Analysis of Microwave Satellite data (AMSU-B) for Detection of Temperature Inversion using Clustering Techniques

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Abstract :

Microwaves play a very important role in remote sensing and particularly meteorology due to their ability to penetrate through clouds, fog and many other environmental conditions, which hamper the other sensing techniques such as visible or infrared. AMSU-B on board the NOAA satellite provides global moisture profile in terms of brightness temperatures. Using the microwave AMSU-B data, a study of one special meteorological phenomenon - temperature inversion - is done here. This paper deals with use of pattern recognition techniques for analysis of AMSU-B data for detection of temperature inversion. Detection of similar patterns is done using two popular clustering techniques, namely Self Organizing Map and Principle Component Analysis. Some of the preliminary experiments and their results have been discussed.

Key-Words: Microwave remote sensing, temperature inversion, Self Organizing Map, Principle Component Analysis.

Introduction:

The Microwaves portion of electromagnetic spectrum have some special properties that make them very important for remote sensing. They have wavelengths longer than visible and infrared enabling them to penetrate through cloud cover, fog, light rains and most other meteorological conditions. They are also relatively less susceptible to scattering unlike the shorter wavelengths of visible and infrared. Thus the role of microwaves in remote sensing cannot be more emphasized. Due to the longer wavelength, the energy at the satellite sensor is lower than that obtained by visible or infrared sensors. Thus to obtain substantial energy, the field of view of microwave sensors are larger, reducing spatial resolution. But the vertical temperature or humidity profiles provided by microwave sensors are invaluable. [1]

Different microwave frequencies react differently to water forms at different levels of the atmosphere. The advanced microwave sounding unit (AMSU-B) is a 5 channel passive microwave radiometer, which uses microwave frequencies to sense atmospheric moisture as a function of brightness temperature, at different layers of atmosphere (roughly at 0-1, 1-3, 4-5, 5-7, 8-10Km), provides global moisture profile. Liquids and ice clouds affect the brightness temperature in terms of change in their emmisivity. [2,3]

The Instrument:

AMSU-B uses five different microwave frequencies (89GHz, 150GHz, and 183.3$\pm$7, $\pm$3, $\pm$1 denoted here by 176GHz, 180.3GHz and 182.3GHz) to study the effect of moisture at different levels of atmosphere in terms of their absorption response. AMSU-B has a nadir resolution of 16km diameter pixel at a nominal satellite altitude of 850km. The AMSU-B instrument consists of a scanning parabolic reflector antenna that rotates once every 8/3 seconds. Each scan line comprises of 90 pixels and covers 50 degrees on each side of the sub-satellite path. [2]

Temperature Inversions:

In general the temperature decreases as one goes up in the atmosphere. But under certain conditions, the temperature may increase as one goes higher and this phenomenon is termed as temperature inversion. Presence of two different layers of air with varying moisture levels can lead to the formation of temperature inversion. This temperature inversion can be associated with higher RH and is usually seen at around 3-6Km height. Night time cooling of ground causes the air close to ground to be cooler than the layer of air above, resulting in the formation of inversion layer called radiation inversion, usually seen at a height of less than 1Km. Fog or a layer of haze near the ground usually accompanies it. The other type of inversion is seen in the tropopause – stratosphere layer (height of around 10 to 12Km), where the temperature ceases to decrease and remains constant and later increase.

The inversion layer in the troposphere, primarily affects the refractive index of air. This in turn has implications on communication systems leading to duct-propagation and channel interference. Another prominent effect of this inversion, is the trapping of pollutants within this layer leading to smog and decrease in air quality. [4]

This work deals with the detection of inversion in the troposphere. The data obtained from AMSU-B is in the form of brightness temperatures at different altitudes. This brightness temperature data is analyzed to study patterns related to different types of inversions. To get an idea of similarity/variation in the data under different inversion conditions, two clustering techniques have been used in this study namely, Principle Component analysis and Self Organizing Map.

AMSU-B data:

As mentioned above, higher relative humidity may be associated with presence of temperature inversion. As AMSU-B data provides information on moisture in terms of brightness temperature, it might provide some signature of the temperature inversion phenomenon. If such a signature is present, analysis using clustering based on identical data can be useful in detection of temperature inversion.

Self Organizing Map (SOM) is a popular Neural Network having a two-layer architecture. It is *trained without supervision* i.e. the training data set does not have the desired output values specified, which is an advantage over supervised training methods (Ref. 8). During training, the input patterns are presented and the network organizes itself. The output of SOM is represented in the form of a two dimensional array of neurodes. SOM clusters the given input data into different classes. The quality of clustering in SOM depends on training provided to the network [5,6,7,8].

Principle Component analysis (PCA) is a popular dimension reducing algorithm. Here also clustering is the process of data analysis. The principle axes are those where the sample point has little or no variance or spread. Plotted against each other, they bring out the interdependence in the data. [9]

Experimentation and Observations:

AMSU-B level 1b data was obtained from NOAA website www.saa.noaa.gov. Using Level 1b and Aquarius software, the pixel wise brightness temperature over required location was obtained. For Ground truth, Radio Sonde data was used as it provides temperature and humidity profiles for specific stations throughout the year. Radio Sonde data for the stations Srinagar and Patiala from the west (considering the effect of western disturbances) and Guwahati and Dibrugarh in the east were selected for the study. Three different experiments were performed in this study.

1) Height dependent analysis with classification based on low, mid and high level inversion i.e. macro scale.
2) Height dependent analysis for only low level inversion that translates into higher resolution study or micro scale.
3) Relation of inversion with humidity.

For all the above experiments, Radio Sonde data was used as ground truth to identify the days and levels of inversion.

Height Dependent analysis on a macro scale

Initially, Radio Sonde data throughout the year 2003 was collected for the above mentioned stations. The days when temperature inversion was seen were separated and tabulated. This inversion was then classified as low level (Below 1 Km, predominantly caused due to night time cooling of ground and air close to it.), mid level (Between 1 and 6 Km, predominantly due to presence of layers of air with different moisture contents) and high level inversion (Beyond 6 Km). Levels beyond 10 Km were considered tropopause (not of much importance for meteorology).

After identifying the days having inversions using Radio Sonde data, corresponding AMSU-B data available around that time was considered. Unfortunately, both the data are not available at the same time. The level of inversion was considered as that height where the temperature increase was registered by the Radio Sonde observation. [10]

Pixel wise Microwave AMSU-B data was collected over about 17 days from January, February and March (2003). The data collected from these stations were classified as:

1. All three levels showing inversions. (all)
2. None of the levels show inversion. (ooo)
3. Low level inversion only (loo)
4. Two levels showing inversions low-middle, low-high, middle-high [llo , lol, oll]
5. High level inversion only (ool)
6. Mid level inversion only (olo)

The data analysis was done using self-Organized map (SOM) and Principle component analysis (PCA). After a few initial unsuccessful attempts, it was realized that during the above mentioned months, Srinagar might have snow cover while the other three locations are snow free. This made it impossible to have one single SOM network for all seasons for the four different places. So it was decided that separate networks would be designed for each station.

Patiala was chosen for immediate analysis. The training set and testing set were made using data from all three months (January, February and March). Data was classified for low, middle and high level inversion. Good clustering was seen with this type of classification for the training data as well as testing data.

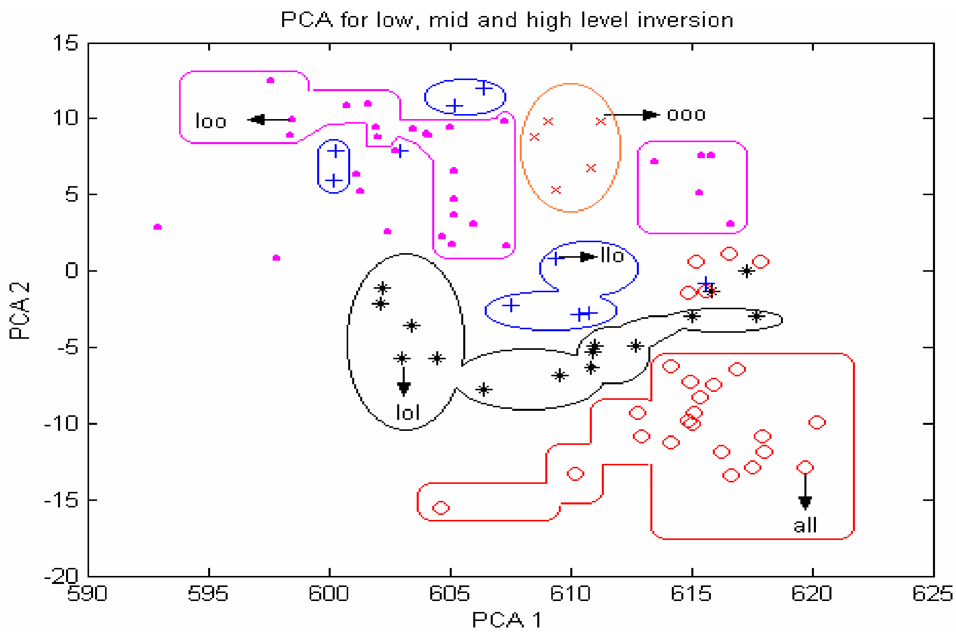


Fig 1 a showing PCA map with clusters indicating different categories.

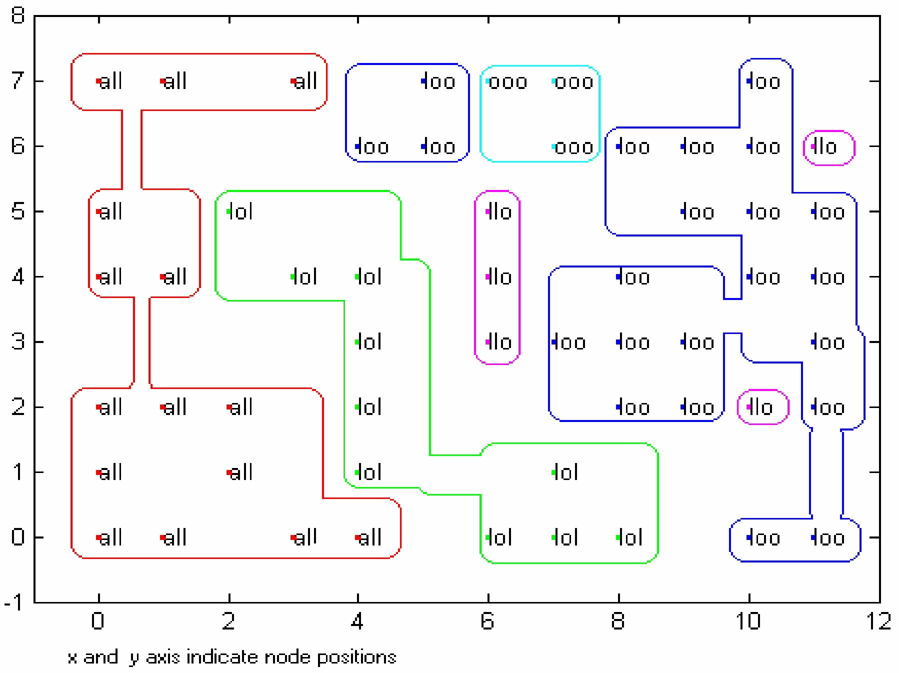


Fig: 1b. SOM Map showing the clustering for the above mentioned groups for training data for Patiala.

As seen from the SOM map, the clustering is seen for the different categories mentioned above. The PCA also shows clustering for the different categories. Both the techniques fail to cluster the 'llo' (i.e. presence of low and mid level inversion and absence of high level inversion) category properly.

Another set of data was used for testing the SOM network. The test results are as tabulated below.

Category of test data	Percentage correctly fired.
All (all 3 levels inversion seen)	60%
1oo (only low level inversion seen)	62%
1o1 (only low and high inversion seen)	Data not available
11o (low and mid level inversion seen)	80 %
000(no inversions seen)	40%

Height dependent analysis for only low level inversion (micro level):

Generally, inversions were present at low-level about 90% of the days in January, February and March as seen from Radio sonde data. The low level inversions were seen at different levels ranging from 0.3Km to 2Km. An attempt was made to detect at what height the low level inversion was present. For this, the height was grouped into 0.3 to 0.5Km, 0.5 to 0.7Km, 0.7 to 0.9Km etc. Also since only low level conditions were analyzed, to avoid any condition from higher levels from affecting the network output, only 89GHz and 150GHz data was used as the input to the network.

Again analysis was done using SOM and PCA. But unfortunately all the results obtained were discouraging. None of the networks used could identify the level of inversion correctly and PCA could not cluster the data either. The same analysis was performed using all the 5 microwave frequencies. But again, clustering was poor.

Analysis of Relation of Inversion with Humidity:

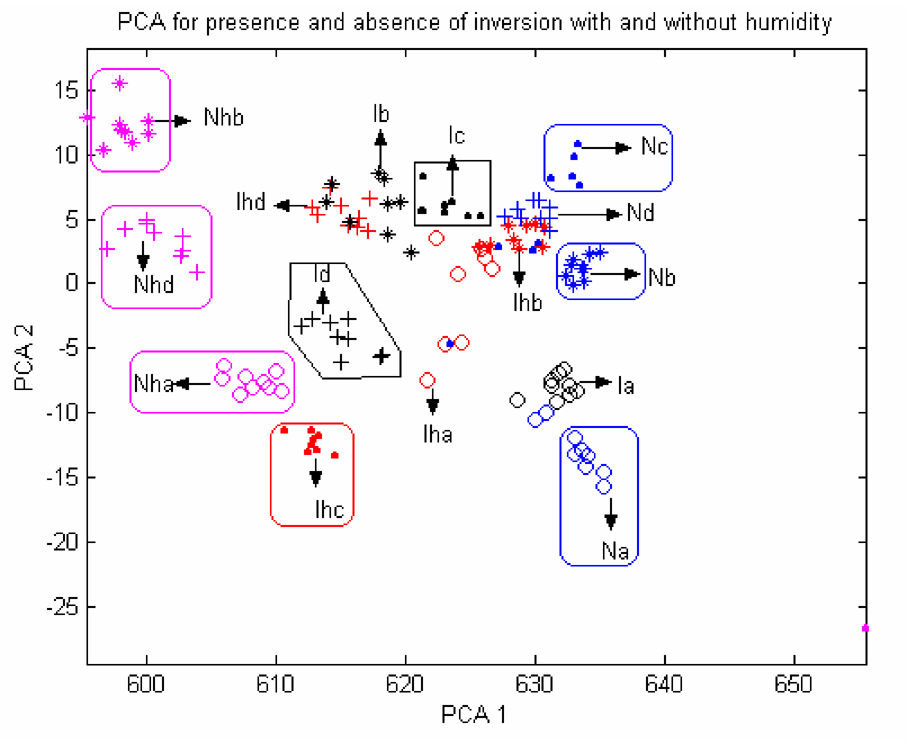
The Radio Sonde data was re-analyzed. Data for Patiala throughout the year 2003 was collected and the days on which inversions were seen were tabulated. This data was then plotted as height of inversion Vs day of month. The days on which inversions were not seen were given a height value equal to zero. Next, the humidity value corresponding to the height at which inversion was seen was tabulated. Only those days on which the humidity level was beyond 75% was selected.

The level of inversion was considered as that height where the temperature increase was registered by the Radio Sonde observation. Humidity levels beyond 75% were accepted as high and below 75% as low. The humidity level at the inversion level was considered and in case of no inversions, the general humidity levels at all the heights given by Radio Sonde except the ground level was considered. Effort was taken to consider the nearest available AMSU-B data with respect to time of Radio Sonde observations, as both the data are not available at the same times.

With these initial definitions, the data was split as inversion data and no-inversion data. Next, the data was further split on the basis of presence or absence of humidity. Thus four different groups were formed:

1. Inversion seen with >75% Rh [Ih]
2. Inversion seen with < 75%Rh [I]
3. No inversion seen but >75%Rh [Nh]
4. No inversion seen but <75%Rh [N]

Again data was trained using SOM and analyzed using PCA. The PCA and SOM Maps are as shown below.



Legend
Iha – 6/1/03
Ihb – 23/3/03
Ihc – 25/6/03
Ihd – 17/9/03

Ia – 27/3/03
Ib – 2/7/03
Ic – 10/9/03
Id – 13/12/03

Nha – 1/2/03
Nhb – 7/7/03
Nhc – 21/8/03
Nhd – 18/12 03

Na – 3/3/03
Nb – 17/5/03
Nc – 16/6/03
Nd – 14/9/03

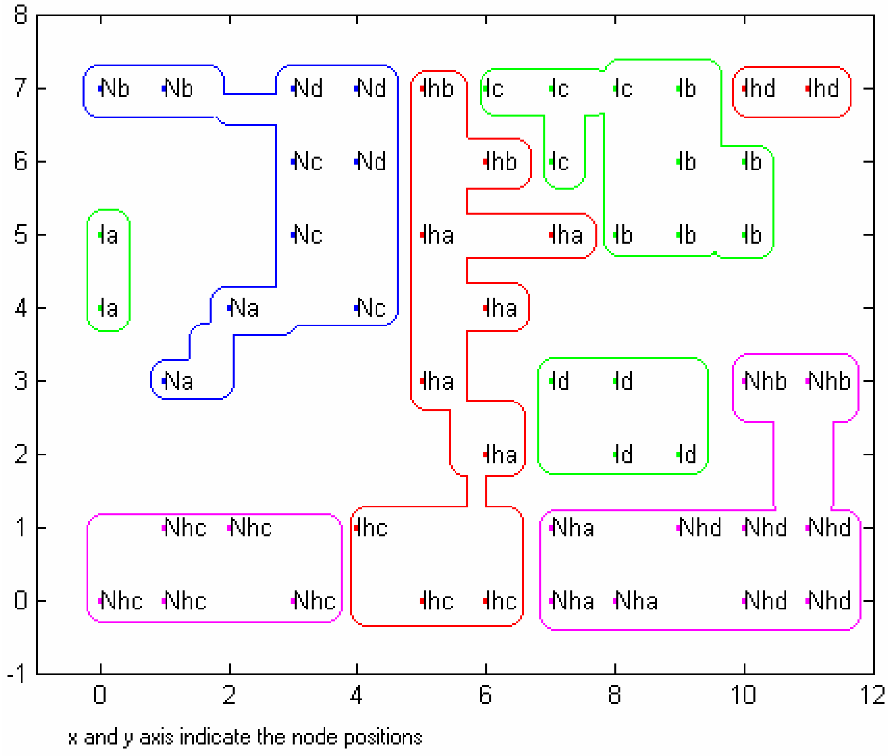


Fig: SOM Map classifying inversion and no inversion into 4 categories.

The above map shows the clustering for the four different classes mentioned above. The index a, b, c, d indicates the data obtained from different days over the year as indicated in legend. Among the two clustering methods used, SOM performed better than PCA.

Another set of data was used for testing the SOM network. The test results are as below:

Category of test data	Percentage correctly fired
Ih (Inversion with high humidity)	77%
I (Inversion with less humidity)	0 %
Nh (No Inversion but with high humidity)	33%

Conclusions:

In the experiment performed for height dependent analysis for low, mid and high level, good clustering was obtained in both PCA and SOM. The clustering shows that there is some relation to inversion layers at different heights and the microwave radiation sensed by AMSU-B also the microwave data is able to distinguish the temperature inversion at different levels.

The height dependent analysis at only low level did not give the expected results. One of the reasons could be incorrect classification of data. Radio sonde data is available at different height intervals which are not same for any 2 days. Sometimes these intervals could be as low as 0.15Km and as high as 1.5Km. In such a situation, it is difficult to determine the exact height at which the temperature inversion started or the depth of inversion. If precise height and depth of inversion is known, categories could be made accordingly and better results obtained.

The analysis of relation between Inversion and humidity gave better clustering. The testing data could identify Inversions with humidity 77% of the times. This is of importance as environmental conditions such as smog occur when humidity content is at the higher side. The analysis would then be very useful. In the absence of adequate levels of humidity, the temperature inversions may not be that significant.

As indicated at the beginning of the experiments, the categorization of data has been crude largely due to want of precise ground truth. The shortcomings with respect to location, and time of inversion and humidity cut off, in the collection of data if overcome, might lead to better clustering and identification. Other parameters such as wind speed if considered might lead to better and more precise results. Work on improving the clustering is being carried.

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