A Multi-Channel Temporally Adaptable System for Continuous Cloud Classification from Satellite Imagery

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Abstract

A new multi-spectral scheme for cloud classification from satellite imagery is proposed which involves two temporally adaptable Probabilistic Neural Networks (PNN's), one for the visible and one for the infrared (IR) channels. This system offers the ability to perform continuous updating during the whole day. The results using five classes are provided which show the promise of the proposed scheme.

1 Introduction

Due to the huge volume of the data that is collected by the Geo-stationary Operational Environmental Satellites (e.g. GOES–8) every day, automatic classification is clearly needed for climatological and many other relevant applications. In recent years, several methods have been proposed. A good review of the available approaches is provided in references [1],[2]. Among the various classifiers that have been employed, the Probabilistic Neural Network (PNN) is more appealing owing to its good classification accuracy and fast training [3]. PNN is a supervised neural network that is widely used in the area of pattern recognition. The original version of PNN [4] is an implementation of the Parzen non-parametric probability density function (PDF) estimation theory. However, this network suffers from structural complexity and extensive computation time during the testing phase. In [5], Streit *et al* introduced a modified version of the PNN that substantially reduces the number of neurons in the recognition layer by using Gaussian mixture models and the Expectation Maximization (EM) algorithm to estimate the network parameters.

In [1], a temporal updating scheme was developed based upon the Gaussian mixture models in [5]. This scheme works on the visible and IR channels from GOES-8 satellite imagery. The basic idea is to exploit the temporal and spatial correlation information between two consecutive frames of the data to account for the changes in the cloud and background features due to temperature (IR) and sun angle variations (visible). This is accomplished by updating of the parameters of the Gaussian mixtures in different classes that undergo changes. Both supervised and unsupervised training schemes were employed depending on the classification results of the PNN and its relation to the result of a context-based predictor [1]. Promising results were reported in this reference on a sequence of GOES-8 images. However, this method has several major shortcomings. The features extracted from both channels are lumped together and presented to the classifier. This does not allow the classification of cloud/no-cloud areas based upon the individual spectral (visible) and temperature (IR) features. Additionally, since the visible data is not available during the night, the system cannot be updated continuously. The latter causes severe problems in the updating process for the next day due to discontinuity of the data. In this paper, a new version of the temporal updating scheme is introduced which circumvents the afore-mentioned problems by employing the two channels separately. During the daytime, two separate PNN classifiers are used for the two channels and their results are fused together to give the final classification results. During the nighttime, however, the PNN classifier for the IR channel alone can provide cloud classification primarily based upon the temperature features. In both cases, the parameters of the PNN classifiers are updated using the schemes described in [1] in order to track the temporal and spatial changes in the cloud/no-cloud areas. The idea behind this scheme is inspired from the way meteorologists label and classify satellite images.

The organization of this paper is as follows. Section 2 gives a brief review of the previous scheme. Section 3 gives the description of the proposed multi-channel system. Section 4 presents the test results of the proposed system and discussion on the results. Finally, Section 5 provides the conclusion and future work.

2 Original Temporal Updating Scheme

The structure of the temporal updating PNN (TUPNN) proposed in [1] consists of three major components, the

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PNN classifier, the contextual-based predictor and a comparator as shown in Figure 1. The visible and IR image data arrive consecutively with one-hour frequency. Prior to classification, spectral and textural features of the data of these channels must be extracted. In [2], several feature extraction schemes, namely singular value decomposition (SVD), wavelet packets (WP), grey level co-occurrence matrix (GLCM) were benchmarked on the GOES-8 imagery data. It was shown that the SVD method provides good discrimination ability and algorithm simplicity. This scheme extracts features that contain contributions from both the spectral and textural aspects from each 8x8 block of both IR and visible channels [2]. Fisher criterion is then used along with the Forward Floating Sequential Selection [6] to select three features from each channel with high discriminatory power. These are then augmented in one feature vector and fed to the PNN. Note that each 8x8 block corresponds to a region of size 32x32 km. The classifier performs a preliminary classification of the data using the network parameters that were updated based upon the data of the previous frame. The classification result of the last frame is also used as inputs to the predictor, which makes a prediction of the current frame by using the contextual information in two consecutive frames. Markov chain method is used in [1] to model the temporal contextual information. The results of the PNN and the predictor are then compared. Those blocks for which the two results match are put into a subset X_1, whereas the rest are put into subset X_2. All the X_1 blocks are used in conjunction with a supervised learning (known label) to fine-tune the parameters of those Gaussian components corresponding to the selected class; while those in X_2 are used together with an unsupervised learning (unknown label) to update the parameters of all the Gaussian mixtures used to model the class distributions. Both learning mechanisms are implemented using an Expectation-Maximization (EM)-based updating strategy [1]. After the updating is completed, the block is classified by the updated TUPNN to give the final classification results.

3 A New Multi-Channel Temporal Updating Scheme

The new multi-channel temporal updating scheme, as shown in Figure 1, consists of two TUPNN's, one for the visible channel and one for the IR channel. These two TUPNN's share the same context-based predictor. The output of this predictor is separately compared with those of the two PNN's and the results of these comparisons are used to update the parameters of the two PNN's separately. The TUPNN for visible channel is trained for 3 different classes, viz.; Land, Water and Cloud, as this channel does not provide height information essential for differentiating 5 classes. TUPNN for the IR channel, on the other hand, is trained for 5 different classes, viz.; Land, Water, Low-level, Middle level and High-level clouds. These two TUPNN's are trained on the early morning, e.g. 7:00am, when both visible and IR channel images become available.

During the daytime, both the TUPNN's provide their separate classification results. Thus, to get the final classification results for each image block, we need to fuse these results together. A multi-layer back-propagation neural network (BPNN) was used to perform decision fusion based upon the results of the two TUPNN's. The TUPNN outputs for the training data are used for training of this BPNN, which combines TUPNN's outputs to classify the image blocks into 5 different classes, viz.; Land, Water, Low level, Middle level & High level clouds. The fusion system output is used as a memory for the predictor, which predicts the class label for each block in the next frame on the basis of the results of the current frame.

During the nighttime, the visible PNN and fusion system indicated by the dotted lines in Figure 1 are shut-off and IR TUPNN takes over to give the final classification results. In this mode, the scheme works in the similar manner as before [1]. Both the TUPNN's are reinitialized with the trained weights when we get the first image pair in the next day morning.

In addition to the multi-channel nature of this new system, there is yet another major difference in the updating phase of the TUPNN's in comparison with that of the previous system [1]. Geographical and topographical information is embedded into the system to improve the classification accuracy and confidence of the updating process. This is accomplished by exploiting the geographical mask when the output of the final AND operation is either Land or Water. In this case, the geographical mask result is given the precedence over the AND results of the two channels. For instance, if the final AND operation labels a particular block as Land whereas the label according to the geographical mask should be Water, then this block is put into X_1 subset for supervised updating of both TUPNN's. Since such blocks are labeled with 100% confidence, their inclusion in the supervised learning clearly improves the accuracy of the temporal updating process. The motivation for inclusion of this extra piece of information is based on the observation that land and water are more likely to be misclassified to each other owing to small temperature and reflectivity differences.

4 Simulation Results

The performance of the proposed system was examined and compared with that of the original TUPNN system in [1] using continuous GOES-8 satellite imagery. One typical image pair obtained at 19 UTC, July 23rd, 1998 is shown in Figure 2. These images of size 512 x 512 pixels (spatial resolution of 5km /pixel) cover the Mid-West and most of the Eastern part of the U.S., extending from the Rocky Mountains to the Atlantic coast. The images cover mountains, plains, lakes and coastal areas where clouds have some specific features that are tied to topography. Florida is located in the lower right, with the Gulf of Mexico in the lower centre part of the image. These sequences are of particular interest because of the presence of a variety of cloud types. Certain high confidence cloud/no-cloud regions were identified and labelled for the training and testing of the systems based on the visual inspection and other related information used by expert meteorologists.

Selected SVD feature vectors (3x1) for each 8×8 block of each channel were applied to the TUPNN's. The goal was to classify each block into five classes, viz., Land (L), Water (W), Low level clouds (LC), Middle level clouds (MC) and High level clouds (HC). Half of the blocks in the labelled areas of two early morning images (7:00am) on 23rd and 24th July 1998 were randomly chosen as the training data set, while the remaining blocks were used as the "validation data" set for this multi-channel system. The validation data set is used to determine the optimally trained PNN based upon this initial data. As a result, the process was repeated for 10 different times and the PNN classifiers with the best performance were used as the final classifiers in the multi-channel system to classify 27 hours of continuous data. During the daytime, fusion system gave the overall accuracy rate ranging from 84 to 95%, while during the nighttime; IR TUPNN gave the overall accuracy rate ranging from 75 to 93%. The fusion system gave the overall accuracy rate of 99%, when it was tested on images at 7:00am on 24th July. The overall mean correct classification was 89%.

The performance of the proposed system was then compared with that of the previous system [1] by running these two algorithms through the same set of test images. Table 1 presents the classification confusion matrix of the previous scheme for the image pair shown in Figure 2. The diagonal elements indicate the number of blocks that are correctly classified while the off-diagonal elements represent the number of misclassified blocks for each class. The overall correct classification rate is around 66%. It can be seen from this confusion matrix that there are a lot of misclassifications between all the classes.

Table 1: Confusion matrix (original TUPNN)

	L	W	LC	MC	HC
L	51	0	128	0	0
W	1	109	111	0	0
LC	1	0	208	102	0
MC	0	0	9	342	4
HC	0	0	1	36	55

Table 2 presents the confusion matrix of the proposed scheme for the same image pair shown in Figure 2. The overall correct classification rate is around 85%. Clearly, the classification accuracies for all the classes except middle level clouds are increased substantially. Comparison of the two confusion matrices reveals that the overall accuracy rate is improved by 19%.

Table 2: Confusion matrix (two-channel TUPPN)

	L	W	LC	MC	HC
L	156	0	20	0	2
W	0	203	16	0	2
LC	10	0	258	43	0
MC	0	1	5	290	59
HC	0	0	0	14	78

One reason for this improved performance might be due to the fact that decomposing the system into two separate channels removes the two-channel feature inter-dependencies in the previous scheme [1]. Additionally, fusion of the two separate decisions using the BPNN can correct for some classification errors in either one of the channels.

The grey-coded classified images that identify different cloud and no cloud areas for both systems on the same image pair are shown in Figure 3. Visual inspection of Figures 3 (a) & (b) reveals that there is substantial improvement in the results of the proposed system as compared to those of the previous system. Figure 4 gives the corresponding expert labelled image with the grey-code map. Figures 5(a) and (b) give the masked results of both systems with respect to the expert labelled areas. Again, these results show that the masked result of the new system more closely matches the expert labelled image than that of the previous system.

Figure 6 (a) shows the overall classification accuracy (P_{cc}) versus time (in hour) for 27 hours of continuous updating. Solid line is used for the proposed system and dotted line is used for the previous system. In this plot, Hour 1 corresponds to 7:00am on July 23rd, 1998, while Hour 27 corresponds to 9:00am on July 24th, 1998. Note that since the previous system cannot operate during the nighttime, the plot for this system is terminated as soon as the visible channel data becomes unavailable. This plot clearly shows that the updating in the new system is certainly more reliable and consistent than in the previous system. Additionally, the nighttime operation leads to acceptable results considering the fact that the system only uses IR channel information. The other plots in Figures (b)-(f) show the comparison between the two systems for all the five classes. The broken lines indicate that there were no labelled blocks for that particular class for the hours in between. These, again, reveal that the proposed system has better accuracy for all the classes except the middle level clouds.

Although, the results of the proposed system show the great promise of this system for continuous operation during the day and night, the plots also point to some problems for classification of Land and Low-level clouds during the nighttime. The reason is attributed to the fact that we are only using the IR channel information during the nighttime, which is not certainly sufficient to discriminate between these five different classes. Thus, in order to improve upon this classification result, it is inevitable to use other information, e.g. difference between Channel 2 and 4. These issues will be addressed in the future studies.

5 Conclusion and Future Work

Till now, there was no automatic cloud classification system that could provide continuous operation due to the unavailability of the visible channel data during the night. A multi-channel (Visible and IR) temporal updating system was introduced in this paper, which provides continuous processing ability. Temporal updating takes place in each channel individually and the results are fused together using a BPNN system. During the daytime both channels participate in decision making, while during the night the decision is made solely based upon the IR channel. Geographical and topographical information is also exploited to aid the classification and updating of land and water classes. The preliminary results in this paper show the great promise of the proposed scheme.

Among the future goals is to build a system that can classify cloud and no-cloud types with typically 10 different classes. The scheme proposed in this paper is an initial stage toward developing a hierarchical cloud classification scheme that will accomplish this goal. After the image is labelled into five classes, each class can be further classified into its several subclasses, e.g., high-level clouds can be divided into Cirrus and Cirrostratus classes. Furthermore, future work would also involve evaluating the robustness of the proposed system on different sets of randomly chosen training data selected from a set of early morning images. During the nighttime, other GOES-8 channels e.g. channel 2 can be used to improve the classification accuracy of Land and Low-level clouds. Partitioning algorithm can also be used, where each 4 x 4 sub-block will be classified four times by using 8 x 8 overlapping blocks. This algorithm takes care of boundary blocks and further improves the overall accuracy as well.

6 References

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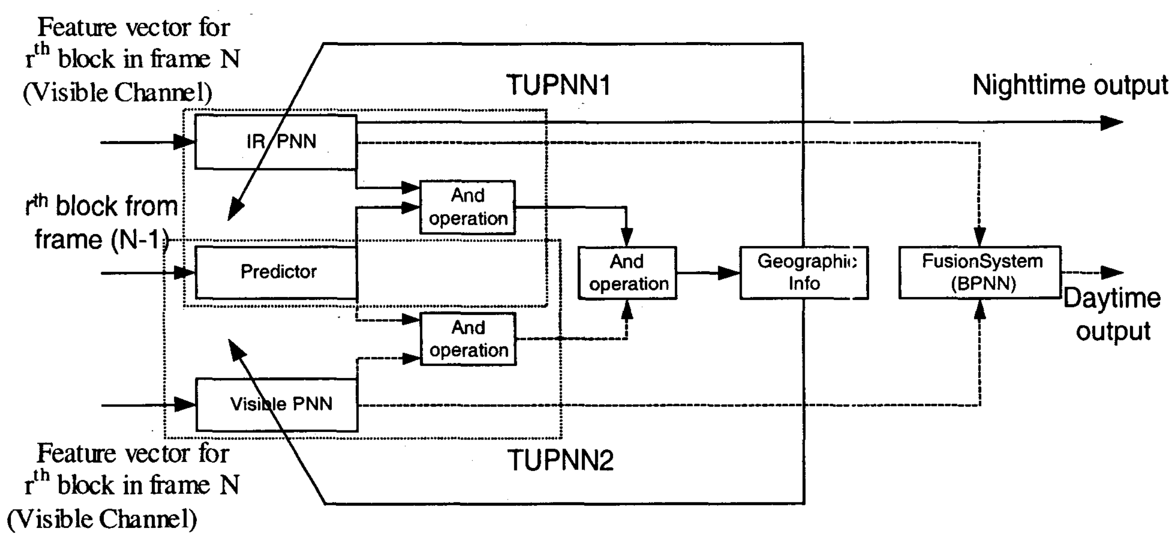
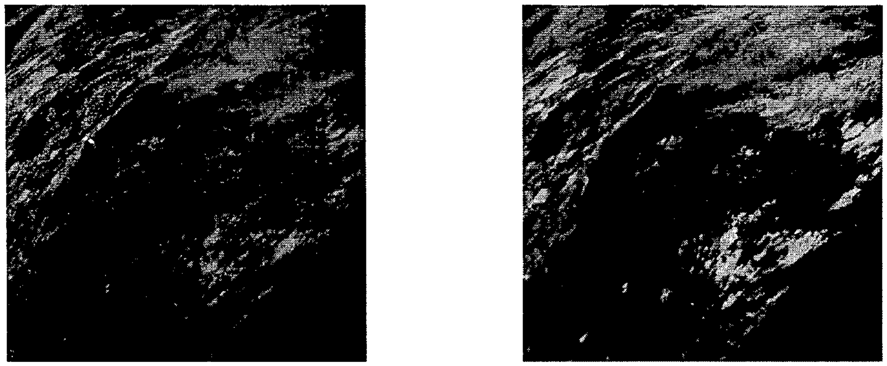
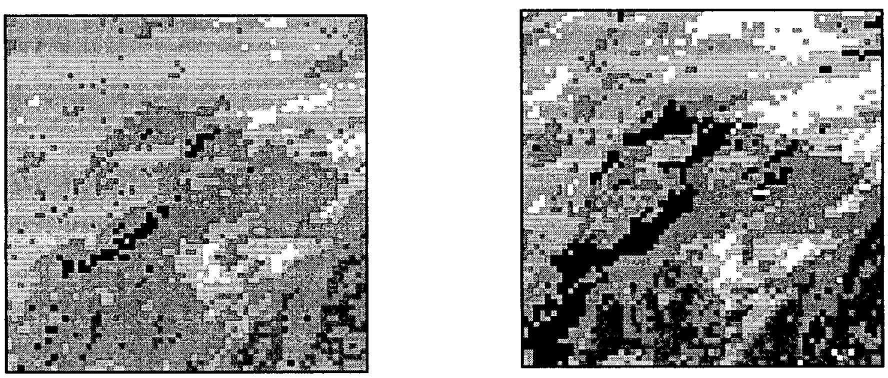


Figure 1: Schematic diagram of the two - channel TUPNN.



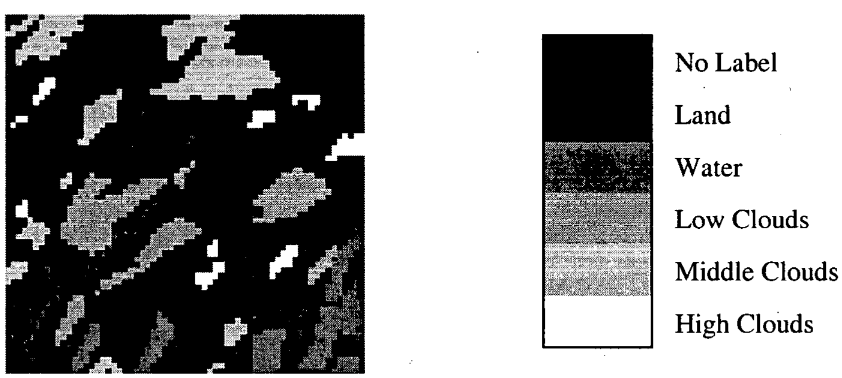
(a) Visible channel (b) IR channel

Figure 2. GOES-8 satellite images obtained at 19 UTC, July 23rd, 1998.



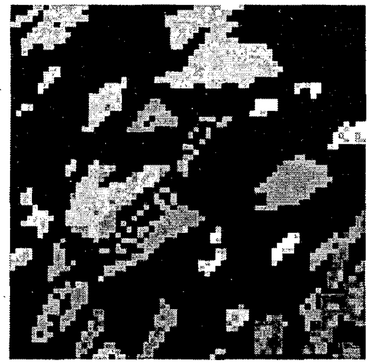
(a) Previous System. (b) Proposed System.

Figure 3. Classification results of the two systems.

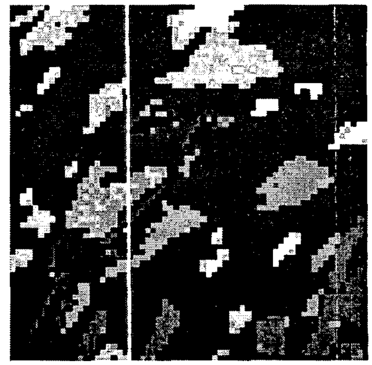


(a) Expert Labelled Image (b) Gray Code Map

Figure 4. Expert labeled image and the gray-code map.



(a) Masked Results (Previous System)



(b) Masked Results (Proposed System)

Figure 5. Masked results of the two systems.

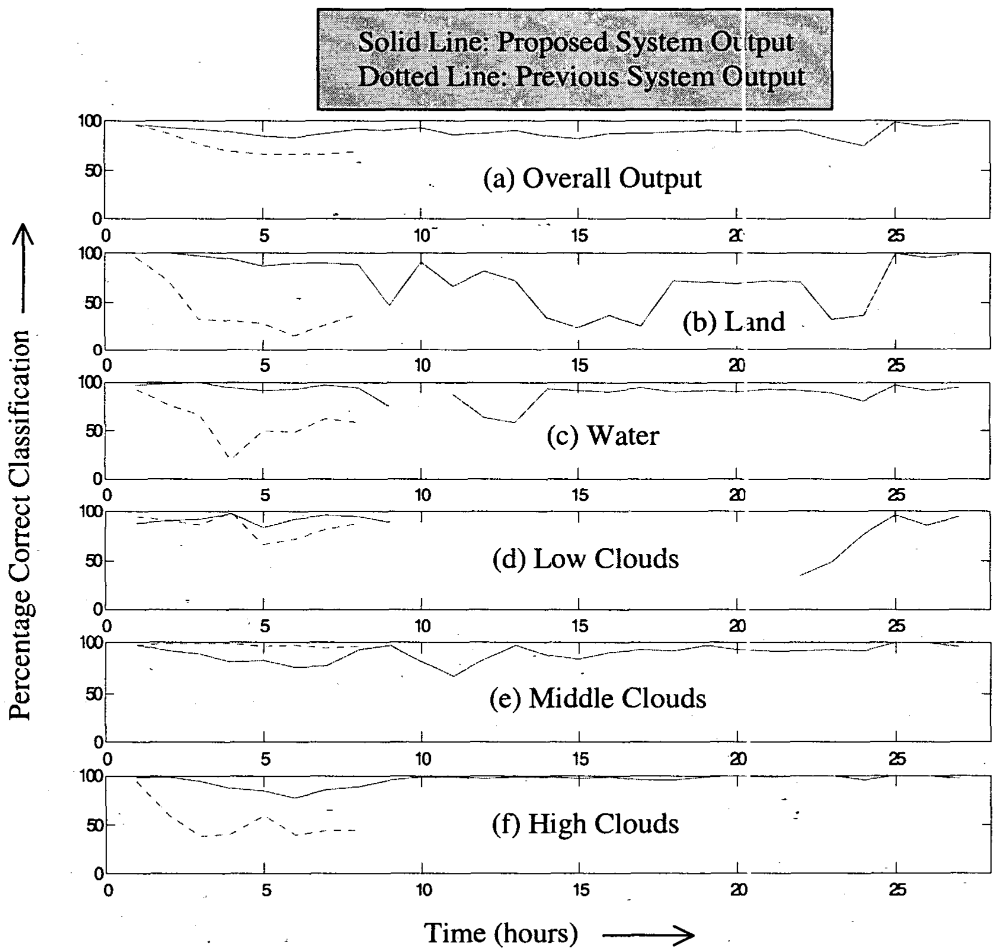


Figure 6. Comparison of the two systems for continuous operation.