TOWARDS AUTOMATION IN OBJECT-BASED CLASSIFICATION

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ABSTRACT

Often in image analysis, a human observer can easily categorise the image into classes of interest. But then, it gets so difficult to reproduce the same result using a computer. The emerging object-based methodology appears to be a better way to mimic the human thought process. Unlike pixel-based techniques which only use the layer pixel values, the object-based techniques can also use shape and context information of a scene texture. These extra degrees of freedom provided by the objects will aid the identification (or classification) of visible textures. However, the concept of image-objects brings with it a huge number of object features. A huge information is associated with objects. The solution of automation depends on how we solve the problem of identifying the features that characterise the classes of interest and then finding the final distribution of the classes in the identified feature space. We present a statistical approach in this direction towards automation in object-based classification.

Key words: Object-based Classification; Image objects.

1. INTRODUCTION

Object-based classification is a promising methodology as it is close to human perception. A typical object-based classification system starts with segmenting the image into smaller homogeneous regions (or image-objects). These objects correspond to approximations of real-world objects [1]. Every object is characterised by several features defined based on layer values, texture, shape and context of the object. Generally, the objects are classified using a defined rule base. This is where the human intervention cannot be avoided, thus hindering the possibility to automate the classification process. With a few input samples for every class and using the enormous object feature-space to our advantage, it is possible to automatically generate such a rule base. However, the pre-condition obviously is a good segmentation result. We used the “Multi-resolution segmentation” of Definiens Professional \textsuperscript{1} software in the present work.

The essential issue is to manage the huge information given by the colour, shape, texture and context of the object. Only a few object features characterise a class and as the degrees of freedom increase, it gets increasingly difficult to identify the optimum features among the huge number of available features. In this article we summarise a few issues related to the object feature-space and thus make an attempt to provide a solution towards automation in object-based classification. It is possible to identify the optimum features based on a separability measure which quantifies the distance between the two random distributions and a simple Bayes’ rule identifies the threshold of separation [2, 3]. Using this, we try to provide different methods leading to a classified image with multiple classes.

2. THEORETICAL BACKGROUND

2.1. Distance between random distributions

A popular measure of distance between two random distributions is the Bhattacharya distance measure (BDM). For two random distributions given by probability density functions $p_1(x)$, $p_2(x)$, the BDM can be given as [2]:

$$B = -\ln \left( \int \sqrt{p_1(x)p_2(x)} dx \right)$$

(1)

For a discrete case, we can approximate eqn. 1 as

$$B = -\ln \left( \sum_i \sqrt{p_1(x_i)p_2(x_i)} \Delta x \right)$$

(2)

$x_i$ refers to the discrete points and $\Delta x$ refers to the sampling interval or typically the width of the bins in the histogram. The discrete probability density function is obtained by normalising the histogram with respect to the total area under the histogram.

The range of $B$ falls in half-closed interval $[0, \infty)$. This range is transformed into the closed interval $[0, 2]$ by using a simple transformation leading to so called Jeffries-Matusita distance measure (JMDM),

$$J = 2(1 - e^{-B})$$

(3)

\footnote{http://www.definiens.com}
$J = 0$ implies that the two distributions are completely correlated and $J = 2$ implies that the distributions are completely uncorrelated.

For every feature, we can calculate the separability between the two classes using $J$. The features which have very high $J$ value are the optimum features which characterise the classes.

2.2. Threshold of separation

We can distinguish two random distributions by using a threshold of separation. For two classes $C_1$ and $C_2$ and an observation $x$, using the Bayes’ rule we get,

$$p(C_1 | x) = \frac{p(x | C_1) p(C_1)}{p(x)}$$

and similarly for $C_2$. We then have

$$p(C_1 | x) + p(C_2 | x) = 1.$$  

These are the only possibilities and the total probability should be 1. The best decision threshold then is given by the relation

$$p(C_1 | x) = p(C_2 | x).$$

On rearranging the terms using the above equations, we have

$$p(x | C_1) p(C_1) = p(x | C_2) p(C_2)$$

(7)

For discrete functions, we can find the threshold as

$$T = x_j, \text{ where } |p(x_j | C_1) p(C_1) - p(x_j | C_2) p(C_2)| \approx 0.$$  

(8)

The degree of misclassification depends on the separability. However, we can overcome this limitation to some extent by carefully shifting the threshold.

3. TOWARDS AUTOMATION

As mentioned earlier, the solution towards automation in object-based classification depends on how we extract the necessary information from the huge information associated with the objects. We demonstrate the procedure first on the simple case of two classes and then extend it to the case of multiple classes.

3.1. The Procedure

The method for extracting a class in an image is illustrated in Fig. 1

* The goal of pre-processing is to increase the homogeneity of the objects. Different image scenario will require different pre-processing steps. Sometimes the pre-processing step can be crucial as the basic step of object-based classification is to first generate approximate real world objects and it requires that these object regions in the image are homogeneous.

* After segmenting the image into primitive objects, few samples are collected. This can be done manually by selecting samples in the image based on human interpretation or statistically by selecting specific regions in the concerned image histograms. For example if the objects of class of interest are characterised by bright regions compared to other objects in the image, then 2-5% of the objects in the image histogram which have high mean values are taken as samples of class of interest and 2-5% of image-objects which have low mean values are assigned as samples to the background class.

* When we have samples of the classes, we can automatically identify the optimal features using the JMDM defined in the eqn. 3. Since the samples cannot give the information about what kind of probability distribution the class has, we first assume that the distribution is Gaussian. However in the next step we try to get an approximate distribution of the classes and thus reassess the feature space. The optimum features will have high $J$ value.

* We now try to identify the approximate probability distributions of the classes and try to validate if the features we identified in the previous step are the best features defining that class. From the samples and features obtained in the earlier stages we cluster the objects into two classes. This will give the approximate distribution of the classes. Any clustering technique such as minimum distance, Fuzzy clustering, etc. can be used. However, to represent all the features on a common scale, a transformation has to be made on the feature values before clustering. This transforms all the feature values in the
range of [0,1]. For every object feature value \( F \) of a particular feature,
\[
F_1 = F - F_{\text{min}} \tag{9}
\]
\[
F' = \frac{F_1}{F_{1\text{max}}} \tag{10}
\]

\( F_{\text{min}} \) is the minimum of the object feature values of that feature, \( F_{1\text{max}} \) is the maximum of values \( F_1 \) obtained in first step. \( F' \) is the transformed feature value of \( F \). A different clustering algorithm can also be used at this stage.

* After the clustering, we again check for the separability of features and hence find the threshold of separation for the features having high \( J \) value. The thresholds are found based on the Bayes’ rule defined in eqn 7. However there will be some misclassification if we just classify the objects based on these thresholds. We can sometimes solve this by moving the threshold away from the mean of the class of interest. This can be achieved by defining a simple criterion using the separability measure. If \( J < 0.5 \), the feature is ignored. Otherwise,
\[
T' = m_2, \quad \text{for} \quad 0.50 \leq J \leq 1.25
\]
\[
T' = (T + m_2)/2, \quad \text{for} \quad 1.25 < J < 1.75
\]
\[
T' = T, \quad \text{for} \quad J \geq 1.75
\]

*Figure 2. Finding the threshold*

The above criterion is based on observations using random data. It has been observed that this criterion is suitable when more features with a better \( J \) value exist. The objects are finally classified using these thresholds. The classification is based on an ‘AND’ operation which is equivalent to sequentially eliminating the background objects from the class of interest using the optimum features.

3.2. Extending it to the multiple classes

We can extend the procedure defined in the previous section to the case of multiple classes in several ways. To give some examples the following methods can be employed.

1. We can sequentially extract one class at a time using the procedure defined in section 3.1. But this can lead to objects with multiple classifications. We can reclassify the objects with multiple classifications using the minimum distance to the distributions.

2. We can use a fuzzy rule base to classify the objects. This method can efficiently minimise the number of multiple classifications.

3. A neural network classifier can be designed based on the samples and the available features.

4. RESULTS

4.1. Extracting Fission-tracks in Microscopic images

The fission-track dating method is now commonly used in geological research but hindered by time consuming track counts and length measurements. Attempts at automation using conventional image analysis techniques on digital data have hitherto proved of limited practical use. To automate the process of counting the tracks, we try to mimic human thinking procedures. We first identify all the tracks in the image and then count the number of tracks by accounting for the number of intersections. The first step in doing that is to automatically classify the tracks and define ‘tracks’ objects. When the tracks are identified, then we can work on identifying procedures to count the individual tracks by counting the intersections. We used the procedure described in this article to develop an algorithm for first identifying the tracks objects in the image of Fig. 3. The box labelled as \( a \) shows an example of how tracks intersect.

*Figure 3. A microscopic image showing tracks to be identified*
With the knowledge that fission-tracks appear dark in the image, we start by collecting the samples statistically from the histogram. The procedure follows as explained in the section 3.1. The result of extracting the fission-tracks is shown in Fig. 4.

4.2. Extracting the morphology of normal faults

Normal faults are formed in the rifts. A rift is a region where the Earth’s crust and lithosphere are under extensioonal strain, hence forming a series of horst and graben segments. The fractures generated in this process of rifting are normal faults. A DEM can be used for identification of the faults as the faults are characterised by steep slopes. The approximations of the gradient of the DEM are used as layers for classification. The faults are characterised by high gradient value as shown in Fig. 6. The result of the automatic classification is shown in Fig. 7. The two colours for faults indicates two directions of the gradient.

4.3. Classifying the Esfahan nuclear facility

This case involves multiple classes. A part of high resolution image (acquired by Quickbird satellite in 2003) of Esfahan Nuclear facility(Fig. 8) is used to classify for various classes such as Buildings, Shadows, Roads and Walls& Limitations. We tried to extract the classes based on the features identified as best features using the separability measure when one class is compared to all the other classes.

Fig. 9 shows the classification result. The high inaccuracy of the classification result is because of improper segmentation. Different classes are extracted at different scales and it is difficult to identify at which scale we have to work with which class. Here most of the Buildings and Roads are classified properly for the segmentation parameters used here.
We intend to extend the present work to classify an image into multiple classes by trying to identify the level of extraction for different classes.

5. CONCLUSION

Object-based classification comes close to human perception. However, the huge information associated with the objects, hinders the proper utilisation of the strength of image-objects. We have shown that the optimum features which characterise a class can be identified. This separates the relevant information from the huge information. We then demonstrated how we can step towards a solution for automatic image classification using image-objects.

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REFERENCES

