$$

in which, the Y^l was combined together as a matrix:

$$Y = \left[Y^1, Y^2, \ldots, Y^{L_1}\right] \in R^{k_1 k_2 \times L_1 N_c} \tag{5}$$

After that, the eigenvectors of YY^T, was obtained and the ones corresponding to the L_2 largest eigenvalues as the PCA filters of the second stage was saved.

$$W_\ell^2 = q_\ell\left(YY^T\right) \in R^{k_1 k_2}, \ell = 1, 2, \ldots, L_2 \tag{6}$$

At the final stage, for each input image of stage2, the following expression was obtained:

$$T_i^l = \sum_{\ell=1}^{L_2} 2^{\ell-1} H\left(I_i^l * W_\ell^2\right), l = 1, 2, \ldots L_1 \tag{7}$$

The function $H(\cdot)$ binaries output results, i.e. the value of the function is 1 for positive inputs and 0 otherwise. For each of the L_1 images T_i^l, $l = 1, 2, \ldots, L_1$ were partitioned it into B blocks, with size of $k_1 k_2 \times B$, and the $2^{L_2} \times B$ histogram matrix in each block ranging from $[0, 2^{L_2} - 1]$ was computed, followed by vectorizing the matrix into a row vector $Bhist\left(T_i^l\right)$. Finally, the $Bhist\left(T_i^l\right)$ of T_i^l, $l = 1, 2, 3\ldots, L_1$ was concatenate as the feature

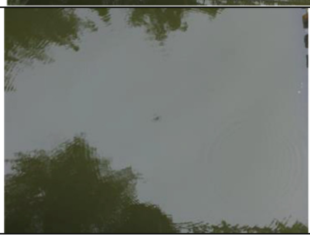
$$f_i = \left[Bhist\left(T_i^l\right), \ldots, Bhist\left(T_i^{L_1}\right)\right]^T \in R^{\left(2^{L2}\right)L_1B} \tag{8}$$

As we use the PCANet was used to extract the features of the images of internal waves, and label the normal water surface pictures with 0 and waves pictures with 1. The model parameters of PCANet include the patch size k_1, k_2, the filters number $L_{1,}L_2$, the number of stages and the block size for histograms. In the experiments, we resize image into 60×60, patch size 7×7, stage number 2, $L_1 = L_2 = 8$, and the block size 7×7 was set. We extract features from PCANet, and then put it into a linear SVM for classification with the attached labels.

4 Experiments

To verify the feasibility of the technique for internal waves detection, the model was applied on an original dataset collected in the lab. The dataset includes 214 images which are taken by the DJI Drone. During the shooting process, the camera took photos by looking straight down from the belly of the drone over the water surface. First, the drone was hovering over the water surface and photos of clam water surface were taken based on regular intervals. Then the production of waves was simulated and pictures were taken to track the waves. Table 1 shows the sample images of two kinds of sates in different conditions in our dataset. The two states are “Clam water surface” and “simulating the production of waves” with corresponding labels of 0 and 1.

Table 1. Image samples of two kinds of states in different conditions in our dataset

State （Label）	Condition 1	Condition 2
Clam water surface （0）		
Simulating the production of waves （1）		

Then the images were normalized to a resolution of 60*60 pixels to extract features with PCANet model, and training linear SVM classifier to detect the waves. Experiment results indicates that the proposed method has achieved reliable results to detect internal wave. Table 2 shows the accuracy rate of the proposed approach based on the dataset collected by the DJI Drone. Result in the dataset achieves 89% accuracy of detection in gray image on average, and 86.645% accuracy of detection in color image on average.

Table 2. Accuracy rate (%) of the proposed approach on the dataset collected by the DJI Drone

Image format	Condition 1	Condition 2	Average
Gray	84.85	93.15	89.00
Color	82.46	90.83	86.645
Average	83.655	91.99	87.82

5 Conclusions

In this paper, a framework for internal waves detection based on feature learning methods was proposed. The internal wave can be detected successfully by using the PCANet. The experiments demonstrated the feasibility of the technique for internal waves feature detection. Additionally, the result shows that accuracy rate improves with the sample size increasing. It was believed that the experiment can be further improved when larger scale dataset is used.

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References

1. Garrett, C., Munk, W.: Space-time scales of internal waves. Geophys. Fluid Dyn. **2**(1), 225–264 (1972)
2. Osborne, A.R., et al.: The influence of internal waves on deep-water drilling. J. Petrol. Technol. **30**(10), 1497–1504 (1978)
3. Zhu, G.: The status and future of research and development of marine environment monitoringtechnology in China. Ocean Technol. (2002)
4. Rodenas, J.A., Garello, R.: Wavelet analysis in SAR ocean image profiles for internal wave detection and wavelength estimation. IEEE Trans. Geosci. Remote Sens. **35**(4), 933–945 (1997)
5. Chen, B., et al.: Internal wave detection and parameter estimation from sar images based on a novel radon transform method. In: International Workshop on Education Technology and Training and 2008 International Workshop on Geoscience and Remote Sensing (2008)

6. Alpers, W.: Theory of radar imaging of internal waves. Nature **314**(6008), 245–247 (1985)
7. Sun, Z., et al.: The influence of internal waves on signal fluctuation in the Yellow Sea. J. Acoust. Soc. Am. **105**(2), 1311 (1999)
8. Chen, C.Y., et al.: An investigation on internal solitary waves in a two-layer fluid: propagation and reflection from steep slopes. Ocean Eng. **34**(1), 171–184 (2007)
9. Rodenas, J.A., Garello, R.: Internal wave detection and location in SAR images using wavelet transform. IEEE Trans. Geosci. Remote Sens. **9**(5), 1494–1507 (1998)
10. Chan, T.H., et al.: PCANet: a simple deep learning baseline for image classification? IEEE Trans. Image Process. **24**(12), 5017–5032 (2014). A Publication of the IEEE Signal Processing Society