UNSUPERVISED SEGMENTATION OF SURFACE DEFECTS WITH SIMPLE TEXTURE MEASURES

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Abstract. In this paper a simple and fast approach to unsupervised segmentation of surface defects is described. A set of simple texture measures (the local binary pattern method) and the statistical self-organizing map are used to detect defects in surface images. Defect detection can be seen as a typical two-class segmentation problem where the desired classes are good surface and defected surface. The main idea in this paper is to train a two-class classifier only with fault-free surface samples which is an unexpected approach. The proposed defect detection is based on the following idea: an unknown sample is classified as a defect if it differs enough from the estimated distribution of fault-free samples. The statistical self-organizing map is used to estimate this distribution. Surface images are used to demonstrate the proposed procedure.

1. Introduction

Image segmentation is a fundamental problem in image analysis. The goal of image segmentation is to partition an image into a set of regions which are uniform and homogeneous. In the best case these regions will have a strong correlation with objects in the image. For example, in industrial inspection the goal of segmentation is often to separate objects from the background. In remote sensing applications we may wish to segment a satellite image into different type of regions (sea, land, clouds, etc.).

Since late 80's neural network techniques have been proposed for image segmentation. The most popular one has been the self-organizing map (SOM) (Kohonen (1995)). Several authors have used the SOM in image segmentation, see, for example, Lampinen and Oja (1989), Lu et al. (1991), Greenspan et al. (1991), Visa (1992), Yin and Allinson (1994), Oe et al. (1994), Haring et al. (1994), Visa and Iivarinen (1997), and Iivarinen and Visa (1998).

In this paper a special type of image segmentation, a two-class segmentation, is considered. A typical two-class problem is defect detection of surfaces (see a review on texture defect detection in Song et al. (1992)) where a classifier is typically trained with samples taken only from a fault-free surface (Unser and Ade (1984); Dewaele et al. (1988); Cohen et al. (1991)). This results in many benefits. A tedious collection of defects is not needed and appearance of new defects do not result in retraining of a classifier. Features extracted from fault-free surface samples are usually assumed to follow a multidimensional Gaussian distribution so that the decision function can be formulated. The segmentation scheme that is used in this paper does not have this restriction; the distribution can be of any shape. The statistical self-organizing map is used to estimate the distribution of fault-free surface samples (Iivarinen et al. (1996); Iivarinen and Visa (1998)).

2. The unsupervised segmentation procedure

The segmentation procedure used in the experiments is done as follows. Scan an image with a small gliding window. For each window area repeat the following steps (Figure 1):

1. **Feature extraction**
   Calculate a set of texture features for a given image window. Collect these features into a feature vector $\mathbf{f}$.

2. **Segmentation**
   Compare $\mathbf{f}$ with the statistical SOM and find the best-matching unit c. Show the minimum error e_c as the output. If $e_c > 0$, the pixel is classified as a defect. Otherwise the pixel is fault-free.

The problem can thus be stated as: *Label the center pixel of the given image window as a defect or as a fault-free pixel.*

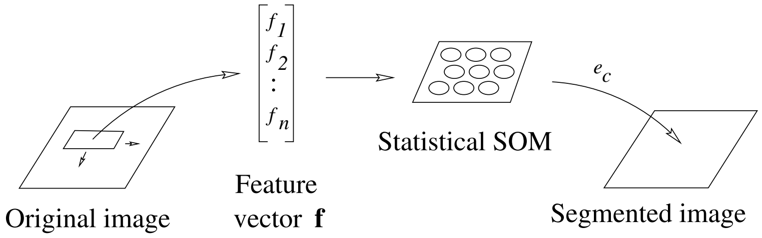

Figure 1. The proposed segmentation scheme.

The error e_c is a kind of Hamming distance between the feature vector $\mathbf{f}$ and the best-matching unit c. It determines on how many feature planes the feature vector $\mathbf{f}$ differs from the best-matching unit c. It takes integer values between zero and n (n is the dimension of the feature vector $\mathbf{f}$).

2.1. The statistical self-organizing map

An extension to the original SOM algorithm, the statistical SOM, is used as a classifier (Iivarinen et al. (1996); Iivarinen and Visa (1998)). It is a simple and fast algorithm that is used to determine if a given unknown sample belongs to a distribution of previously encountered samples. No Gaussian assumptions of the shape of the distribution have to be made; instead, the distribution can be of any shape. The SOM is used to estimate this distribution, and then a new decision function is formulated to each SOM unit. The resulting network structure is called the statistical SOM. For more information on the statistical SOM, see Iivarinen and Visa (1998).

3. Feature extraction

Three simple measures are used for texture characterization: a local binary pattern (LBP), a simple contrast measure, and a mean value. These measures are extracted from small 3x3 image windows. The LBP and the contrast measure are defined in the following, and the mean value is simply the average of all the nine pixels in a 3x3 image window.

3.1. A local binary pattern

A local binary pattern (LBP) method is a two-level version of the texture unit method (He and Wang (1991)). It has been used successfully in metal surface inspection (Pietikäinen et al. (1994)) and it performed well in a recent comparison (Ojala et al. (1996)). The texture unit elements $TU_k(\mathbf{x}),\ k = 1, 2, ..., 8$, are simple functions of gray level values I around a given pixel position $\mathbf{x}$. The texture unit element $TU_k(\mathbf{x})$ is given as

$$TU_k(\mathbf{x}) = \begin{cases} 0 & \text{if} \quad I(\mathbf{x}+\mathbf{d}_k) < I(\mathbf{x}), \\ 1 & \text{if} \quad I(\mathbf{x}+\mathbf{d}_k) \geq I(\mathbf{x}) \end{cases} \tag{1}$$

where $\mathbf{d}_k,\ k = 1, 2, ..., 8$, are displacement vectors. They define a $3{\times}3$ neighborhood (from left to right and from top to bottom) of the center pixel $\mathbf{x}$.

The texture unit number TN is a unique number that is assigned to each different binary pattern in a 3x3 window,

$$TN(\mathbf{x}) = \sum_{k=1}^{8} TU_k(\mathbf{x}) 2^{k-1}. \tag{2}$$

For each 3x3 image window, there are $2^8 = 256$ possible texture unit numbers.

3.2. A simple contrast measure

In addition to the texture unit number TN, a simple contrast measure was also proposed in Ojala et al. (1996). It is computed after the texture unit element calculation and it is a difference of the mean gray level values of the pixels with $TU_k(\mathbf{x}) = 1$ and the pixels with $TU_k(\mathbf{x}) = 0$.

4. Experimental setup and results

Surface defect detection is used to test the proposed scheme. It is a typical two-class segmentation problem. Defect detection is based on the following idea: an unknown sample is classified as a defect if it differs enough from the estimated prototypes of the distribution of features extracted from fault-free samples.

The surface images were quantized to 256 gray levels. The statistical SOM had 25 units. The size of the training set was 100000 feature vectors extracted from fault-free samples taken randomly from the image in Figure 2(a). It is important to have enough training data available, otherwise the density estimation cannot be done accurately.

The LBP is a gray-level invariant measure. The contrast is invariant to shifting of the gray-scale but not to scaling. In our case, these features find mainly border areas between defects and a good surface, and also even areas like holes. The mean value brings the gray-level dependency into the feature set and fills defect areas, but also finds dark defects whose borders are smooth (the LBD and the contrast will not find these ones). The mean value is an essential feature here

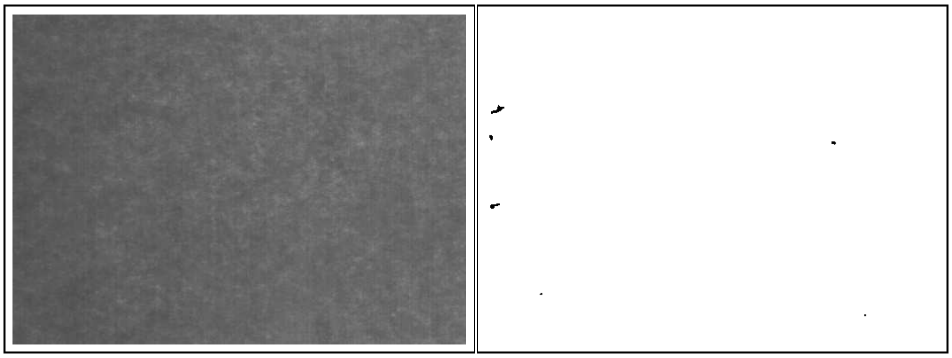

Figure 2. A surface image used for training and its segmentation with the proposed method. Defects are marked with black color.

since many dark defects have their texture similar to a good surface; only the average gray-level value is different. Thus these defects cannot be found only with gray-level invariant texture measures. On the other hand, there are other defects that cannot be found with pure gray-level thresholding. So in this case there is a need for both the gray-level invariant measures and the gray-level dependent measures.

In Figure 2 is the surface image that was used in training and its segmentation. As expected, only few pixels are classified as a defect. Three defect images (that were not used in training) with their segmentations are shown in Figure 3. The whole test set consisted of 87 defect images. The morphological closing operation has been applied to all segmentations to close small gaps between found defects. The first image has some dark spots, the second image has a large hole with some dark and light areas around it, and the third image has a few holes with some weak areas around them. All defects are found nicely and accurately. There are only few misclassifications due to slight formation errors and noise. It is important for a defect detection algorithm that no good surface is classified as a defect. This is more important than to detect every weak defect.

5. Conclusions

The results of experiments with surface images are encouraging. The proposed scheme offers several advantages over the traditional gray-level thresholding schemes. It is general in the sense that it can be applied to defect detection of different types of surfaces. The characteristics of a fault-free surface are learned automatically from samples which results in a fast and easy learning of new surfaces. The texture features are simple ones and they are calculated from small 3x3 image windows which makes them a promising approach when considering real-time implementations.

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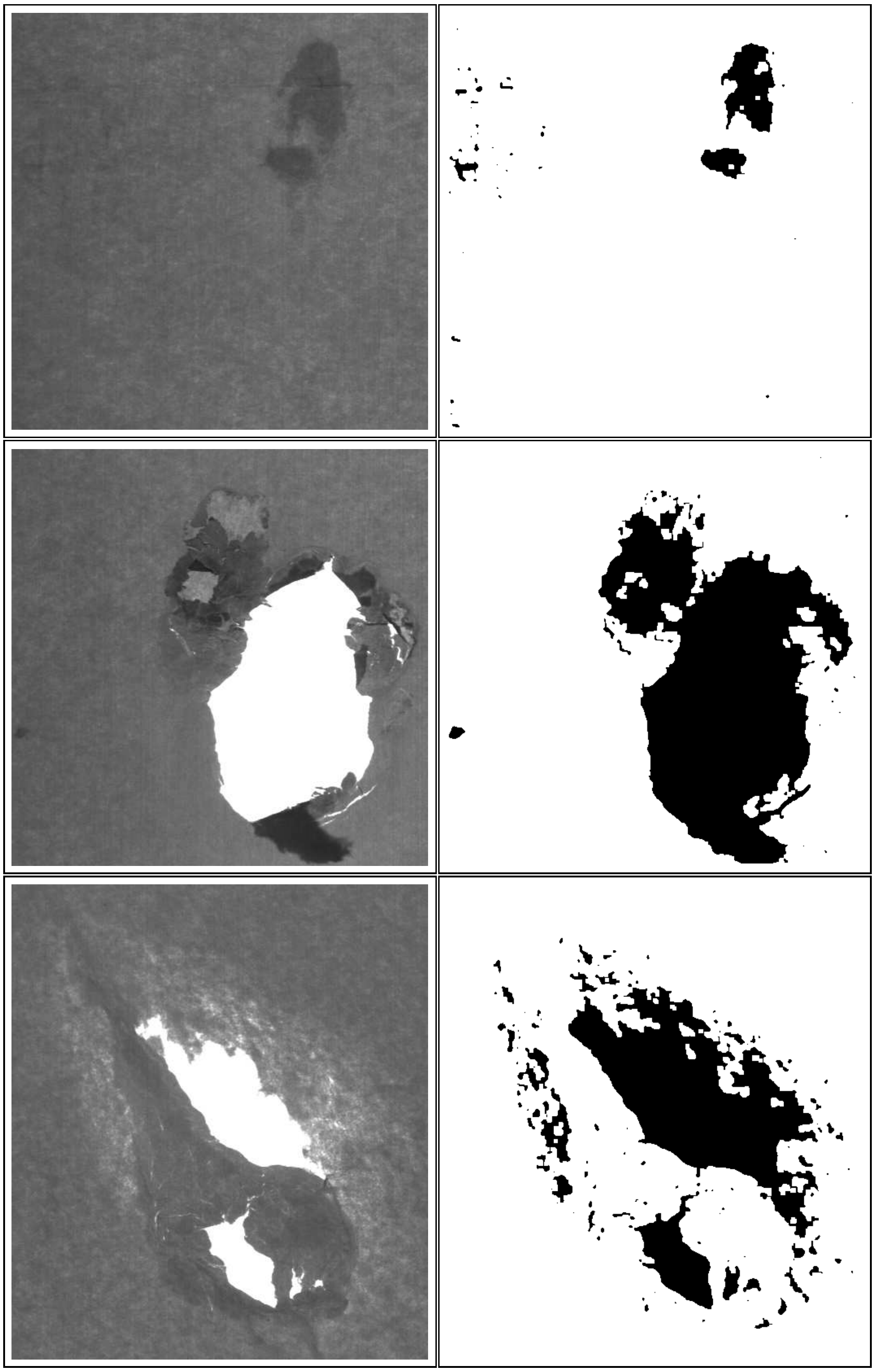

Figure 3. Surface images and their segmentations with the proposed method. Defects are marked with black color.

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