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Automatic Classification of Tahitian Pearls - Image Processing & Communication - IPC 2014

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Summary. Tahitian pearls are currently classified manually by pearl experts. This process is time consuming and furthermore subjective for some of the quality parameters such as colour, form or lustre. In this paper we present our ongoing work to implement an automatic classification of Tahitian pearls out of images. An automatic classification can help to accelerate the quality evaluation process as well as to minimize the subjective influence of the human classification. For this purpose different image segmentation and machine learning methods are used. In the following sections we explain our methodology, show first results for several sub-steps and give new ideas for greylevel edge detection and colour classification.

Key words: Pearl classification, image analysis, edge detection, colour classification

1 Introduction

Grown in the clear warm water of the Polynesian lagoons, the Tahitian pearl has fascinated humans since centuries. On the international market the pearl is known by the name 'Queen of Pearls', due to its pureness, its colour diversity and its brilliant lustre. As a result of its high reputation, the pearl is an important source of income for the French Polynesian government. During the years 2008 to 2010 the pearl contributed averagely with over 60 % to the total exports of French Polynesia with an annual average value of over 90 million Euros. To keep the high reputation of the Tahitian pearl the local government implemented a quality grading system, not allowing exporting pearls which does not satisfy the quality standards. To define the quality of a pearl several parameters are evaluated (form, size, defects, lustre, colour and minimal nacre thickness). This evaluation is nowadays done manually by pearl experts from

the 'Direction de Ressources Marines et Minières (DRMM)'¹. This manual classification is problematic in two ways: First of all, the pure amount of over 1 million exported pearls per year is difficult to handle, as each pearl has to be classified separately. Second, the classification of several parameters, such as form, colour and lustre is highly subjective. The goal of our project is to automatically classify pearls out of images, using image processing and machine learning techniques. An automatic classification gives the possibility to accelerate the quality evaluation process as well as it allows minimizing the influence of subjectivity during the human classification. A third reason to implement an automatic classification is to support the scientific work of the 'Centre IFREMER du Pacifique'². One of their research groups is analysing the factors that influence the quality of a pearl during the cultivation process. Therefor correlation calculations between growing parameters (geographic location of the pearl farm, species of the breeding oyster, etc.) and the pearls quality are done. As a correlation calculation depending on subjectively classified quality parameters is not very trustworthy, an automatic classification of the parameters is required. To analyse the quality parameters of a pearl, we use two different kinds of images. To determine the 'outer' parameters colour, size, form, lustre, and defects, colour images of the surface of a pearl were taken (Figure 1). For each pearl four images were shot, to capture as much surface information as possible. The minimal thickness of the nacre on

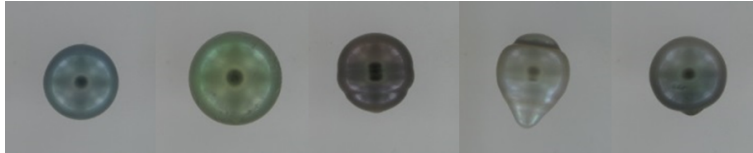


Fig. 1. Colour images of five Tahitian pearls.

the other hand cannot be evaluated from the outside. For this purpose X-ray images are taken at the DRMM. In Figure 2 on the left an X-ray image of a Tahitian pearl can be seen. The light round object in the middle of the pearl is the pearls nucleus. It is an artificially formed sphere which is inserted in a pearl oyster (*Pinctada margaritifera* in French Polynesia). Around this nucleus the oyster deposits a form of calcium carbonate, the nacre. The minimal thickness of the nacre is accordingly the minimal distance between the outer surface of the nucleus and the outer surface of the pearl. Currently this distance is measured manually by an employee of the DRMM (a video explaining this process in detail can be found under³). In the following three sections we present our methodology to automatically determine and measure the named

¹ <http://www.peche.pf>

² <http://wwwz.ifremer.fr/cop>

³ <https://www.youtube.com/watch?v=JvKBSK6jbgw>

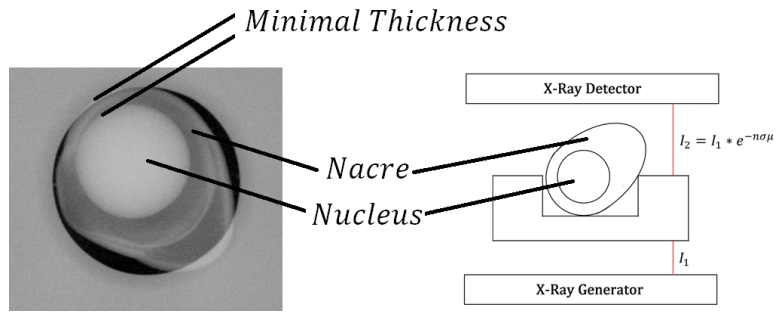


Fig. 2. X-ray image of a Tahitian pearl (left) and a schema of the capturing (right).

quality parameters. In the next section graylevel edge detection for analysing the X-ray images is discussed. In the third section the segmentation and information extraction of the colour images is shown. The fourth section deals with colour classification, followed by the conclusion in the fifth section.

2 X-Ray Images

To determine the minimal thickness of the nacre, the minimal distance between the artificial nucleus within the pearl and the outer surface of its surrounding nacre has to be measured. For this purpose X-ray images of the pearl are taken. The resulting images contain 4 major regions: The light background, the dark background, the nucleus and the nacre (Figure 3). To mea-

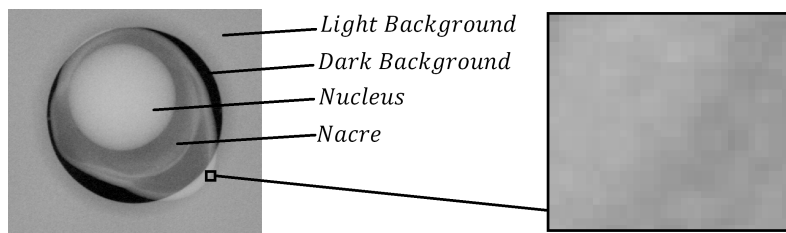


Fig. 3. Four different regions in the X-Ray image have to be segmented to measure the minimal nacre thickness (left). On the right, a detail showing the transition between the pearls nacre and the light background can be seen.

sure the distance between the nucleus and the nacre the 4 regions have to be segmented. Over the recent years many approaches for greylevel image segmentation have been published. The classical approaches include techniques like Canny, Prewitt or Sobel edge detection [1-5]. Although these techniques are a standard in greylevel edge detection, some major drawbacks are known. These classical operators look pixel-wise for sharp intensity gradients in an

image. A transition between different objects in the image, which ranges over many pixels without any sharp intensity difference between single pixels, is hard to detect (as for example between the nacre over the light background and the light background itself in Figure 3 on the right). A threshold to separate edges from objects has to be defined for the whole image, which does not take into account a heterogenic character of an image with objects of different homogeneity and edges of different intensity. The obtained edges are not necessarily connected, meaning a post processing of the obtained edges is necessary. Our current work evaluates the possibilities of another theory for greylevel image edge detection. The approach is to aggregate pixel of a monotonous gradient together and afterwards analyse these gradients. The advantage over the classical techniques is that transitions between objects without a sharp pixel-wise gradient might as well be detected. In Figure 4 on the left a detail of intensity values of a column of pixels of the X-ray image can be seen. The rectangles mark the pixels that belong to a monotonous ascending or descending gradient. On the right side of the image is a binary result of

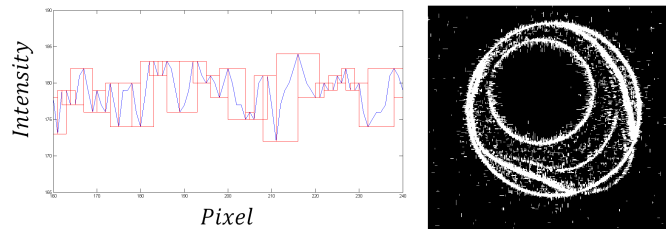


Fig. 4. Grouped pixels that form part of a monotonous gradient (left). On the right a binary image that shows row- and column-wise gradients bigger than 15.

thresholding every obtained gradient of the original X-ray image column- and row-wise. The threshold was set to a minimal gradient value of 15. It can be seen that transitions between regions that do not include a sharp pixel-wise gradient can be detected as well. Anyhow a global threshold for an image is to the authors' opinion generally not a satisfying approach, as it doesn't respect a heterogeneous character of an image. Our current research deals with finding solutions to discriminate between objects and edges independently of the gradients' size [6].

3 Colour Images

As mentioned, the colour images of the pearls are used to determine the parameters size, form, lustre, defects and colour. For this purpose multiple segmentations have to be done. In the case of the colour images, the crucial regions can be detected with less effort compared to the X-ray images.

Multiple global thresholds of the Intensity value obtained by converting the image to the HSI (Hue, Saturation, Intensity) space lead to the results shown in Figure 5. On the right side of each segmented area is the pearls quality parameter this region defines. For each parameter feature vectors, mathemat-



Fig. 5. Different segmented regions of a colour image of a Tahitian pearl and the quality parameters that are described in these regions.

ically describing a quality parameter, have to be calculated. These vectors will later be classified by machine learning algorithms. The mathematical description of a parameter to classify is an essential part of the classification. If the mathematical description of a parameter does not correlate with the human classification, the later numeric classification will not be satisfying. It is of advantage to generate a broad range of feature vectors out of which those with the highest descriptive power can be chosen afterwards. This can be done before the classification with a separate correlation analysis (Principal component analysis, Self-Organizing Maps or linear discriminant analysis for example [7-9]) or with an iterative classification process, evaluating the classification results for different constellations of feature vectors. Several examples for features can be seen in Figure 6.

Quality Parameter	Features					
Form, Size						
	Cross section area	Biggest distance	Symmetry axis	Biggest inner circle	Smallest outer circle	Geometrical objects
Lustre						
	Percentage of surface, diffusion, intensity, colour					

Fig. 6. Different possible features for the quality parameters form, size and lustre.

4 Toward Colour Classification

To classify the quality of a pearl each quality parameter will be classified independently. This is due to the fact that the parameters are of different and independent character. For the classification of the size and the amount of defects no advanced machine learning algorithm is necessary. These two parameters are objectively measurable and can be directly graded in classes defined by pearl experts or governmental guidelines. For the parameters form, lustre and colour instead more effort has to be done, since classes defined by humans can only be described by subjective criteria. A key role plays the classification of the pearls colour. It is a crucial parameter for the pearls quality but colour classification is still an open problem in the domain of colour image processing. If an image is in RGB or related formats, colour object classification is a three dimensional problem. In our previous work [10] we reduced the classification problem to a two dimensional one. In the cited work we integrated the Hue-Saturation model in the RGB colour space. A separation of achromatic from chromatic values directly in the RGB space was done. The separation bases upon a projection of RGB vectors along a line through origin and the original vectors to a two dimensional plane with the achromatic line as normal vector (Figure 7). The projection contains all chromatic information based on the definition of the HSV (Hue, Saturation and Value) space, while suppressing achromatic information. The projection

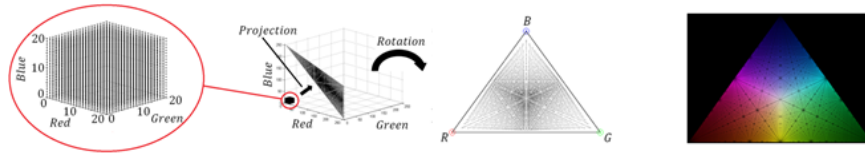


Fig. 7. A projection of RGB vectors to a plane with the achromatic line as normal to separate achromatic from chromatic information in the RGB space (left two images). The projection is afterwards turned into screen (third image). On the right side a coloured representation of the projection containing additional projection points can be seen.

furthermore corresponds to the linear character of the RGB space. It means a line separating the projection in two parts describes a certain proportional relation of RGB values to each other and therefore corresponds to the additive character of the RGB space. For an automatic classification of colour based on this theory, an approach with linear SVM (Support Vector Machine) seems promising [11-13]. The SVM can be used to linearly separate between two pearls of different colour, by dividing the projection in two parts. This linear separation correlates with the human biological processing of colour, as the projection is the barycentric representation of the RGB space. It corresponds as well to the human perception of colour, as the projection integrates the

perceptual HSV model in the RGB space. In Figure 8 two different segmented

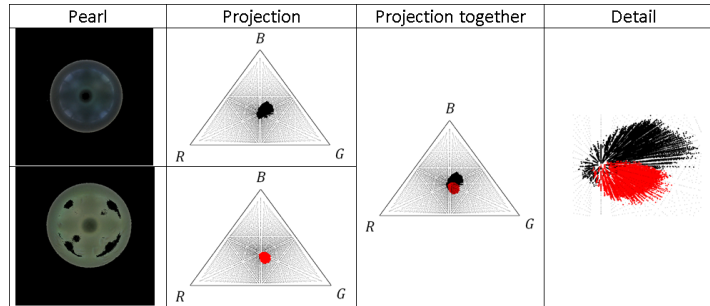


Fig. 8. On the left side two different segmented pearls are shown. In the second row the RGB vectors of each image are projected to suppress achromatic information. The two images on the right show the projection points of both images together.

pearls are shown. On the right side of each pearl the projection of the RGB vectors of the pearls describing the chromatic information in the linear RGB geometry can be seen. Due to the fact that several projection points of the two pearls overlap, a soft-margin SVM seems an adequate choice. Our current analysis deals with the implementation of soft-margin linear SVM to identify colour vectors that uniquely describe a certain colour of a pearl. According to these results the goal is to implement an artificial reproduction of the human classification of the pearls colour.

5 Conclusion

In the present paper we introduced our ongoing work to implement an automatic classification of Tahitian pearls. A general methodology to classify pearls out of X-ray and colour images was given. In the second section a new idea for greylevel edge detection was sketched and first promising results were shown. In the third part possibilities to describe quality parameters gained out of colour images were discussed. In the fourth section an idea of colour classification based on our previous work on colour space theory was explained. Our current work deals with further developing the greylevel edge detection algorithm, to avoid global thresholding. An analysis of different machine learning algorithms to classify the calculated feature vectors to obtain a classification of the pearls quality is part of our current work as well.

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