Automatic Visual Inspection of Ceramic Plates based on SIFT and SURF Descriptors

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Abstract

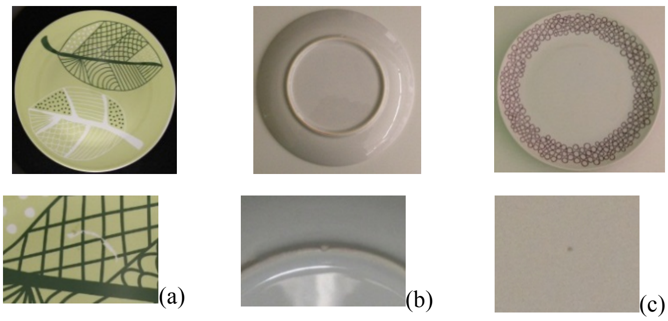
This paper concerns the problem of automatic visual inspection of ceramic plates. It will be studied two classes of plates and three groups of defects. Based on Scale Invariant Feature Transform (SIFT) or Speeded Up Robust Features (SURF) descriptors and a simple decision system based on a neural network we got very promising results with real experiments. Due to the generality of these algorithms we expect to easily solve another type of defects in different classes of plates.

1 Introduction

A large number of pottery factories rely on human workers to most of the inspection operations that should be carried out in a production line. At first glance it seems that would be easy to automatize these inspections based on computer vision. However, due to the large variety of plates and other dishware that circulates on conveyors in different stages of the production it is almost impossible to guarantee a pre-defined stable part positioning and stable lighting conditions. It is probably due to this fact that literature about this subject is not abundant [1]. There are quite a good number of papers in ceramic tiles e.g. [2], [3]. [4] deals with the inspection of different type of objects and use SIFT descriptors.

In this work we selected three groups of defects in two types of plates (Fig. 1). We define:

- A spoiled ceramic decals in one type of plates (Fig 1a)
- B missing glass on the back in the other type of plates (back) (Fig. 1b)
- C granules in the same type of plates (front) (Fig. 1c)



(a) (b) (c)

Figure 1: Examples of plates e respective defects of type A,B and C

This paper is organized as follows. Section 2 briefly describes the main techniques used in this work. Section 3 discusses the lighting conditions and presents the derived algorithms and obtained results for the different defects. Finally, Section 4 presents the conclusions and future work.

2 Related Techniques

Scale Invariant Feature Transform (SIFT).

In a very brief description this algorithm, developed by David G. Lowe [5], [6], can be divided in the following two majors steps:

- Interest points localization.
- Build interest points descriptors.

Both steps are quite complex to achieve the claimed invariance. The first one includes building a scale space at different image sizes (octaves). This space will allow replacing the evaluation of second order derivatives by Difference of Gaussians (DOG), from where interest points with sub-pixel accuracy are evaluated. The second step involves assigning an orientation to the interest points and building their descriptors. These are evaluated collecting gradient directions and magnitudes around each one. This is carried out in a 16 by 16 window around interest points. This window is still divided in sixteen 4 by 4 windows where gradient magnitudes and orientations are put into a 8 bin histogram. Hence, this gives rise to 128 descriptors for each interest point. These descriptors still suffer some kind of normalization [6].

Speeded Up Robust Features (SURF)

SURF was first presented by Herbert Bay et al. in 2006 [7]. It is partly inspired by the SIFT descriptor. Like the SIFT method the first two steps rely on a scale-space representation and first and second order differential operators.

The originality of the SURF method is that these operations are speeded-up by the use of an integral image and box filters techniques. The interest points evaluation is based on the computation of the discrete Hessian operator at several scales using box-filters. They are these box filters that approximate the second order derivatives. For each key point, in order to achieve rotation invariance, is evaluated the dominant orientation by considering the local gradient orientation distribution, estimated with Haar wavelets. The descriptors, a 16x4 vector, are built corresponding to a local histogram of the Haar wavelet responses. Like the SIFT descriptors these features still suffer some kind of normalization.

Hough transform

Due to the characteristic shape of the plates (circular) it is quite useful the Hough transform [8] to detect circles in the images. This well-known transform was first concerned with the identification of lines in an image, but later the Hough transform has been extended to identifying positions of arbitrary shapes, most commonly circles or ellipses. In our case the problem is facilitated because we know how many circles we expect in our images and even approximately their ratio.

3 Implemented methods

3.1 Image acquisition. Illumination

The illumination of quite reflective ceramic plates is very challenging. Indeed with normal illumination the reflexes invalidate any tentative to find sometimes very small defects. Inspired in commercial solutions a low cost dome was designed and quite satisfactory images (Fig. 2) were obtained.

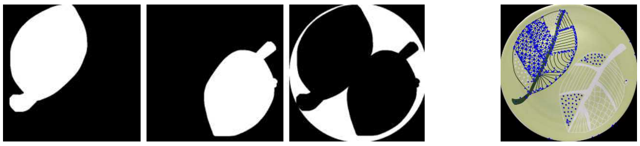
(a) (b) (c)

Fig. 2. (a) Dome used to take pictures and images without (b) and with dome light (c)

3.2 Defects of type A

To study the problem, a set of 24 images were used corresponding to 4 plates each one in six different positions. All the plates have defects and the goal was to find them automatically.

It was decided to base our approach classifying the points of interest found by the SIFT algorithm. After some attempts it was found that was better to apply local fine tuning to the different regions of the image, namely, the black sheet, the white sheet and the remaining plate (Fig. 4). To find these regions the images were rotate to a standard position. Notice that images in two different plates are not absolutely equal, otherwise a simple subtraction would be enough to find the defect. An examples of interest points obtained with this plate is given also in Fig 3.



(a) (b) (c) (d)

Fig. 3. Regions of the plate the plate (a-c) and points of interest (d)

The classification of the interest points obtained by the SIFT algorithm as defect or no defect was carried out by a neural network. Applying this algorithm to all the images it was achieved quite encouraging results.

3.3 Defects of type B

These defects are quite hard to detect. Special light conditions would help but we wish to make it as simple as possible. Because these defects correspond indeed to a given disruption to an usual pattern we tried again to use one of the SIFT inspired features.

Despite using again neural networks as final classifier we follow a different approach to this type of defects. The algorithm can be described in the following steps:

Find the region of the interest (ROI) of the plates using the Hough transform (Fig 4a).

Find the points of interest using one of the methods described in Section 2. Select those that are inside the interest region, Fig 4b.

Let it be N the total number of points of interest of the plate k each one with m features (m=128 (SIFT) or m=64 (SURF) and define $d_k(j, i)$ the descriptor i $(i = 1 \dots m)$ of the interest point j.

Define a global descriptor for the plate k as:

$$g_k(i) = \frac{1}{N}\sum_{j=1}^{N} d_k(j, i)$$

Each plate is now characterized by a vector of m features. To train the neural network were used 14 images without defects and 20 with defects and the percentage allocated for training and validation was respectively 50% and 30%. The neural network is type feed forward with one hidden layer with 70 neurons.

(a) (b)

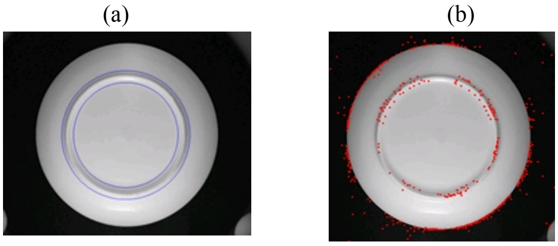


Fig. 4. a) ROI,; b) Interest points.

Several experiments were carried out. It was even verified whether only the number of interest points, evaluated by the different methods studied above, found in the ROI were enough to distinguish the plates. The conclusion is that was not possible, mainly due to illumination problems. On the other side the use of SURF descriptors and a neural network allowed a very high success with the evaluation test.

3.4 Defects of type C

This type of defects corresponding to very small black spots is important to be detected at least in the central region of the plate without any decals. The solution would be trivial with ideal lighting conditions, but no classical methods resulted with real images. Again it was tried to use interest points found for one of the methods referred above. It was used 10 plates, 6 without defect and 4 with defect. This number of plates should be bigger, however, it was verified that were found interested points using the SURF method inside the ROI, only in the case of existing defect. These results (Fig. 5) are quite promising, even if you need to introduce a more powerful decision rule to deal with a bigger number of plates.

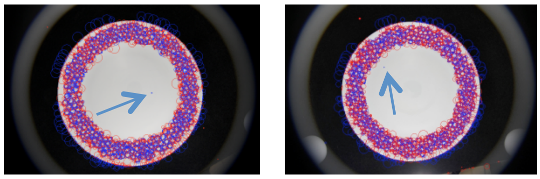


Fig. 5. Results for different plates. The defect is signalized with an arrow.

4 Conclusions and future work

Results show that the use of the class of invariant SIFT or SURF descriptors give promising results in industrial visual inspection of ceramic pottery in particular plates. Using a set of plates provided by a ceramics manufacturer (MatCeramica) and using images taken in condition reproducible in real situations it was possible to get very promising results in most studied situations.

As future work it is necessary to study bigger collections and other type of defects. We are conscious that putting these techniques to work in the production lines still involves a hard work mainly for providing faster algorithms implementation probably running in different computers. Illumination is also a concern but one advantage of these algorithms is its robustness to contrast and brightness changes [4].

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