

Defect Detection on Imaging Surfaces by Using Multi-Scale Image Analysis

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Abstract

The proposed method for automatic defect detection is based on a time-effective algorithm of multi-scale and structure-adaptive analysis of pictures obtained from imaging surfaces. Application of the concept of image multi-scale relevance function in the framework of visual attention mechanism provides a quick and reliable location of regions of attention with potential defect indications considered as objects of interest on images. The relevance function is a local image operator that has local maxima at centers of the objects of interest or their regular parts, which are termed primitive patterns. A detailed structure-adaptive image analysis is performed within the regions of attention in order to make the final decision on defect presence in a current focus-of-attention point. The method requires a simple parameter learning procedure applied to sample images of imaging surfaces prior the automatic inspection. The testing results indicate on the superiority of the relevance function approach to location of defect indications in images over the known computer vision methods for defect detection.

Introduction

It is well known that defects on imaging surfaces of printing/copying devices may result in a considerable loss of resulting image quality. Visual detection of defects on imaging surfaces by a human operator is inefficient due to its low reliability and considerable consumption of man/time resources. The automatic defect detection requires picture acquisition facilities which can register images in a computer memory directly from the imaging surfaces or from paper prints obtained by using the imaging surface under inspection in the printing/copying device. In the computer, the images are analyzed on the presence of local objects of interests with specified shape and size that serve as defect indications related to the imaging surface. They differ from the background by their intensity or may have a different texture pattern as compared to the texture of the background. However, the known methods of computer vision yield not satisfactory results of automatic detection in the case of imaging surfaces because the defect indications have a low contrast in images with noisy and textured background.

The basic approach to enhancement and binary segmentation of such defect indications is the computation of difference image between the original image and the evaluated background image obtained from the original one. The known methods of edge detection belong to this approach as well. Then, the resulting binary segmentation of defect indications is made by the application of a thresholding operation to the obtained difference image. In the framework of this approach, termed as dynamic thresholding, the known methods differ by the manner of evaluation of the background intensity and selection of a threshold value for binarization.[1-3] Usually, the threshold is determined from local or global histograms based on the assumption of a two-mode image histogram. However, this initial assumption is rarely fulfilled because of the large values of image intensity gradient or textured background.

Another and relatively new approach to flaw detection is the multi-resolution image analysis by using a wavelet representation.[4-6] This method has the advantage of being able to detect efficiently different in size and location local objects as indications to defects. This approach does not take into account possible shape of defects and their textured intensity that restricts its application in diagnostics imaging.

The automatic defect detection method described in this paper is based on time-effective algorithms of multi-scale and structure-adaptive analysis of images taken from imaging surfaces. Application of the concept of image multi-scale relevance function in the framework of visual attention mechanism provides a quick and reliable location of regions of attention with potential defect indications considered as object of interest on images. The relevance function is a local image operator that has local maxima at centers of the objects of interest or their regular parts. A detailed structure-adaptive image analysis is performed within the regions of attention in order to make the final decision on defect presence in a current focus-of-attention point. The preliminary testing results indicate on the superiority of the relevance function approach to location of defect indications in images over the known computer vision methods for defect detection.

Modeling of Images with Objects of Interest

It is known that the model-based approach to image processing and analysis provides better results as compared with conventional (heuristic) image processing methods. The underlying image model for detection applications should include a shape description of potential defects. For this purpose, the properties of object planar shape as well as intensity properties are considered separately within a region of interest containing an object on the background.

An efficient approach to represent the planar shape is the multi-scale morphological image model describing the objects of interest by using structuring elements, axes of symmetry, skeletons, as well as the contour description. One initial structuring element S_0 of minimal size as a set of points on the image grid is selected that determines the resolution and scale of imaged objects. It possesses a symmetric disk shape in order to ensure the rotation invariance as well as a reasonable approximation of different shapes. Two types of scales can be well distinguished: *uniform scales* and *logarithmic scales*. The structuring element at the scale k in the uniform scale system is formed as a consecutive binary dilation (denoted $\oplus$) by S_0, i.e. $S_k=S_{k-1}\oplus S_0$. The size in pixels for kth scale S_k is given by its disk radius r_k.

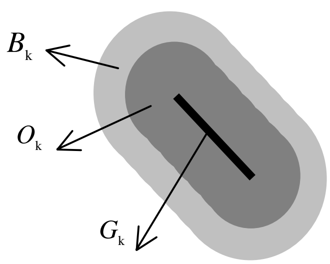


Figure 1. Formation of a primitive object of interest.

The generation of planar shape of a simple imaged object can be modeled in the continuous case by a growth process.[7] The formation of every isolated object starts from a single point named *a seed*. The seed begins to grow along a *generating line* (straight or curve) named the growth path. In the discrete case, the growth path is represented by a generating set. The generating set is one-pixel wide connected set of points, each of them except for the end points have two neighboring points. The growth process of imaged objects starts at largest scale if used in a multi-scale representation and can be modeled by means of generation of the so-called primitive objects. A *primitive object* at scale S_k of the uniform scale system is formed using two structuring elements: object structuring element $S_a=S_k$ and background structuring element $S_b=S_{k+1}$. The domain region U_k of a primitive (isolated) object consists of two distinct sets of points O_k and B_k, $U_k=O_k\cup B_k$, $O_k\cap B_k=\varnothing$, which are formed by using the operation of dilation ($\oplus$) of a single generating line (set) G_k (see Fig. 1)[7]:

$$O_k = G_k \oplus S_k \ and \ B_k = (G_k \oplus S_{k+1}) \setminus O_k . \qquad (1)$$

A simple model is adopted for multi-scale object formation using the primitive objects at different scales: primitive objects are just concatenated by their generating lines to form a connected domain region of a simple local object. The same modeling is applied to model the texture object region and texture background region. However, it consists of generating multiple objects at smaller scale as compared to S_{k+1}. For example, a sequential object generation by growth was used based on the logarithmic scale system in which simple objects of scale S_{k+1} were sequentially generated one after another in order to have an alternating and repetitive (quasi-periodic) texture pattern. Also probabilistic shape transformation was apply to size of structuring element used and generating lines while modeling random shape deviations.

Within object and background regions the intensity is modeled by a conformable polynomial regression (CPR) model.[8] In each image point, the intensity value is represented as a polynomial function with variable coefficients plus a random noise value in order to represent the non-homogeneity of image intensity and the background texture. Intensity properties are computed as functions of polynomial coefficients estimated within a neighborhood window of a current point.

Object Detection Using Multi-Scale Relevance Function

The notion of relevance function originates from the principle of edge detection by local extrema of derivative operators. The relevance function $R\{f(i,j)\}$ is an image local operator which takes larger values in points belonging to an object of interest rather than in the background points: $R\{g(i,j)\}\geq R\{g(m,n)\}$ for $\forall\ (i,j)\in O$ & $\forall\ (m,n)\in B$, where O and B are the object region and the background support region within a window $U=O\cup B$. Additionally it is required that the function $R\{g(i,j)\}$ takes local maximal values at the supposed centers of location of an object of interest, which coincide with the points of object generating sets.

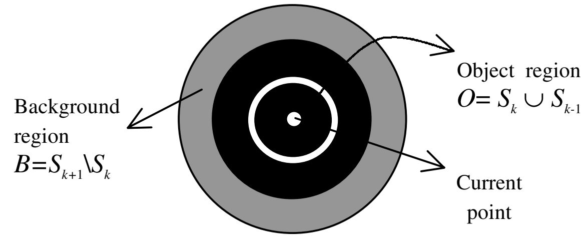


Figure 2. Regions O and B in the definition of a two-scale relevance function.

Considering a single scale S_k, let the object region $O(i,j)$ be a symmetric structuring element centered at point (i,j) and the region $B(i,j)$ be a ring around it such that $O=S_k$ and $B=S_{k+1}\backslash S_k$ (Fig. 2). Assuming the morphological model of local objects coupled with the CPR model (of degree 0 or 1) of image intensity, the relevance function $R\{g(i,j)\}$ can be defined as

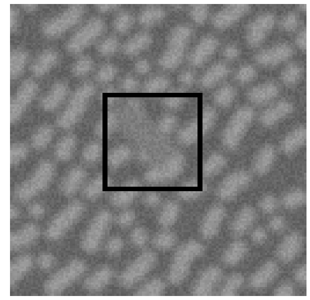
$$R\{g(i,j)\} = (f_O(i,j) - f_B(i,j))^2 - \alpha \cdot (f_O(i,j) - a)^2 , \qquad (2)$$

where $f_O(i,j)$ and $f_B(i,j)$ are the mean intensity values of $g(i,j)$ in the regions $B(i,j)$ and $O(i,j)$, respectively, a is called the object *intensity of reference* which has to be determined during the first detection of an object of interest, α is a constant coefficient. The first term in Eq. (2) considers the region salience by the object contrast, whereas the second term is aimed at consideration of the object homogeneity constraint supposing the polynomial modeling of object intensity. The explicit value of α is derived from the maximum likelihood selection of the relevance function extrema if assuming the CPR model to be valid and an appropriate distribution for object contrast and for object homogeneity measure. It has been proved that for the case of the CPR model without present noise the relevance function takes the maximum at the center point of a primitive object. Insignificant shift in the location is introduced by the present noise depending on the noise variance. The multi-scale relevance function is obtained from Eq. (2) by substituting the estimate $f_O(i,j)$ by the mean values of K respective partial estimates computed over all K available scales $S_0,...,S_{K-1}$, whereas a single background region B is used.

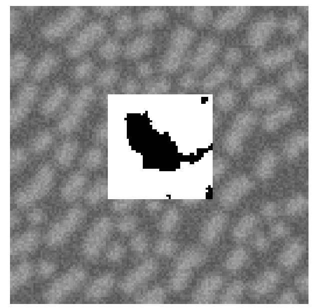
Since in many applications of diagnostics imaging the background and object regions are textures, a preliminary texture property extraction is made. Then, the relevance function is applied not to the initial intensity image, but to the computed property map.

The relevance function $R\{g(i,j)\}$ by Eq. (2) have to be computed within a region of interest and has its maximal value in the *focus of attention*. The focus of attention defines a new region to be analyzed, the *region of attention*, that is centered at the focus of attention. At this stage, the *actual scale* of current object of interest is determined in focus of attention using the concept of relevance function and the proposed multi-scale model of object shape.

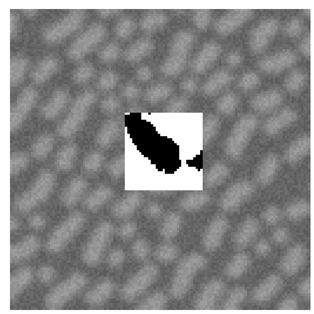
The binary segmentation is performed within the region of attention if at all. Before the binarization, an *initial hypothesis* is generated and tested on the object presence at the focus of attention.[8] The estimated value of object contrast is tested on its significance with respect to the noise variance. The presence of an object means that the current image fragment is a two-region segment containing an object or its part on the background. If the current region of attention satisfies the condition of the CPR model, then it is segmented into two regions: object and background. Otherwise, the next region of interest will be considered, usually, at the vicinity of the current region of attention. The segmentation is made by a *floating thresholding* operation which is derived from the likeli-hood ratio principle when assuming the CPR model is valid.[8]



(a)



(b)



(c)

Figure 3. Object localization experiments with a synthetic noisy image containing an object of interest (defect) superposed on a textured background: (a) initial image fragment with a defect to be detected; (b) result of localization and binarization at larger scales; (c) result of localization and binarization at medium scales.

Experimental Results

The described approach to detection and binarization of local objects have been tested on synthetic and real images from industrial diagnostic imaging including the photoreceptor surfaces. Fig. 3 shows one instance of the application of the described detection algorithm to an image fragment of defect located on textured (non-homogeneous) background. The main purpose of the testing on synthetic images was the performance evaluation during localization and binarization of low-contrast images and images with textured background. For example, the graph in Fig. 4 shows experimental dependence of the location bias on the noise level for the synthetic image of a bar-like object on the textured background in Fig. 3. Note that the center of the bar can be determined as the conventional center of the object only at larger scales used, whereas the using of the medium scales provides just centers of respective parts of the bar (Fig. 3 (b) and (c)). The conventional methods of intensity segmentation are unable to detect and segment such an object whereas the method of relevance function applied to the property map provided good results that are tolerant to present noise and invariant to scale changes.

The proposed algorithm allows a fast (almost real time) multi-scale image analysis since it takes 4-6 seconds of a frame (256x256) processing on PENTIUM PC, 400 MHz.

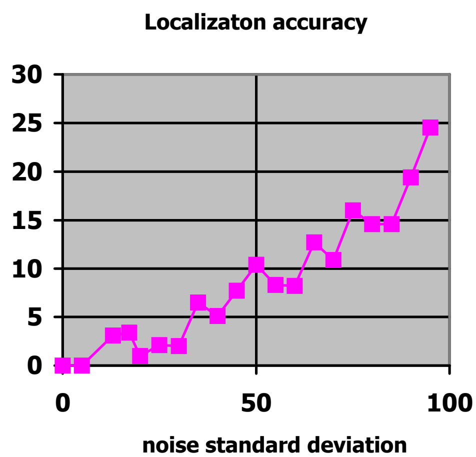


Figure 4 . Defect localization accuracy (in pixels) vs. noise standard deviation.

Conclusion

Theoretical (model-based) analysis and experimental results have proven the robustness of the proposed algorithm for defect localization and binarization due to the following features of the relevance function approach. The preliminary testing of initial hypothesis on the fragment relevance allows to discard non-relevant (without defects) fragments and to diminish the false alarm errors. The introduced concept of the multi-scale relevance function in application to object detection provides a quick location of local objects of interest with various sizes and orientations. The use of a variable binarization threshold by the principle of likelihood ratio contributes to a reliable binarization at high gradient values of image intensity.

References

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Biography

Roman M. Palenichka graduated in applied mathematics from Lviv Polytechnic Institute (Ukraine) with a honor diploma in 1979. He obtained his Ph.D. degree in computer science in 1986 from the Glushkov Institute of Cybernetics in Kyiv, Ukraine. His major fields of expertise are computer graphics, image processing, and computer vision in application to industrial and medical diagnostics imaging. Dr. Palenichka has published over 42 scientific papers in International journals and conference proceedings and is a co-author of three books including the Dictionary of Computer Graphics and Image Analysis.