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Estimating Reflectivity of DWR Images by Analysing Different Colour Spaces through Distance Measures

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Abstract

In Image processing, Content based image retrieval (CBIR), is a developing trend when textured objects are present. Colour is amongst one of the most important feature used in image retrieval from databases. CBIR is useful in extracting location specific reflectivity information from the colour bar provided along with the DWR image. Images from different colour spaces such as RGB, HSV, LAB, YCbCr are used to extract exact colour information. Doppler Weather Radar (DWR) image data from Indian Meteorological Department (IMD) located at Chennai has been collected and analyzed. Extracting reflectivity from DWR images plays an important role in predicting the type of convective cloud. Accurate measurement of reflectivity helps in identifying the type of cloud. In this paper, eight different distance measures such as Euclidean, Standard Euclidean, City block, Minkowski, Chebychev, Mahalanobis, cosine and correlation are compared. The Best combination of colour space model with a distance measure giving least / minimal error is presented.

Keywords: CBIR, Colour space, Distance metrics, DWR, Reflectivity

INTRODUCTION:

Clouds play a crucial role in earth's exposure to radiation (solar and extra-terrestrial radiation) causing changes in climate due to their interaction [1]. Analysis and understanding the nature of clouds is important in flight planning and aviation [2] providing a better warning mechanism of impending disasters, such as tornados [3]. Voluminous work has been done to classify clouds based on the total sky image, whole sky images and satellite imagery (e.g., Ebert, 1992; Inoue, 1987; Lamei et al., 1994; Yool et al., 1992; Lee et al., 1990). DWR based convective cloud classification is an observational technique which has received greater attention from researchers in the field. Convective clouds are classified by human observers who have received professional training at meteorological stations [4]. Despite their unquestionable usefulness, this method implies a high cost of human resources and incidental human error. Results obtained by different observers may be divergent leading to differing conclusions. Therefore, automatic DWR based convective cloud classification technique is urgently required in this field.

Colour images hold greater amount of information than a gray level image. Reflectivity can be found by looking at the colour bar provided on the right side of the image. Selection of wrong colour may seriously impact the results. Colour is one of the most extensively used low-level features in retrieval of images from databases. They are usually very robust to noise, no image degradation, no changes in size, resolution or orientation. Since colour alone has little semantic meaning, colour features tend to be more domain independent compared to other features such as shape or texture. Colour histogram, representing the joint probability of the intensities of the three colour channels, is the simplest and the most often used colour feature. To measure similarity between close but not identical colours Ioka and Niblac introduced an L2-based metric [5], [6]. A large number colour spaces are provided in the literature such as RGB, YCbCr, HSI, Lab, etc. Each model has its own advantage. Depending on the type of application, suitable colour model has to be selected.

A large number of distance metrics are available in literature for measuring the similarity of colour in images which need processing. Distance transform, an important tool in image processing and pattern recognition, measures the distance of each point to the nearest point from a set of feature pixels. In distance transform, binary image specifies the distance from each pixel to the nearest non-zero pixel. Important application areas of CBIR are Military, Biomedicine and Web image classification.

In this paper, different distance metrics were chosen and applied on DWR images to extract reflectivity for different colour spaces and identify the best possible combination that fits the requirement. In section 2, datasets for our model are discussed. In Section 3, colour models and different distance measures are discussed.

In section 4, methodology for reflectivity extraction is explained. In section 5, results are analyzed.

Datasets:

DWR Reflectivity images (Doppler weather radar max (Z) product) from the Indian meteorological department (IMD) located at Chennai have been downloaded continuously at 10 minute intervals since November 2015 and a database is maintained [15]. Data collected up to December 2016 has been used for analysis. Random test patterns were generated using MATLAB for comparing the texture colour with colours provided in the colour bar.

Color Space and Distance Measures

This paper discusses about various color spaces available in the literature and the best color model is chosen for our area of interest. The perception of a color is a subjective process. For accurate measurement of reflectivity, the color information need to be extracted accurately. The color information needs to be checked with the various color provided on the color bar using various distance measures.

(a) Colour Models:

Colour model is defined as a digital representation of possible contained colours [7]. Humans perceive colour through attributes such as hue and saturation. Colour model is a system for measuring colours that are perceived by human beings. It is a process of mixing different values as a set of primary colours. Each colour space has its own advantage and disadvantage. A Colour space model is chosen based on the application. Colour models are divided into three categories. First, device oriented colour model, relates to signal from the device and the resultant colour that is displayed [8]. It finds application in TV and display systems. Second, User oriented colour model, creates a path that existed between the human and the device that handles the colour information. Third, device independent colour model is not affected by properties of the device. For transmission of colour images, third model is suitable. RGB, YCbCr model comes under Device dependent classification. HSV model comes under user oriented device dependent class. L*a*b* model comes under device independent classification.

For Human visual system, YCbCr model is popularly used. This model has one luminance component (Y) and two chrominance components (Cb and Cr). It is not an absolute colour space. It is used in TV Broadcasting and Digital video steaming. It is perfect for image compression.

The L*a*b* colour model determines the colour depending on its position in a 3-D colour space. L represents the brightness of colour. The value of L is 0 for black and 100 for white. ‘a ’ shows the degree from green to red. ’ b ‘shows the degree from blue to yellow. This model is used in evaluation of colour difference, colour matching system, advertising, Graphic art, digitized paintings and multimedia products.

A remarkable property of RGB representation is the issue of surfaces. While ignoring ambient light, normalized RGB is invariant (under certain assumptions) to changes of surface orientation relative to the light source [Skarbek and Koschan 1994]. RGB model uses Red, Green and Blue as primary colours. Proper combination of these primary colours with different weights results in various colours. This model is commonly used in computer graphics; Image processing, Analysis and storage. Printers and devices use secondary colours instead of primary colours.The Main advantage of this model is no transformation is required to display it on the screen. With this model, it is difficult to determine specific colour and recognition of colours and this could pose problems [9].

HSV model uses Hue, Saturation and Value as three components. This model is used by human beings in identifying and describing colours. The Purity of the colour is determined by the hue component. A Measure of the degree to which a pure colour is diluted by white light is defined by saturation component. The value defines the gray level value of the colour. Value defines the gray level component, whereas colour is defined by hue and saturation components. This model closely relates to human sensing properties of colour vision. This model is used in computer graphics, Image processing, computer vision, image analysis, Design Image, Human vision, Image editing software and Video editor. Advantage of this model is that segmentation can be done based on hue component.

(b) Distance metrics:

Distance transforms, measure the closeness of two points in a space. Distance transform in colour space measures the closeness of a colour with that of reference colour values. The distance function need not consider all features in an image equally. There are a number of distance metrics available in literature. In this paper, we review some of the existing distance metrics and select the best metric in colour space.

The distance transform in image processing between pixels has to satisfy the following properties [14]

i. $D(p,p) = 0$

ii. $D(p,q) = D(q,p)$

iii. $D(p,r) \leq D(p,q) + D(q,r)$

Euclidean distance, measures the proximity between two points in a colour space. It is a straight line distance between two points. Euclidean distance between two points is given at eq (1). City block distance measures the path between the pixels based on N4 Distance (4 connected neighborhoods). Chessboard distance measures the path between the pixels based on N8 Distance (8 connected neighborhoods) [10]. Quasi-Euclidean metric, measures the total Euclidean distance along a set of horizontal, vertical, and diagonal segments. Standard Euclidean distance is calculated from standardized data. Standardized values are obtained by subtracting the mean value of the pixel value and divided by standard deviation. The standard Euclidean distance is given in eq (2) and (3)

$$d_{euclid} = \sqrt{\sum_{i=1}^{3}(x_i - y_i)^2} \qquad (1)$$

$$standardized\ value = \frac{pixel\ value - mean\ value}{standard\ deviation} \qquad (2)$$

$$d_{Seuclid} = \sqrt{\sum_{i=1}^{3}\frac{(x_i - y_i)^2}{\sigma^2}} \qquad (3)$$

Minkowski metric is widely used for measuring the similarity between objects. The term r is known as Minkowski factor. When r is 1, it is the Minkowski distance (L1 Norm) and when r is 2, it is equivalent to Euclidean distance. Minkowski relation is given in eq (4). The ‘w’ in the equation specifies the weight given for each term in the equation. Distance between two points in an image is based on a strictly horizontal and / or vertical as opposed to the diagonal path. Manhattan distance is the simple sum of horizontal and vertical components, whereas the diagonal distance might be computed by applying the Pythagorean Theorem [11]. Manhattan distance is given in eq (5)

$$d_{minkowski} = \sqrt[r]{\sum_{i=1}^{p}(w_i\,|x_i - y_i|)^r} \qquad (4)$$

$$d_{manhattan} = \sum_{i=0}^{3}|x_i - y_i| \qquad (5)$$

Chebychev distance takes maximum coordinate difference into account. Correlation takes into account the similarity between two colours. Cosine distance calculates the angle between two points in a 3-Dimensional space. Chebychev distance is given in eq (6)

$$D_{Cheby} = \max(\ abs\ (X_i - Y_i)\ ) \qquad (6)$$

METHODOLOGY:

DWR MAX (Z) Reflectivity images obtained from IMD Chennai is collected once in every 10 minutes. The image contains Reflectivity information up to 250Km around Chennai, is shown at Figure 1. Pseudo-colour is assigned to image by IMD and each colour signifies different Reflectivity over a location. The height corresponding to a maximum value of Reflectivity through west to east is found from the right hand side display. The height of maximum reflectivity when viewed from south to north is projected over the top. Cloud top height above 6 km and Reflectivity above 45 dBZ have been considered as thunderstorm / Cumulonimbus (Cb) cloud (Suresh and Bhatnagar, 2005).

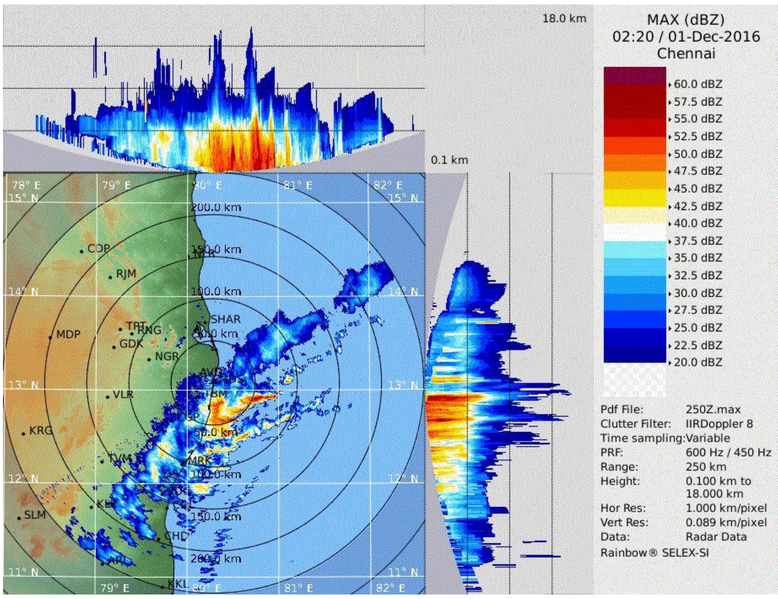

Fig 1: DWR Reflectivity Image from IMD Chennai

An image having no Reflectivity information is taken as reference image. Pre-processing is done on the current image to make the image suitable for this application. Images downloaded from the internet contain noise, filtering is done to remove noise. Offset image is obtained by subtracting the reference image from the current image which displays convective information. Offset image is converted into a binary image using hard thresholding technique. Image closing is done to remove the checkerboard effect at the edges. Colour information at a particular point is compared with colour bar provided on the right side using different distance metrics.

RGB model is suitable for displaying. It is converted into other colour spaces such as YCbCr, HSV and LAB. Different distance metrics are applied on the image and lists the best possible distance metric in a colour space for the reflectivity extraction application.

RESULTS:

DWR image contains a colour bar provided at the top right of the image. It contains 17 different colours, each colour representing the Reflectivity value from 20dBZ to 65dBz in steps of 2.5dBZ. Test patterns were generated randomly within the limits of colour bar range with 10% deviation from the actual value. These values in RGB colour space are simulated using MATLAB for different distance metrics and percentage of error is tabulated below in Table 1. Different iterations in the RGB model prove that Euclidean and Standard Euclidean distance metric show better performance.

Table 1: Percentage of error in RGB space for different distance metrics

Sample size	Euclidean	Seuclidean	Cityblock	Minkowski	Chebychev	Mahalanobis	Cosine	Correlation
340	5.59	5.59	5.59	5.69	5.79	14.41	25.59	46.18
850	5.18	5.18	5.28	5.18	5.18	12	26.24	42.35
1275	5.41	5.41	5.51	5.41	5.41	12.82	25.47	40.71
1700	5.49	5.49	5.49	5.49	5.49	12.31	26.59	44.08
3400	6.09	6.09	6.29	6.19	6.2	14.53	26.56	42.47
5100	6.20	6.20	6.20	6.20	6.20	13.22	25.73	41.53

Table 2: Percentage of error in HSV space for different distance metrics

Sample size	Euclidean	Seuclidean	Cityblock	Minkowski	Chebychev	Mahalanobis	Cosine	Correlation
340	20.59	22.06	19.41	20.59	40.88	28.24	31.18	55.29
850	20.35	20.82	19.18	20.35	38.59	25.76	28.47	56
1275	21.35	22.12	19.41	21.35	39.47	27.65	29.71	57.59
1700	21.96	22.67	20.86	21.96	39.76	28.08	30.51	55.84
3400	23.71	24.53	21.85	23.71	41.62	30.62	31.82	59.09
5100	23.49	24.22	21.41	23.49	40.88	29.37	30.47	57.33

Table 3: Percentage of error in LAB space for different distance metric

Sample size	Euclidean	Seuclidean	Cityblock	Minkowski	Chebychev	Mahalanobis	Cosine	Correlation
340	13.53	10	11.76	13.53	14.41	22.06	23.53	43.24
850	10.12	7.65	10.24	10.12	12.24	21.41	21.76	40.12
1275	10.41	9.18	10.24	10.41	10.94	20.35	21	40.82
1700	11.84	10.9	12.16	11.84	12.24	21.57	21.96	40.63
3400	11.47	10.03	11.71	11.47	12.15	22.18	22.03	40.71
5100	11.51	9.80	11.73	11.51	12.08	21.71	21.75	41.27

Table 4: Percentage of error in YCbCr space for different distance metrics

Sample size	Euclidean	Seuclidean	Cityblock	Minkowski	Chebychev	Mahalanobis	Cosine	Correlation
340	5.88	6.18	6.47	5.88	5.59	14.41	12.35	14.71
850	5.29	5.41	5.53	5.29	5.65	12	11.41	13.18
1275	5.94	6	6.76	5.94	6.12	12.82	11.71	13.59
1700	6.43	6.35	6.90	6.43	6.9	12.31	12.16	13.8
3400	6.68	6.44	7.26	6.68	7.15	14.5	12.2	13.6
5100	6.65	6.59	7	6.65	7.31	13.22	12.65	13.61

The image is converted into HSV colour space, as it has hue component in a separate plane which can distinguish colours. Test patterns were simulated using MATLAB for different distance metrics and error percentage is at Table 2, below. City block distance metrics show better performance when compared with other metrics in this colour space.

The image is converted into LAB colour space; it has A and B components, in different planes, which can distinguish colours. Test patterns were simulated using MATLAB for different distance metrics and error percentage is at table 3, below. Standard Euclidean distance metric is having the least error percentage when compared with other distance metrics, in this colour space.

Values in RGB colour space are converted to YCbCr colour space because it can better separate the luminance and chrominance components. It is better to check chrominance and neglect the luminance part. Test patterns were simulated using MATLAB for different distance metrics and error percentage is at table 4, below. Euclidean distance metric is having the least error percentage when compared with other distance metrics.

CONCLUSION

In this paper, convective cloud parameters such as reflectivity, cloud base height, cloud optical depth and cloud top height are extracted from DWR located at IMD Chennai for different locations. Images downloaded from IMD are stored in RGB space. It is converted to other colour spaces which introduces some error. Different distance metrics applied on various colour spaces are compared and the best metric in different colour spaces is presented. Present technique of extracting reflectivity information from DWR is robust to noise.

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