Clouds Height Classification Using Texture Analysis of Meteosat Images

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Abstract:

In the present work, pattern recognition is carried out by the contrast and relative variance of clouds. The K-mean clustering process is then applied to classify the cloud type; also, texture analysis being adopted to extract the textural features and using them in cloud classification process. The test image used in the classification process is the Meteosat-7 image for the D3 region.The K-mean method is adopted as an unsupervised classification. This method depends on the initial chosen seeds of cluster. Since, the initial seeds are chosen randomly, the user supply a set of means, or cluster centers in the n-dimensional space.The K-mean cluster has been applied on two bands (IR2 band) and (water vapour band).The textural analysis is used where six parameters are calculated from the Co-occurrence matrix. These parameter were inserted in the K-mean. The best classifier feature is the angular second moment. When we use the angular second moment is used with any textural feature a good result were obtained for cloud classification, since the angular second moment gives indications on cloud homogeneity.

Key words: Texture analysis, k-mean, Co-occurrence, clouds height

Introduction:

Automatic classification of remotely sensed image regions involves a label assignment to each image point, each label refers to a certain pattern in the real world scene. Therefore, a number of descriptive values will be associated with each image point. Each descriptive value has a definite meaning in a certain application. These sets of values that are associated with each image point are usually referred to as a pattern. Moreover, the characteristics that define the basis of an adopted pattern are known as features. A pattern, thus, represent a set of the measurements for an adopted feature. Hence the classification process can be described as a form of pattern recognition, or the identification of the pattern associated with each pixel position in an image in terms of the characteristics of the object at the corresponding point on the earth surface [1]. There are two major approaches for the classification; the first is known as a supervised classification and the second is known as unsupervised classification. We can use the textural analysis in the calculation of some composition coefficient in the classification process or we can use the statistical coefficient for the classification purpose.Texture is a measure of the homogeneity in the neighborhood of the pixel [2].

K-mean Classification: The k-means algorithm is based on the mechanism of shifting the cluster centers in order to optimize the performance index of the clustering. Many developments in the k-means algorithm are found in the literature,

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but the basic steps are the following [3]:

1. Choose k-initial cluster centers Z_1, Z_2, Z_3,..... Z_k :

The only parameter, which should be specified by the user in the k-means algorithm, is the number of desired clusters. The initial positions of the cluster centers are sometimes specified by the user or sometimes determined by following a particular method. Different methods may be used to select the initial position, among these:

1. The arbitrary selection from the image data,
2. The selection of the farthest points.

2. Distribute the samples among the clusters:

Samples should be assigned to the clusters according to its nearest cluster center, i.e.: For all j=1,2,3,K; where i ≠ j, $S_i(n)$ is the set of samples whose cluster center is Z_i (n) where n indicates that this is the nth iteration of this procedure.

3. Compute new cluster centers for

$$X \in S_i(n) \text{ if } \|X - Z_i(n)\| \le \|X - Z_j(n)\| \qquad (1)$$

each set $S_j(n)$:

Find a new value for each Z_i. The new cluster center, Z_i (n+1), will be the mean of all the points in S_i (n) such that:

$$Z_i(n+1) = \frac{1}{N_i} \sum_{x \in S_i(n)} X \quad \dots(2)$$

4. Compare Z_i (n) and Z_i (n+1) for all i:

Compute the distance between all the pairs of clusters (i.e., the new and old centers in each consecutive iteration if there is no overall substantial change; terminate the procedure, otherwise return to step 2.

Co-occurrence Matrices

An important and powerful statistical texture analysis algorithm is the co-occurrence matrices. The co-occurrence matrix is a two dimensional histogram, which indicated to number of times that pairs of intensity values occur in a given spatial relationship [4].

The co-occurrence matrices are constructed by considering that every pixel have eight neighbors (horizontally, vertically and diagonally at 45 degrees). It is also assumed that the matrix of relative frequencies of gray levels co- occurrence can specify the texture-context information. Some of the texture measures can be obtained from these matrices, (like homogeneity and the contrast) [5].

Suppose an image to be analyzed is rectangular and has N_x resolution cells in the horizontal direction and N_y resolution cells in the vertical direction. Suppose that the gray tone appearing in each resolution cell is quantized to N_g levels, in order to keep the size of the co-occurrence matrix manageable since each pixel amplitude is re-quantized over the range 0 < = a, b<= N_g-1 [6]. During the computation four brightness value spatial dependency matrices are derived, each matrix correspond to the spatial dependency along certain orientation (0º, 45º, 90º, and 135º).

The texture is specified by the matrix of relative frequencies of co-occurrence p (i, j), which indicate the number of times that each two neighboring pixels of an image, separated by a distance (d), will have gray tone (i) for one pixel and (j) gray tone for the other pixel. Such matrices of gray tone spatial dependence frequencies are the functions of the angular relationship between the neighboring pixels, as well as a function of the distance between them [7].The co-occurrence matrices are based on the repeated occurrence of the gray-level configuration in the considered texture. This configuration

varies rapidly in fine textures, more slowly in coarse textures.
The texture classification can be based on criteria (features) derived from the co-occurrence matrices [8].
1.Contrast (f1), i.e. moment of inertia:

$$f1=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}(i-j)^2 P(i,j)\ldots(3)$$

This is the moment of inertia of the matrix around its main diagonal. It is a natural measure of the degree of spread of the matrix values.
2. Inverse difference moment (f2) that is called local homogeneity:
The value of the local homogeneity is high when the diagonal concentration is high.

$$f2=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}\frac{p(i,j)}{(1+(i-j)^2}\ldots(4)$$

3.Correlation (f3):

$$f3=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}\frac{P(i,j)(i-\mu_x)(j-\mu_y)}{\sigma_x\sigma_y}\ldots(5)$$

Where

$$\mu_x=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} i.P(i,j)$$

$$\mu_y=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} j.P(i,j)$$

$$\sigma_x=\sqrt{\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} i^2.P(i,j)-(\mu_x)^2}$$

$$\sigma_y=\sqrt{\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} j^2.P(i,j)-(\mu_y)^2}$$

Where μ_x, μ_y, σ_x, σ_y are the rows, columns sum means and standard deviations respectively.
The correlation is high when the values are uniformly distributed in the matrix and low otherwise
4. Angular second moment (f4):

$$f4=\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} P(i,j)^2\ldots\ (5)$$

The angular second moment feature is a measure of homogeneity of the image.
5.The contrast (f5):
The contrast feature is a difference moment of the P matrix and a measure of the local variations present in an image.

$$f5=\sum_{n=0}^{N_G-1} n^2\left[\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1}.P(i,j)\right]$$

$$\text{where}\,|i-j|=n\ \ldots\ (6)$$

6. Entropy (f6):

$$f6=-\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} P(i,j).\log(P(i,j))\ldots(7)$$

$$f7=\frac{HXY-HXY1}{\max(HX,HY)}\qquad\ldots(8)$$

$$f8=(1-EXP(-2(HXY2-HXY))^{0.5}\qquad\ldots(9)$$

$$HXY=-\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} P(i,j).\log(P(i,j))$$

$$HXY1=-\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} P(i,j).\log(P_x(i).P_y(j))$$

$$HXY2=-\sum_{i=0}^{N_G-1}\sum_{j=0}^{N_G-1} P_x(i).P_y(j).\log(P_x(i).P_y(j))$$

7- information measures of correlation(f7),(f8)

In our classification process we have use the moment of inertia, the correlation, angular second moment, information measure of correlation, entropy and inverse difference moment.

The Classification Using the Texture Analysis and K-mean Algorithm

The texture analysis is one of the methods, which can be used in image classification. With the help of K-mean clustering algorithm, the unsupervised classification method based on textural methods have been applied; such a system can be considered as a hybrid method to classify the cloud type. The textural features have been calculated for the cloud region by using (IR2 and the WV) bands. The result is inserted in the k-mean clustering algorithm. the image sample is shown in figure(1).

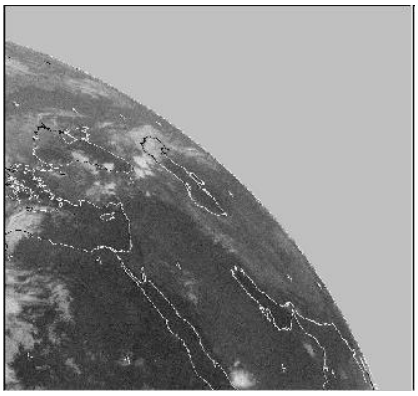

Fig. (a) The Meteosat-7 images for D3-region in IR2 band

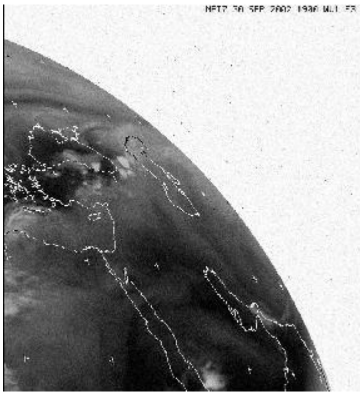

Fig.(b) The Meteosat-7 image for D3-region (the water vapor band)

Fig.(1) represent the Meteosat-7 images for the D3- region

Using the angular second moment of IR2 band with:

a- Angular second moment of Water Vapor band.

b- Correlation of Water Vapor band.

c- Moment of inertia of Water Vapor band.

d- Entropy of Water Vapor band.

e- Inverse difference moment of Water Vapor band.

f- Information measure of correlation of Water Vapor band.

Table (1) presents the variance of angular second moment with (a, b, c, d, e, f). From table (1) in the second and third column the first class with high variance value corresponds to low level cloud, since the low cloud has high temperature and high variance, the low clouds are (Cumulus, Stratus, Stratocumulus).

The fifth and third class with low variance and low temperature represent the high cloud (Cirrus, Cirro-Cumulus, Cirro- Stratus).

The second, forth and sixth classes represent the middle level cloud (Alto-Cumulus, Alto-Stratus and Nibostratus)

Figures (2), (3), (4), (5), (6) and (7) show the result of the classification process, each region carries a specific color.

Table (1) The variance for the angular second moment of IR2 band with angular second, correlation, moment of inertia, entropy, inverse difference moment and information measure of correlation of Water Vapor band for cloud regions.

Class No.	Angular Second Moment with Angular Second Moment	Angular Second Moment with Correlation	Angular Second Moment with Moment of Inertia
1	0.520	3.348	1.178
2	4.140×10^{-2}	0.212	0.226
3	4.766×10^{-3}	9.185×10^{-3}	9.337×10^{-3}
4	0.244	0.743	0.233
5	5.152	6.475×10^{-4}	1.108×10^{-3}
6	4.559	3.935×10^{-2}	4.359×10^{-2}
Class No.	**Angular Second Moment with Entropy**	**Angular Second Moment with Inverse Difference Moment**	**Angular Second Moment with Information Measure of Correlation**
1	0.108	0.390	1.472
2	0.355	4.981	4.083×10^{-2}
3	1.229×10^{-2}	7.223	1.006×10^{-2}
4	5.548×10^{-2}	0.194	0.214
5	5.303×10^{-4}	3.388×10^{-2}	4.088×10^{-3}
6	0.034	3.604×10^{-2}	9.397

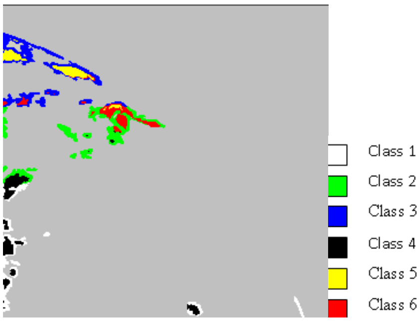

Fig. (2) The classification result of the cloud regions by using the angular second moment of IR2 band and angular second moment of water vapor band, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

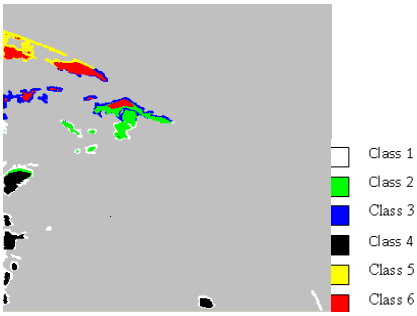

Fig.(3) The classification of the cloud regions by using the angular second moment and correlation, where class1 is low cloud, class2, 4, 6 are middle clouds,class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

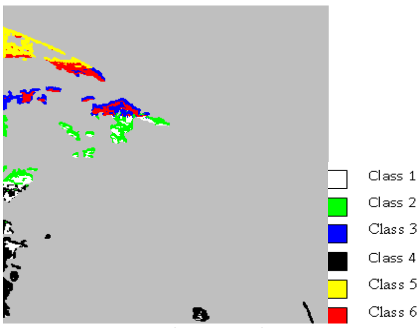

Fig. (4) The classification of the cloud regions by using the angular Second moment and moment of inertia, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

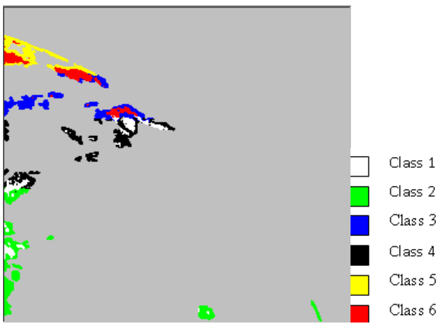

Fig. (5) The classification of the cloud regions by using the angular second moment and entropy, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

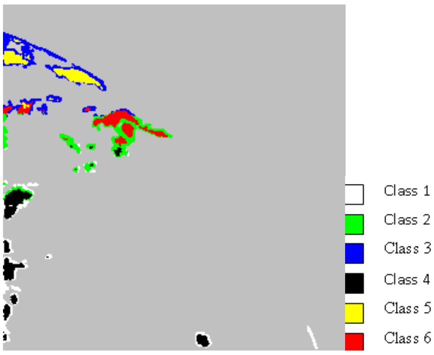

Fig. (6) The classification of the cloud regions by using the angular second moment and inverse difference moment, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

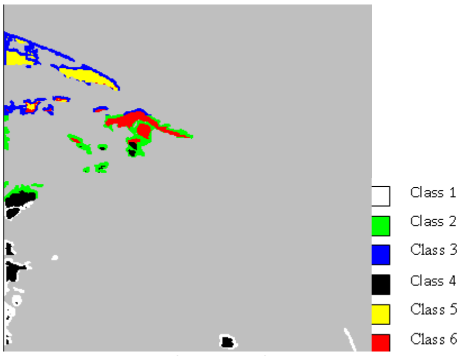

Fig. (7) The classification of the cloud regions by using the angular second moment and information measure of correlation, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

Uses the moment of inertia of IR2 band with:

a-Moment of inertia of Water Vapor band.

b-Inverse difference moment of Water Vapor band.

c-Entropy of Water Vapor band.

Table (2) listed the variance for moment of inertia with the moment of inertia, inverse difference moment and entropy.

1.using the moment of inertia of IR2 band with the moment of inertia of Water Vapor band, the second class with maximum value represent low cloud, the fifth class with minimum value represent the high cloud.

2.using the moment of inertia of IR2 band with the inverse difference moment of Water Vapor band, the maximum value is in the forth class which represent the low cloud, the sixth class with minimum value represent the high cloud.

3.using the moment of inertia of IR2 band with the entropy of Water Vapor band, the first class which represent the low cloud has high variance, the sixth class with minimum value represent the high cloud.

Table (2) The variance of the moment of inertia of IR2 band with moment of inertia, inverse difference moment and entropy of Water Vapor band for cloud regions.

Class NO.	Moment of Inertia with Moment of Inertia	Moment of Inertia with Inverse Difference Moment	Moment of Inertia with Entropy
1	7.709×10^{-4}	2.604×10^{-3}	0.746
2	0.11	8.827×10^{-3}	8.746×10^{-2}
3	2.788×10^{-2}	1.779×10^{-4}	1.507×10^{-2}
4	5.664×10^{-2}	3.126×10^{-2}	9.298×10^{-2}
5	1.969×10^{-5}	8.086×10^{-4}	1.612×10^{-2}
6	2.834×10^{-3}	1.091×10^{-4}	3.715×10^{-4}

Figures (7), (8) and (9) show the classification of cloud region.

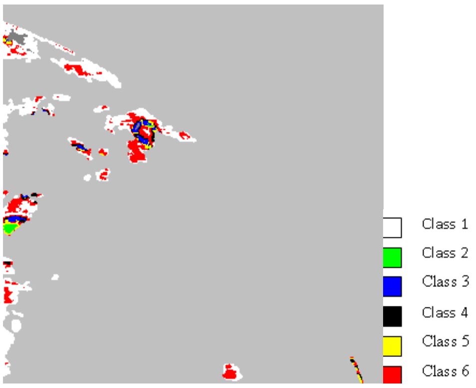

Fig.(8) The classification result of the cloud region by using the moment of inertia IR2- band and the moment of inertia of Water Vapor band, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

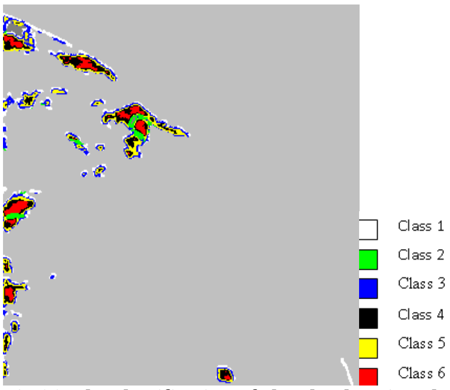

Fig.(9) The classification of the cloud regions by using the moment of inertia and the inverse difference moment, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

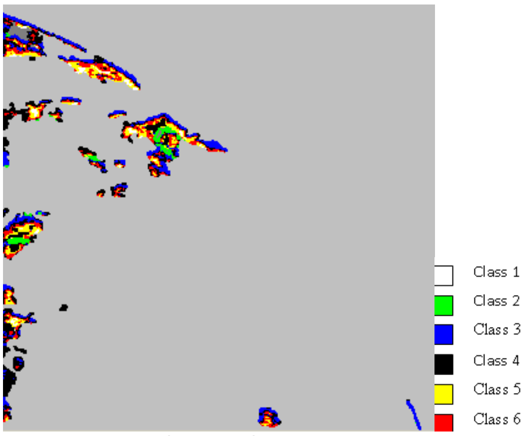

Fig.(10) The classification of the cloud regions by using the moment of inertia and the Entropy, where class1 is low cloud, class2, 4, 6 are middle clouds, class 6 is higher than class 2 and class 2 is higher than class 4, class 3, 5 are higher clouds where class 3 is lower than class 5.

Discussion:

In the present work the k- mean and textural analysis work together in order to classify the cloud height and type. the best classifier feature is the angular second moment when it is used with other textural feature, because the angular second moment gives information about the homogeneity from table (1) we can see that the high variance value corresponding to low level cloud which represent (cirrus,cirro-cumulus, cirro-stratocumuluse). the low variance of cloud represented the high cloud which are (cirrus, cirro- cumulus, cirro-stratuse). the middle level cloud which are (cumulus, alto-stratus and nibostratus). table(1) and figure(2 to 6) represent the result of classifying the cloud type. table (2) using the moment of inertia of one band which is IR2 with the other textural feature and this feature textural gives good classifying cloud type. this can be seen from the figures (8 to 10)

the best classifying technique is when we use the k-mean with co-occurrence.

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تصنيف ارتفاع الغيوم باستخدام التحليل النسيجي لصور القمر الصناعي الميتيوسات

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الخلاصة:

في هذا البحث، يمكن الحصول على تميز الأنماط بواسطة التباين وحساب التغاير لصور الغيوم . حيث يتم تطبيق عملية تجميع K-كوسيلة لتصنيف انواع الغيوم، لقد تم اعتماد تحليل النسيج لاستخراج بعض الخصائص التي تستخدم في عملية تصنيف انواع الغيوم. الصور التي تم استخدامها في عملية التصنيف هي صور القمر الصناعي الانوائي المتيوسات-7 حيث الصوره الماخوذه هي لمنطقة-D3 التي تشمل العراق ومنطقة الخليج والمناطق المحيطه به. لقد تم اعتماد طريقة التصنيف الغير موجه وهي طريقة عنقدة k ويتم اختيار البذور الأوليه بشكل عشوائي، عملية عنقدة k تم تطبيقها على حزمة بخار الماء والحزمه التحت الحمراء، ان طريقة التحليل النسيجي هي احد الطرق المهمه لتصنيف ارتفاعات الغيوم حيث تم استخدم مصفوفة التدرج اللوني ومن خلالها تم حساب بعض الخصائص الاحصائيه، عملية المزج بين طريقة التحليل النسيجي وطريقة تجميع k ساعدت باختيار افضل الخصائص الاحصائيه لتصنيف ارتفاعات الغيوم حيث اعتبر العزم الثنائي الزاوي هو افضل الخصائص الاحصائيه لتصنيف ارتفاعات الغيوم.