DECISION TREE CLASSIFICATION MODEL FOR DETECTING AND TRACKING PRECIPITATING OBJECTS FROM SERIES OF METEOROLOGICAL IMAGES

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ABSTRACT:

Accurate detection and identification of convective (cumulonimbus) clouds, which are potentially precipitating objects, as well as tracking cloud movement, are important tasks to locate and predict precipitation. In the present work, a Decision Tree classification model was used to locate and track precipitating objects from series of GOES-13 meteorological image sub-scenes covering the territory of Colombia, located to the northwest corner of South America. Results show that it is possible to infer a classification model that can be used repeatedly for accurately locating and tracking precipitating objects from multispectral meteorological images.

1. INTRODUCTION

Knowledge of convective systems' cloud processes and their evolution is important for understanding weather and climate, particularly over the tropics (Vila et al., 2008). In both equatorial and mid tropical latitudes, cumulonimbus (*Cb*) clouds are responsible for causing extreme weather conditions; these clouds intense convection causes the formation of Mesoscale Convective Systems (MCS) (Liu et al., 2014). A MCS is a convective system' *Cb* cloud that produces a contiguous precipitation area ≥ 100 km in at least one direction (Houze, 2004).

SCM pose a serious risk to aviation and may impact crops and urban populations because rapidly changing weather on various spatial and temporal scales may occur within and near *Cb* clouds (Liu et al., 2014). A large number of MCS is located in Colombia, which according to data from Tropical Rainfall Measuring Mission (TRMM) during the period 1998-2002, contribute approximately 70% of annual precipitation (Sakamoto et al., 2011). In this country disasters caused by heavy precipitation produced by SCM, hit much of the country between the second half of 2010 and the first half of 2011, causing devastating effects on the population and on local, regional and national economy (Colombia Humanitaria, 2010).

Observations of SCM are an important source of data for assimilation in weather forecasting and for monitoring climate trends (Liu et al., 2014). In this regard, images of the Geostationary Operational Environmental Satellites (GOES) have shown a high potential for detection and monitoring of SCM (Goyens et al., 2012).

A recent study investigated the possibility to improve precipitating objects detection over the Colombian continental territory from five meteorological channels rather than a single IR channel (Ramírez and Lizarazo, 2014). That study was conducted to detect and extract precipitating objects from a series of GOES-13 meteorological image sub-scene. Such study applied three machine learning algorithms including support vector machine (SVM), random forest (RF) and decision tree (DT) and compared them with the infrared brightness temperature threshold (IR-BT)

method. Accuracy assessment was conducted using STEP (Lizarazo, 2014) using a set of NASA Tropical Rainfall Measuring Mission (TRMM) images as reference.

The results of that study suggested that the machine learning DT is more accurate for detection of precipitating objects, compared to the conventional method IR-TB, while that SVM and RF results may not be acceptable for practical applications. The DT algorithm yielded a classification model tree which exhibits a very simple structure, with only two partitions, selecting thermal-infrared (TIR1) and water vapour (WV) as the most important channels.

In contrast to such study, this article aims to: establish whether it is possible to have a classification model that can be used repeatedly, and not requiring visual interpretation of imagery for every cloudy day. The evaluation was performed for the driest day and the wettest day of 2014 and 2015. In this case, a set of Global Precipitation Measurement (GPM), a well-established satellite weather radar system, with higher resolution than TRMM was used as reference.

2. DECISION TREE CLASSIFICATION MODEL

DT decomposes the space's attributes in P disjoint sets, K_r with $n \in \{1, \dots, P\}$, using decision rules or cuts that are orthogonal to the axes' attributes. Therefore, a decision rule can be described as a simple expression of the form $X_i \geq T_i$, o $X_i < T_i$ where T_i is some threshold, which makes this operation easy to understand by the user (Lizarazo, 2008).

In previous study, the DT algorithm yielded a tree which exhibits a very simple structure, from a meteorological image taken by the Geostationary Operational Environmental Satellite (GOES-13) for twenty-two half-hour periods for one day in 2013. Date and time for this study were selected to ensure a similar number of class representatives at the instant on April 03, 2013 at 21:15 hours Coordinated Universal Time (UTC) (201304032115, this is the date format used in the data set) taken as reference.

This tree was obtained using the Gini impurity measure, selecting thermal-infrared (thermal-IR) and water vapour (WV) as the most

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important bands. The Gini impurity measure, is a measure of the distribution of the class' label on the node, taking values in [0,1], where 0 is obtained when all the elements in a node fall into the same class. DT uses the Gini impurity measure to select the cut decision with the lowest impurity in each node (Tan et al., 2005). Formally, the impurity measure Gini given by Equation 2, for x_i attribute with $i \in \{1, \dots, n\}$ in the t node (Khalilia et al., 2011).

$$I(t_{x_i}) = 1 - \sum_{c=0}^c \left(\frac{n_{ci}}{a_i} \right)^2 \quad (1)$$

where n is the number of branches in the node t
 N is the samples' number
 n_{ci} is the samples' number with value x_i belonging to class c
 a_i is the samples' number with value x_i in the node t

The Gini index of a partition is the weighted average of the Gini impurity measure the different values of X attribute, given by equation 2 (Khalilia et al., 2011).

$$Gini(t, X) = \sum_{j=1}^j \frac{a_j}{N} I(t_{x_j}) \quad (2)$$

Figure 1 shows DT algorithm classification model obtained previously, which exhibits a very simple structure, with only two partitions. Thermal-infrared (TIR1) and water vapour (WV) channel were selected as the most important channels, and the model accuracy was 98%.

Figure 1. Decision tree obtained by the DT algorithm

The tree in Figure 1 defines the following classification rules in terms of brightness temperatures (Tb): (i) If channel TIR1 is < 301 K then the object is Cs (Clear Sky); (ii) If channel TIR1 is ≥ 301 K and the channel WV is < 209 K then the object is Nr (Non-Rainfall Cloud); and (iii) If channel TIR1 is ≥ 301 K and the channel WV is ≥ 209 K, then the object is Rc (Rainfall Cloud). The 35% of training pixels fulfil the first rule, 39% the second rule and 26% the last rule. This result is similar to obtained in a previous work (Feidas et al., 2000), where the cloud classification scheme developed for the thick opaque convective clouds correspond to classes with the lower Tb in both the IR channel (below 223 K) and WV channel (below 223 K).

3. DATA AND METHODS

3.1 Study area

This study was conducted over a tropical region comprising 5062400 km^2 , with predominance of Colombian territory, which is located in the northwest of South America as shown in the dashed window of Figure 2a. s

Figure 2. The study area:(a) South America. (b) Colombia.

3.2 Data

Meteorological images comprise a series of 88 sub-scenes in mode A (8-bits), taken by the Geostationary Operational Environmental Satellite (GOES-13) every half hour from 11:45 to 22:15 hours Coordinated Universal Time (UTC) for four different dates: (i) May 08, 2014, the rainiest day of 2014 with a precipitation of 19307.4 mm; (ii) December 22, 2014, the least rainy day of 2014 with a precipitation of 225.9 mm; (iii) January 06, 2015, the least rainy day of 2015 with a precipitation of 81 mm; and (iv) October 13, 2015, the rainiest day of 2015 with a precipitation of 11900 mm. The GOES Imager covers from visible (VIS) to thermal infrared (TIR) spectral regions with 5 spectral channels at spatial resolutions ranging from 1 km to 8 km (Table 1).

Channel number	Central wavelength	Spatial Resolution	Channel description
1	0.52-0.72 μm	1 km	Visible (VIS)
2	3.78-4.03 μm	4 km	Mid Infrared (MIR)
3	6.47-7.02 μm	8 km	Water Vapor (WV)
4	10.2-11.2 μm	4 km	Thermal Infrared (TIR1)
5	12.9-13.8 μm	4 km	Thermal Infrared (TIR2)

Table 1. Characteristics of GOES Imager

Reference data for accuracy assessment was selected from a NASA Global Precipitation Measurement (GPM) data set, well-established satellite weather radar system, merged with high quality (IR) precipitation and monthly surface precipitation gauge data that provides half hourly consistently calibrated, uniformly gridded with spatial resolution about 10 km at the Equator, global precipitation data product *GPM_3IMERGHH* with appropriate error and metadata information (Hou et al., 2014).

3.3 Methods

The method proposed here comprises (Figure 3): (i) data pre-processing to convert image counts to physical quantities using the Equations 3 and 5 and match pixel size, spatial extent and spatial reference systems; (ii) pixel-based supervised cloud classification using the DT algorithm classification model obtained previously; (iii) creation of precipitating objects by binarisation and vectorization of the classified image; and (iv) accuracy assessment. The GPM precipitation amounts were also binarised, thus obtaining a set of reference precipitating objects to perform validation using STEP method (Lizarazo, 2014). STEP provides

Figure 3. Methodology

four (4) similarity metrics for characterization of classified objects compared with reference objects: (i) *shape* similarity; (ii) *theme* similarity; (iii) *edge* similarity; and (iv) *position* similarity. The accuracy assessment focuses on convectives system' clouds having an area larger than 2400 km^2 . This threshold was chosen following a previous work (Sakamoto et al., 2011) on life cycle convective systems over Western Colombia.

Albedo (A) is calculated as:

$$A = \left(\frac{ND_{VIS}}{255} \right)^2 \quad (3)$$

where ND_{VIS} are counts values in Mode-A visible channel

Brightness temperature (Tb) is calculated as:

$$Tb = 330K - \frac{ND_{IR}}{2}; \text{ if } ND_{IR} \leq 176 \quad (4)$$

$$Tb = 418K - ND_{IR}; \text{ if } ND_{IR} > 176 \quad (5)$$

where ND_{IR} are counts values in Mode-A infrared channel

4. RESULTS AND DISCUSSION

Overall accuracy was computed, similar to how overall accuracy is computed in the traditional error matrix, from *shape*, *theme*,

edge and *position* similarity OBIA indices calculated by comparing thematic and geometric properties of classified precipitating objects with their corresponding reference precipitation objects, using a weighted area instead of the actual area for compensation of the unequal probability sampling, assigning to each classified precipitation object that matches (intersects) a given reference precipitation object a similarity value in the $[0, 1]$ interval (Lizarazo, 2014).

Table 2 summarizes overall STEP similarity indices for each twenty-two date under evaluation. For the rainiest day of 2014 (20140508) the *shape* index presents variations in validation interval between 92% and 95%, the *theme* index between 87% and 94%, the *edge* index between 97% and 99% and the *position* index was 100% for all instants. In contrast for the rainiest day of 2015 (20151013) the *shape* index presents variations in validation interval between 95% and 97%, the *theme* index between 91% and 93%, the *edge* index between 98% and 100% and the *position* index was 100% between 98% and 100% for all instants.

Day	Shape	Theme	Edge	Position
20140508	[0.92,0.95]	[0.87,0.94]	[0.97,0.99]	[1.00,1.00]
20141222	[0.94,1.00]	[0.93,1.00]	[0.99,1.00]	[0.98,1.00]
20150106	[0.98,0.99]	[0.98,0.99]	[1.00,1.00]	[1.00,1.00]
20151013	[0.95,0.97]	[0.91,0.93]	[0.98,1.00]	[1.00,1.00]

Table 2. Overall thematic and geometric accuracy predictors for the MCS

While for the least rainy day of 2014 day (20141222) the *shape* index presents variations in validation interval between 94% and 100%, the *theme* index between 93% and 100%, the *edge* index between 99% and 100% and the *position* index between 98% and 100%. In contrast for the least rainy day of 2015 (20150106) the *shape* index presents variations in validation interval between 98% and 99%, the *theme* index between 98% and 99%, the *edge* index and the *position* index were 100% for all instants.

The results suggests that the best aspect is *position*, followed in their respective order by *edge*, *shape* and *theme*. There are no significant differences between the two dates rainiest and the two dates less rain, shown be suitable for practical applications.

A visual comparison among the time's instants under evaluation also was performed for detected cloud objects. Figure 4 shows an instant by each date under evaluation.

For the instant 201405081545 UTC (Figure 4a) of rainiest day of 2014 the overall STEP similarity was *shape* 95%, *theme* 93%, *edge* 99% and *position* 100%, for this instant there are 21 precipitating objects which are located mainly on the Pacific, central and eastern regions of Colombia, on west region of Venezuela, on Amazon region of Brazil and on Ecuador and Peru, with areas between 1922 km^2 and 117164 km^2 .

For the instant 201510131945 UTC (Figure 4d) of rainiest day of 2015 the overall STEP similarity was *shape* 96%, *theme* 92%, *edge* 98% and *position* 100%, for this instant there are 55 precipitating objects which are located mainly on the Pacific, the Caribbean, central and west regions of Colombia and on Venezuela, with areas between 1005 km^2 and 170715 km^2 .

For the instant 201412221715 UTC (Figure 4b) of least rainy day of 2014 the overall STEP similarity was *shape* 96%, *theme* 97%, *edge* 100% and *position* 100%, for this instant there are 2 precipitating objects which are located mainly on the Colombian and Brazilian Amazon region, with areas of 3544 km^2 and 11475 km^2 .

Figure 4. Precipitating cloud objects detected at four dates. Blue colour fill represent DT classified precipitation objects, cyan colour border represent GPM reference precipitation objects and dashed red colour represent a window for analysis.

For the instant 201501061945 UTC (Figure 4b) of least rainy day of 2015 the overall STEP similarity was *shape* 98%, *theme* 98%, *edge* 100% and *position* 100%, for this instant there are 3 precipitating objects which are located mainly on the Brazilian Amazon region, with areas between 2873 km^2 and 7690 km^2 .

Figure 5 shows views of precipitating objects that correspond to the dashed windows in the Figure 4. In this Figure it is possible to observe that there is a strong locational match between predicted precipitation objects and reference prediction objects. However there are slight differences regarding shape and edge.

Results demonstrate how well a decision tree (DT) based classification model, inferred from a single-date GOES imagery, can be repeatedly used on different dates. This eventual transferability of empirical obtained models needs to be confirmed in more extensive experiments. However, these results suggest that machine learning techniques may be useful for better understanding meteorological phenomena as well as for improving manual methods currently used for cloud detection and tracking.

5. CONCLUSIONS

The main objectives of the study were accomplished: (i) evaluating the potential of using the classification model yielded by DT on many dates; and (ii) establishing that it is possible to have a classification model that can be used repeatedly for locating and tracking precipitating objects from multispectral meteorological images.

According to this study's results the best geometry aspect in the detection of precipitating objects from DT model is the *position*, that is, DT is able to locate accurately precipitating objects.

From the practical point of view, this work suggest a transferable decision classification model that can be used repeatedly for

Figure 5. Views of precipitating objects. Blue polygons represent DT classified precipitation objects and cyan edge polygons represent GPM reference precipitation objects.

locating and tracking precipitating objects from multi-temporal meteorological images, defined explicit classification rules useful for operational applications, with no visual interpretation of imagery for every cloudy day.

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