AUTOMATIC EVALUATION OF DEGRADATION OF PAINT COATINGS THROUGH EM ALGORITHM

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ABSTRACT

An unsupervised application for the visual analysis of metallic substrates and paint coatings is presented. Model based classification is used for the analysis of metallic substrates while a segmentation of the image is required to distinguish between paint and substrate or between paint and rust for the analysis of paint coatings. A unified framework based on the Expectation-Maximization (EM) algorithm is presented to solve both analyses. The EM algorithm is used both as a colour-based identification method for measuring cleanness properties of the substrate's surface, and also as a colour-based segmentation method for extracting the paint regions of the coating's surface. An initialisation method and a pre-processing step are proposed to avoid false segmentations. Experimental results on real samples show more repeatability and accuracy than the results obtained by human visual inspection. Each analysis has been visually illustrated with a representative example.

1. INTRODUCTION

Classical segmentation techniques [1,2] are suitable for segmentation of images composed by objects where each pixel clearly belongs to an object or to the background. However, they are not suitable for several applications in which the regions of interest are distributed without spatial coherence. In this paper we propose a colour-based segmentation based on the Expectation-Maximization (EM) algorithm as a solution to this kind of images.

This method has been tested on images of painted surfaces for assessing the quality either of the coating or the substrate. In this application there are some coating pictures, like those showing a rusted surface, in which, rather than objects, we simply find a range of colours without spatial coherence. Some of the colours in the middle of the range are difficult to assign to a particular region. In order to overcome this uncertainty, we pose this segmentation problem in a probabilistic framework, by using the EM algorithm.

Nowadays the analyses of coatings and substrates are carried out through human visual inspection, which leads to subjective results that may be inaccurate and influenced by human factors. The proposed method avoids this subjectiveness and assures repeatability in the results.

The remainder of the paper is organised as follows. Section 2 gives a brief description of the EM algorithm used as basis of the colour segmentation technique. Section 3 refers to the arrangement of the input colour data set before applying the EM algorithm. Sections 4 to 6 describe the implementation of three of the analyses: substrate cleaning, rust analysis and measurement of coating thickness. The concluding remarks are drawn in section 7.

2. COLOUR SEGMENTATION USING THE EM ALGORITHM

The EM algorithm is a parameter estimation technique based on a criterion of maximum likelihood (ML). One of the most widely used applications is that of estimating the parameters of a density function described as a gaussian mixture [3,4,5]. The equations to obtain the parameter estimations can be found in [5,6].

In a colour-based segmentation context, the colours of the pixels of the image are considered a realization of a random variable drawn from a gaussian mixture distribution [4]. Each gaussian is to be though as a colour model that describes the average and variance of one family of colours. Thus, each pixel is supposed to be generated by a weighted combination of colour models. Once the EM algorithm has produced the estimations of the parameters, each pixel is classified in the colour model that has contributed in a greater extent to the colour of that pixel. The classification of all the pixels results in the colour segmentation of the image.

However, the straight application of this algorithm leads to erroneous segmentations due to either the use of a non-adequate colour space or to a great difference between the number of pixels associated to each model. Hence, a pre-processing step is required as described in the following section.

3. ARRANGEMENT OF THE COLOUR DATA SET

In our application, the colours of the pixels are initially expressed in the RGB colour space. Several works [7,8] find that in colour segmentation problems it is more suitable to use the HSV colour space, not only because it separates the luminance and colour information, but also because it corresponds better to how people perceive colour, that is, in terms of hue (idea of colour), saturation (vivid or pale) and value (bright or dark).

Since the hue parameter is an angle, the data set cannot be introduced to the EM algorithm right after the conversion to the HSV space. For example, two red colours can have hue values of 1° and 359°. Although both samples are practically the same colour, the different values of the hue component would cause the EM algorithm to consider them as samples that are far from each other, thus being assigned to different regions. Therefore, it is necessary to describe the data set in a new coordinate system such that similar colours measure small distances within the HSV colour space. The new coordinate system is a Cartesian XYZ-space whose Z-axis is the axis of the HSV cone.

The colour segmentation using the EM algorithm can be influenced by a possible disproportion of the regions to be segmented, that is, one colour model predominates among the others. In this case, the gaussians tend to converge near the zone of the predominant colour in the colour space. The variance of the gaussian that gets closer is notably smaller than the other variances, producing a very restrictive colour model. This problem can be compensated by means of a colour filter that keeps only one sample for each colour present in the image. In this way, the EM algorithm shall only consider the colour range of the image without being affected by the colour occurrence. The result is that the gaussians are better distributed along the colour data set, the variance of the gaussian closer to the predominant colour increases and therefore the segmentation of the image improves remarkably.

Figure 1 depicts an example of this situation by segmenting the green branches of the pumpkins , where the orange colour is clearly predominant. This example allows the comparison of the resulting segmentation of the green branches either using the colour filter or not.

Since the filtering implies a reduction of the colour data set, there is a side effect by which the convergence of the EM algorithm is speeded up. The time of convergence depends on the amount of disproportion of the colours: the higher the disproportion is, the faster the algorithm shall converge.

4. ANALYSIS OF THE CLEANNESS OF THE METALLIC SUBSTRATE

The paint coatings are applied over the surface of a metallic substrate. This substrate must be clean. There are three levels of cleanness, which are designated –from cleanest to dirtiest – as patterns A, B and C. Each pattern is described by a colour that has been previously learned during a calibration stage that measures the average colour from a sample of that pattern.

In general, the surface of a substrate may present different levels of cleanness. This analysis consists in measuring the area belonging to each cleanness pattern, which can be solved by means of a colour-based segmentation.

Let us suppose that the pixels of a substrate image are drawn from a distribution composed by a mixture of four gaussians designated as A, B, C (associated to the pattern colour models) and D (comprising those colours that differ from all patterns). The gaussians A, B and C are initialised in the colour associated to its pattern. The gaussian D is initialised in the colour that measures the greatest distance from all the patterns. Note that we first assume that all colour models are present in the image. After applying the EM algorithm, we can verify the actual number of models by examining the location of the gaussians after the convergence. This number may be less than four for two reasons: 1) because a gaussian has converged far from its colour model (which means that the associated pattern is not present) or 2) because two gaussians have converged in the same position (indicating that one of the patterns is not present in the image). In the latter case, we keep the gaussian that is closer to its pattern.

If the actual number of gaussians is still four, then the substrate image is already segmented. Otherwise, it is necessary to apply again the EM algorithm with the actual number of gaussians, since the previous result was based on an erroneous assumption.

Figure 2 shows an example of analysis of the cleanness of a metallic substrate that presents exclusively the three patterns.

5. ANALYSIS OF RUST

The analysis of rust measures the percentage of rusted area on the surface of a paint coating. The pixels of the images under examination may belong to either the coating or rust colour models. Unlike the previous case, these models are not known a priori, as the colour of the coating may be any and the colour of the rusted area depends on the level of oxidation. We make use of the EM algorithm configured with two gaussians to learn these models from the colour data. The gaussians are initialised using the k-means algorithm, which has shown an excellent performance in all the evaluated cases. Figure 3 shows an example in which rusted regions are detected over a green paint coating.

6. MEASUREMENT OF COATING THICKNESS

The thickness of the paint coating applied over the surface of the metallic substrate is a measurement that can also be done through colour segmentation. For this analysis, a cut is made on the surface of the coating. The coating thickness can be then obtained, using trigonometry, from the angle of the edge of the blade and the width of the cut. The region inside the cut shows the substrate, which has a different colour from the coating. Therefore we can segment this region by using the EM algorithm, which like in the previous analysis, is configured with two gaussians initialised with the k-means algorithm. Once the region of the cut is segmented, we may measure its width by projecting the pixels to the axis of the cut. This generates a function that provides the measure of the widths of the cut for each transversal section. The final value of the width can be obtained by computing the average of this function. For simplicity, the orientation of the cut is extracted and compensated so the cut is aligned along the horizontal axis, thus facilitating the computation of the projection.

Figure 4 shows an example of extraction of the thickness of a coating.

7. CONCLUDING REMARKS

The EM algorithm is a powerful technique that is able to perform a colour-based segmentation of complex images where, in general, the pixels do not shape objects, but rather take values from a colour range without spatial coherence (see picture in Figure 3). The segmentation is based on the assumption that the pixels in the image have been generated by a combination of some colour models. This brings on two interesting applications of the EM algorithm: 1) unsupervised learning of colour models from the image data —provided the number of models— and 2) identification of predetermined models present in the image data. Examples of the former are provided in the analysis of rust and the measurement of the coating thickness, where after assuming the presence of two colour models (paint or rust regions and inner or outer regions of the cut) we make use of the EM algorithm to learn these models. An example of the latter application is the analysis of the cleanness of a metallic substrate, which consists in detecting the presence of three preset models described by the cleanness patterns A, B and C.

The initialisation of the gaussians depends on the type of application; for colour model learning we use the k-means algorithm and for model identification we initialise the gaussians in the locations described by the colour models to be identified.

We have shown that the straight application of the EM algorithm for segmentation is inaccurate when one colour model predominates significantly among the others. Our approach introduces a colour filter that only takes one sample of each different colour present in the image, thus compensating the disproportion and enhancing the segmentation, as illustrated in Figure 1. The application of this filter has the side effect of speeding up the convergence of the EM algorithm.

8. ACKNOWLEDGMENTS

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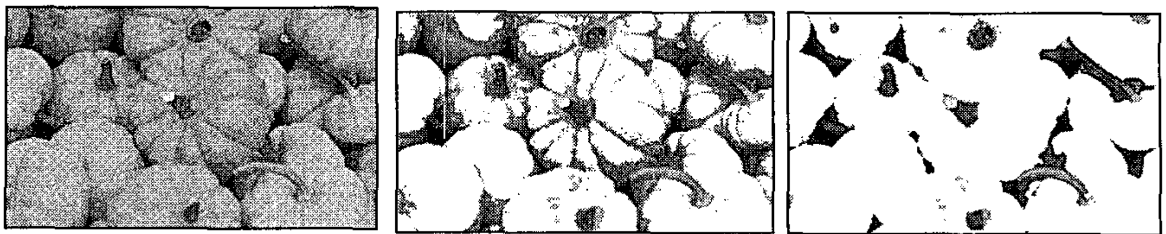

Figure 1. Example of the influence of colour disproportion in the segmentation results. From left to right: pumpkins image, segmentation of the green branches and enhanced segmentation by using the colour filter.

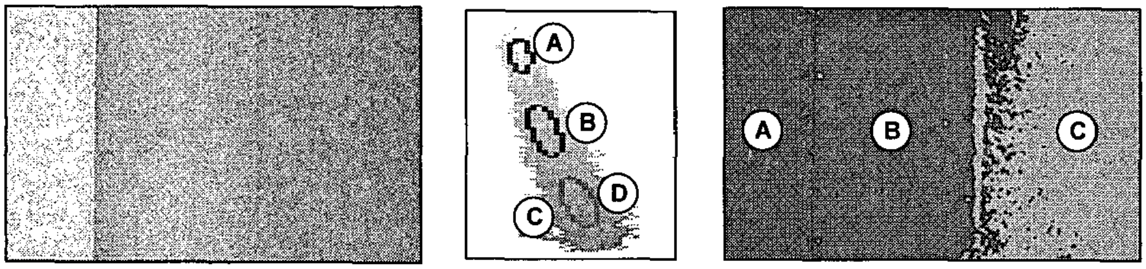

Figure 2. Example of a metallic substrate that presents the three regions matching patterns A, B and C, respectively. In this case there are no pixels classified as "dirt". This can be deduced by examining the position of the four gaussians in the colour space after the convergence (see the picture in the center). Note that gaussians C and D have converged in the same position. Since gaussian C is near to pattern C, gaussian D is discarded. The result of applying again the EM algorithm with the three gaussians A, B and C is shown on the right. Patterns A, B and C are depicted in red, blue and green, respectively.

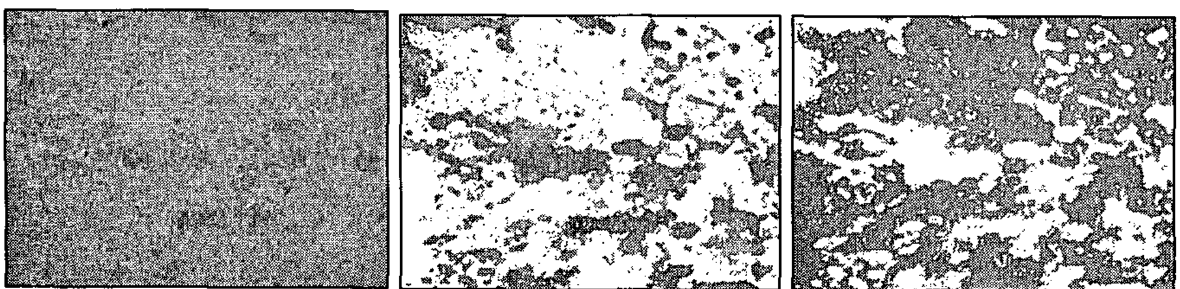

Figure 3. From left to right: input image showing a rusted surface and segmented images containing the rusted region and the paint region, respectively.

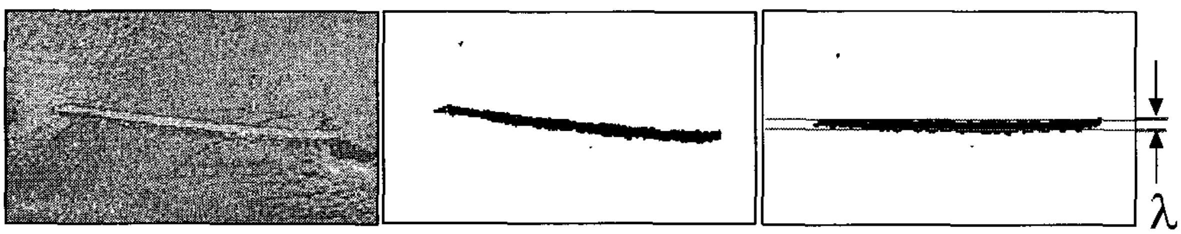

Figure 4. From left to right: input image, segmented region of the cut and measurement of thickness (λ), measured over the horizontally oriented cut.