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METHODS OF MEASUREMENT OF AVIATION DETAILS WITH USAGE OF ROBOTIC VISION COMPLEXES

In given article are described methods of image analysis. Image analysis is the term that is used to embody the idea of automatically extracting useful information from an image of a scene. The more commonly used image analysis techniques include template matching, statistical pattern recognition, and the Hough transform. application. Techniques vary across a broad spectrum, depend-ing on the complexity of the image and, indeed, on the complexity of the information to be extracted from it. The important point regarding image analysis is that this information is explicit and can be used in subsequent decision making processes.

Key words: *image analysis location, identification, inspection, template.*

Introduction

The important point regarding image analysis is that this information is explicit and can be used in subsequent decision making processes. Techniques vary across a broad spectrum, depending on the complexity of the image and, indeed, on the complexity of the information to be extracted from it. The more commonly used image analysis techniques include template matching, statistical pattern recognition, and the Hough transform. Unfortunately, this classification is not particularly useful when one is trying to identify a technique for a potential application. However, we can also classify the types of analysis we wish to perform according to function. There are essentially three types of things we would wish to know about the scene in an image. First, we might wish to ascertain whether or not the visual appearance of objects is as it should be, i.e. we might wish to inspect the objects. The implicit assumption here is, of course, that we know what objects are in the image in the first place and approximately where they are. If we don't know where they are, we might wish to find out. This is the second function of image analysis: location. Note that the location of an object requires the specification of both position and orientation (in either two dimensions or three dimensions). Also, the coordinates might be specified in terms of the image frame of reference (where distance is specified in terms of pixels) or in the real world where distances correspond to millimetres, say. The latter obviously necessitates some form of calibration, since initial measurements will be made in the image frame of reference. Finally, if we do not know what the objects in the image are, we might have to perform a third type of analysis: identification.

If the objective of the image analysis is to find objects within the image and identify, or classify, those objects then an approach based on statistical decision theory may be the most appropriate route to take. The central assumption in this approach is that the image depicts one or more objects and that each object belongs to one of several distinct and exclusive pre-determined classes, i.e. we know what objects exist and an object can only have one particular type or label.

1. Template matching

Many of the applications of computer vision simply need to know whether an image contains some previously defined object or, in particular, whether a pre-defined sub-image is contained within a test image. The sub-image is called a *template* and should be an ideal representation of the pattern or object which is being sought in the image. The template matching technique involves the translation of the template to every possible position in the image and the evaluation of a measure of the match between the template and the image at that position. If the similarity measure is large enough then the object can be assumed to be present. If the template does represent the complete object for which you wish to check the image, then the technique is sometimes referred to as 'global template matching', since the template is in effect a global representation of the object. On the other hand, local template matching utilizes several templates of local features of the object, e.g. corners in the boundary or characteristic marks, to represent the object.

1.1. Measures of similarity

Apart from this distinction between global and local template matching, the only other aspect which requires detailed consideration is the measure of similarity between template and image. Several similarity measures are possible, some based on the summation of differences between the image and template, others based on cross-correlation techniques. Since similarity measures are widely used, not just in this image template matching situation, but also for evaluation of the similarity between any two signatures (i.e. characteristic signals), such as when comparing shape descriptors, it is worth discussing these similarity measures in more detail. We will look at measures based on Euclidean distance and cross-correlation.

A common measure employed when comparing the similarity of two images (e.g. the template t(i,j) and the test image g(i,j) is the metric based on the standard Euclidean distance between two sectors, defined by:

$$E(m,n)=\sqrt{\left\{\sum_i\sum_j\left[g(i,j)-t(i-m,j-n)\right]^2\right\}}. \quad (1)$$

The summation is evaluated for all i such that (i - m) is a valid coordinate of the template sub-image. This definition amounts to translating the template t(i, j) to a position (m,n) along the test image and evaluating the similarity measure at that point.

The similarity measure based on the Euclidean distance is quite an appealing method, from an intuitive point of view. To see why, consider a complete one-dimensional entity, e.g. size (represented by, say, length). To compare the difference in size of two objects, we just subtract the values, square the difference and take the square root of the result, leaving us with the absolute difference in size:

$$d=\sqrt{([s_1-s_2)]^2}. \quad (2)$$

Extending this to the two-dimensional case, we might wish to see how far apart two objects are on a table, i.e. to compute the distance between them. The difference in position is simply:

$$d=\sqrt{\left[(x_1-x_2)^2+(y_1-y_2)^2\right]}. \quad (3)$$

Similarly, in three dimensions

$$d=\sqrt{\left[(x_1-x_2)^2+(y_1-y_2)^2+(z_1-z_2)^2\right]}. \quad (4)$$

Thus, when searching for a template shape, the template is effectively moved along the test image and the above template match is evaluated at each position. The position (m, n) at which the smallest value of E(m,n) is obtained corresponds to the best match for the template.

Before proceeding to discuss the mechanism by which we can classify the objects, let us first take a look at some representative features that we might use to describe that object.

Most features are either based on the size of the object or on its shape. The most obvious feature which is based on size is the area of the object: this is simply the number of pixels comprising the object multiplied by the area of a single pixel (frequently assumed to be a single unit). If we are dealing with grey-scale images, then the integrated optical density (IOD) is sometimes used: it is equivalent to the area multiplied by the average grey-level of the object and essentially provides a measure of the 'weight' of the object, where the pixel grey-level encodes the weight per unit area.

2. Components of a statistical pattern recognition process

There are effectively three components of this type of pattern recognition process: an object isolation module, a feature extraction module, and a classification module. Each of these modules is invoked in turn and in the order given, the output of one module forming the input of the next. Thus, the object isolation module operates on a digital image and produces a representation of the object. The feature extraction module then abstracts one or more characteristic features and produces (so-called) feature vector. This feature vector is then used by the classification module to identify and label each object.

Since we will be covering some of these topics again in more detail later on, e.g. methods for object isolation and description, we will just give a brief overview of the representative techniques at this stage.

Object isolation, often referred to as 'segmentation', is in effect the grouping process which we discussed in the preceding chapter. The similarity measure upon which the grouping process is based in this instance is the grey-level of the region.

3. Simple feature extraction

Most features are either based on the size of the object or on its shape. The most obvious feature which is based on size is the area of the object: this is simply the number of pixels comprising the object multiplied by the area of a single pixel (frequently assumed to be a single unit). If we are dealing with grey-scale images, then the integrated optical density (IOD) is sometimes used: it is equivalent to the area multiplied by the average grey-level of the object and essentially provides a measure of the 'weight' of the object, where the pixel grey-level encodes the weight per unit area.

Quite often, the distance around the perimeter of the object can be useful for discriminating between two objects (quite apart from the fact that one can compute the area of the object from the perimeter shape). Depending on how the object is represented, and this in turn depends on the type of segmentation used, it can be quite trivial to compute the length of the perimeter and this makes it an attractive feature for industrial vision applications.

Features which encode the shape of an object are usually very useful for the purposes of classification and because of this, has been entirely given over to them. For the present, we will content ourselves by mentioning two very simple shape measures: rectangularity and circularity. There are two popular measures of rectangularity, both of which are easy to compute. The first is the ratio of the area of the object to the area of the minimum bounding rectangle:

$$R=A_{object}/A_{min.bound.rectangle}. \quad (5)$$

This feature takes on a maximum value of 1 for a perfect rectangular shape and tends toward zero for thin curvy objects.

The second measure is the aspect ratio and is simply the ratio of the width of the minimum bounding rectangle to its length:

$$\text{Aspect ratio} = W_{\text{min.bound.rectangle}} \big/ L_{\text{min.bound.rectangle}} \,. \quad (6)$$

The most commonly used circularity measure is the ratio of the square of the perimeter length to the area:

$$C = \text{À}_{\text{object}} \big/ \text{Đ}^2_{\text{object}} \,. \quad (7)$$

This assumes a maximum value for discs and tends towards zero for irregular shapes with ragged boundaries

Conclusion

The final stage of the statistical pattern recognition exercise is the classification of the objects on the basis of the set of features we have just computed, i.e. on the basis of the feature vector.

If one views the feature values as 'coordinates' of a point in n-dimensional space (one feature value implies a one-dimensional space, two features imply a two-dimensional space, and so on), then one may view the object of classification as being the determination of the sub-space of the feature space to which the feature vector belongs. Since each sub-space corresponds to a distinct object, the classification essentially accomplishes the object identification.

For example, consider a pattern recognition application which requires us to discriminate between nuts, bolts, and washers on a conveyor belt.

Assuming that we can segment these objects adequately, we might choose to use two features on which to base the classification: washers and nuts are almost circular in shape, while bolts are quite long in comparison, so we decide to use a circularity measure as one feature. Furthermore, washers have a larger diameter than nuts, and bolts have an even larger maximum dimension.

Thus, we decide to use the maximum length of the object (its diameter in the case of the nuts and washers) as the second feature.

If we then proceed to measure these feature values for a fairly large set of these objects, called the training set, and plot the results on a piece of graph paper (representing the two-dimensional feature space, since there are two features) we will probably observe the clustering pattern shown in fig. 1 where nuts, bolts, and washers are all grouped in distinct sub-spaces.

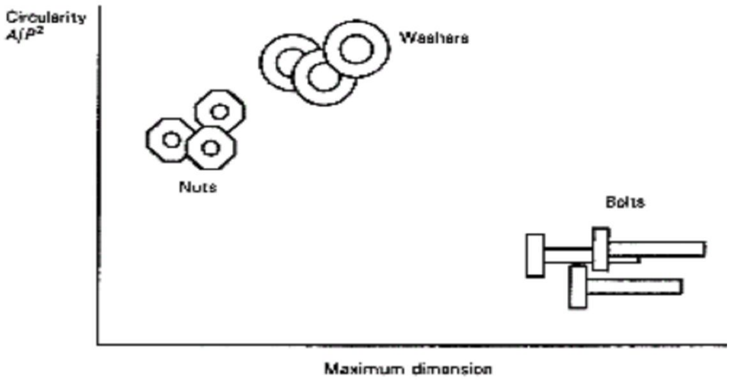

Fig. 1. Feature space

At this stage, we are now ready to classify an unknown object (assuming, as always, that it is either a nut, a bolt or a washer). We generate the feature vector for this unknown object (i.e. compute the maximum dimension and its circularity measure A/P2) and see where this takes us in the feature space (see fig. 2).

The question is now: to which sub-space does the vector belong, i.e. to which class does the object belong?

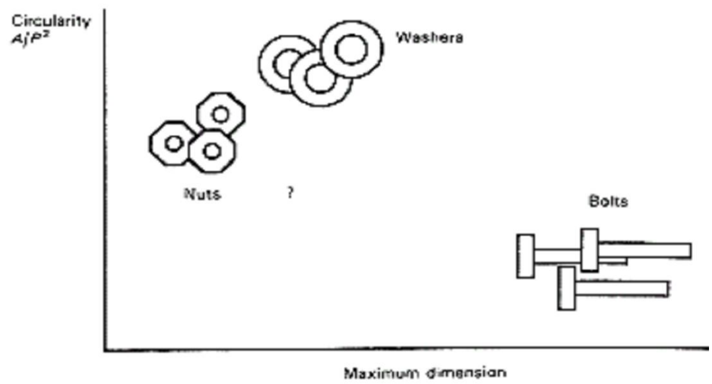

Fig. 2. Coordinates of unknown object in the feature space

One of the most popular and simple techniques, the nearest-neighbour classification technique, classifies the object on the basis of the distance of the unknown object vector position from the centre of the three clusters, choosing the closest cluster as the one to which it belongs. In this instance, the object is a nut (see fig. 3).

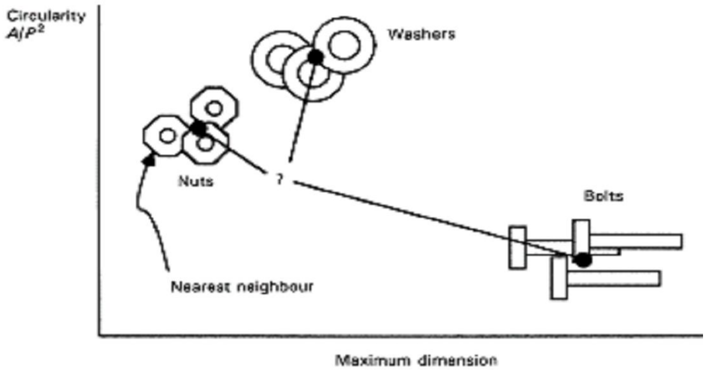

Fig. 3. Nearest neighbour classification

This technique is called, not surprisingly, the nearest-neighbour classifier. Incidentally, the position of the centre of each cluster is simply the average of each of the individual training vector positions.

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ПОЛІПШЕННЯ ВІЗУАЛЬНОЇ ЯКОСТІ ЦИФРОВОГО ЗОБРАЖЕННЯ ШЛЯХОМ ПОЕЛЕМЕНТНОГО ПЕРЕТВОРЕННЯ

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У даній статті описані методи аналізу зображення. Аналіз зображення - термін, який використаний, щоб втілити ідею автоматичного вилучення корисної інформації від зображення сцени. Розглянуті методики аналізу зображення складаються зі співставленням з шаблоном, статистичне розпізнавання та – перетворення Гауса. Методики аналізу зображень змінюються в залежності від складності зображення також від метода за яким отримане зображення буде оброблятися для подальшого прийняття рішення. Важливим аспектом відносно аналізу зображення є те, що ця інформація є явною та може бути використана у подальших процесах прийняття рішення.

Ключові слова: ідентифікація, визначення, шаблон, цифрове зображення.

МЕТОДЫ ИЗМЕРЕНИЯ АВИАЦИОННЫХ ДЕТАЛЕЙ С ПОМОЩЬЮ РОБОТОТЕХНИЧЕСКИХ КОМПЛЕКСОВ

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В данной статье описанные методы анализа изображения. Анализ изображения - термин, который использован, чтобы воплотить идею автоматического извлечения полезной информации от изображения сцены. Рассмотренные методики анализа изображения включают сравнение с шаблонами, статистическое распознавание образов и – преобразование Гаусса. Методики анализа изображений изменяются, в зависимости от сложности изображения и а также от метода анализа полученного изображения и дальнейшего принятия решения., Важный аспект относительно анализа изображения – то, что эта информация является явной и может использоваться в последующих процессах принятия решений.

Ключевые слова: идентификация, определение, шаблон, цифровое изображение.

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