Object detection in grayscale images based on covariance features

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***Abstract*—Analysis approach for detection of specific objects in noisy grayscale digital images is described. It is based on calculation of specific coefficients revealing covariance properties of overlapping fragments of pre-processed images. The approach is aimed at detection of rather small foreign objects over the background of larger ones. Before the actual analysis, pre-processing of the images based on median filtering is performed in order to separate small foreground objects from larger background ones. The method was developed and approved within the project related to development of X-ray systems for industrial inspection.**

***Keywords*—image processing, pattern recognition, object detection, covariance features.**

I. INTRODUCTION

Detection of specific objects is one of the most common tasks to be solved by computerized image processing systems for industrial inspection, medical diagnosis and other applications. Sophisticated pattern recognition and image classification methods have been developed for that [see 1..4]. Modern digital image processing systems, in particular those developed for automated industrial inspection, often require real-time operation (especially conveyor systems) and at the same time use high resolution of the acquired images in order to expand the application range. As a result, image size in pixels dramatically increases and, consequently, requirements for computing power to implement image processing algorithms in real time grow up.

On the other hand, combination of high speed and high resolution implemented by modern image detectors results in lower signal-to-noise ratio of acquired images. This creates another challenge to processing algorithms and forces to use statistical approaches in order to obtain stable results.

Considered detection methods were developed taking into account the circumstances mentioned above. The developed methods have to be suitable for real-time operation and capable to process input images with low signal-to-noise ratio. The particular task considered was detection of rather small foreign objects over the background of larger ones. Examples of such applications are found in food industry where small or thin objects (stones in grain packages, small foreign objects in meat, fishbones in fish fillets etc.) must be detected in food samples using the X-ray inspection system.

Let us assume that the digital image of the object of interest is obtained by some image acquisition system and is represented by matrix $\boldsymbol{A} = (a_{ij})$, $i = \overline{1, N}$; $j = \overline{1, M}$ (M - number of rows, N - number of columns) of rational numbers corresponding to image pixels. Due to the acquisition conditions, each value is influenced by additive Gaussian noise with mean value 0 and variance σ^2. Values of image pixels are inversely proportional to the object thickness (or mass) at the particular position (in some cases, a special linearization procedure is performed as part of image pre-processing to achieve that). Our task is to detect small "foreign" objects over the background of larger "normal" ones. Fig. 1 illustrates an example of such task.

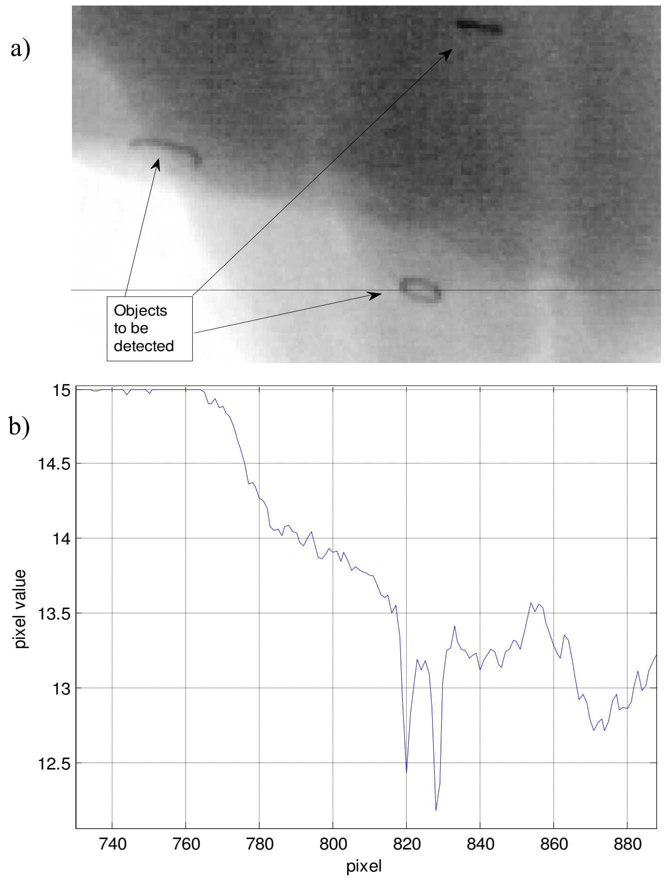


Fig. 1. a) Sample image fragment with objects to be detected; b) profile of the line marked in a).

Objects of interest are characterized by sharp brightness changes in neighboring pixels which are not observed for the “normal” background objects. It can be easier noticed in the line profile of the line occupied by such object (see Fig. 1b), given by the vector of pixel values $L_i = \left(a_{ij}\right), j = \overline{1, M}$. Shape of the objects may vary and they can be represented by small compact sets of neighboring darker pixels (e.g. related to stones) or darker pixels in several neighboring rows or columns (e.g. related to fishbones).

II. BACKGROUND COMPENSATION BASED ON MEDIAN FILTERING

Objects to be detected can be placed in brighter and darker regions of the image. If such object is placed in thinner area of the background object, pixel values related to it may be higher than pixel values related to darker region of the “normal” background object so that it is not possible to solve the detection task by simple thresholding. To compensate for the darkness change of the background object, an approach based on median filtering is proposed.

Median filtering is often used in image processing for removing the so-called “salt and pepper” noise, i.e. randomly spaced individual pixels with brightness values that considerably differ from the neighboring pixels. By varying the filter size, it is possible to remove small objects of different sizes from the image. Usually this operation is performed as two-dimensional (2D) one, often in such a way that brightness value of each pixel is replaced by median value (central value from all involved values sorted in ascending order) of neighboring 3x3 pixels.

Median filtering can be also used to solve the opposite task- extracting small objects over the varying background. This is achieved by subtracting the median-filtered image from the original one. To speed up real time operations, one-dimensional median filtering is proposed, calculated for horizontal and vertical line profiles. Such operation over the image by rows can be performed to obtain filtered image $\boldsymbol{B^r} = (b_{ij})$ on the basis of the following expression:

$$b_{ij} = \begin{cases} 0, \; if \;\; j < (l-1)/2 \\ a_{ij} - median\left(a_{ik}, \, k = \overline{j-(l-1)/2, \, j+(l-1)/2}\right) \\ 0, \; if \;\; j > M-(l-1)/2) \end{cases} \tag{1}$$

where l - length of the median filter (odd number). Similar operation should be performed over the image by columns to obtain image $\boldsymbol{B^c}$ and resulting matrix $\boldsymbol{B} = \boldsymbol{B^r} + \boldsymbol{B^c}$ calculated to retain objects of small size over any of the axes. Length of the filter should be matched to the size of the objects to be retained in the image. For example, to retain objects with size 3 pixels over the considered axis, value l=7 should be used to guarantee that such objects will not be treated as background.

Result of such filtering applied to image illustrated in Fig. 1a is shown in Fig. 2. It may be noticed from the line profile that the changes of pixel values related to background object are compensated, the pixel values in the image are centered and low values obtained for pixels related to small objects to be detected. Regions of the image not containing any small

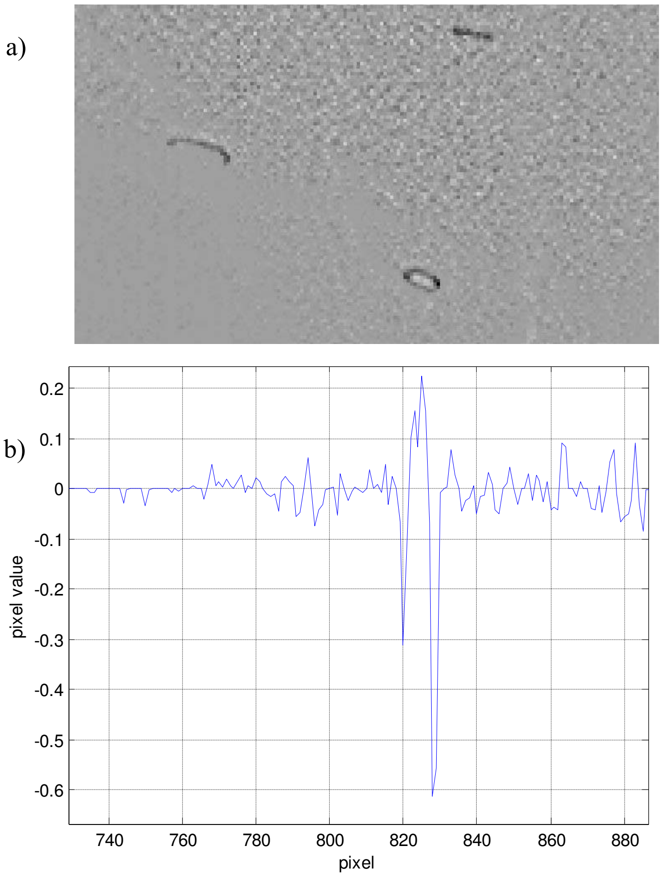


Fig. 2. Result of background compensation based on median filtering: a) image fragment; b) line profile.

object are transformed into a noise image. For the particular conditions illustrated in Fig. 1,2, foreign objects can be detected by simple thresholding of image obtained after filtering. However, if the image acquisition is performed with lower signal-to-noise ratio, fluctuations of pixel values due to acquisition noise may prevent usage of such simple approach. For these cases, calculation of coefficients related to covariance of neighboring pixel values is proposed for proper detection.

III. IMAGE REPRESENTATION AND CALCULATION OF COVARIANCE-RELATED FUNCTION

For detection of small objects based on calculation of statistical features it is feasible to process images by fragments with size related to expected size of objects to be detected. Fragment size and overlapping of fragments should be chosen such that there should always be a fragment containing the detectable foreign object in full. The simplest approach is to set a fragment size twice as large as object size and use overlapping of fragments equal to half the fragment size on both axes.

Simplest statistical characteristics, namely mean value and variance can be used to reveal the presence of foreign object in fragment of filtered image $\boldsymbol{B}$. However, such characteristics are not informative enough in low signal-to-noise cases when the pixel values due to measurement noise may be comparable in magnitude to values obtained as a result of presence of a foreign object. The objects to be detected are characterized by low values of several neighboring pixels that are perceived also by humans as an indicator of presence of some object in the image. Mathematically such an indication can be given by the higher correlation between the neighboring pixel values that is not observed in case of a noise image.

Image fragment given by matrix $\boldsymbol{B} = (b_{ij})$, $i = \overline{1, N}; j = \overline{1, M}$ can be represented also by one-dimensional vector $\boldsymbol{x}$ of size MN by reordering the corresponding matrix elements as follows:

$$x = (b_{11,} b_{12}, \ldots, b_{1M}, b_{21,} b_{22}, \ldots, b_{2M}, \ldots, b_{N1,} b_{N2}, \ldots, b_{NM}). \quad (2)$$

Let us calculate the following function characterizing auto-covariance properties of vector $\boldsymbol{x}$:

$$C_r = \sum_{s=1}^{(M-O)N} x_s x_{s+r} \;, r = \overline{1, ON-1} \;, \quad (3)$$

where O- maximum analyzed distance in rows of the fragment (for the particular task, O=2).

Fig. 3 shows the obtained function for image fragments of size N=M=24, containing and not containing foreign object. It can be noticed that, for the image fragment not containing foreign object, values of function C_r are close to 0. At the same time, for the image fragment containing foreign object, values of function C_r related to neighboring samples (r=1, r=24, r=25) are significantly larger and reveal the presence of the object. To detect the object, it is sufficient to calculate C_r only for the values of r corresponding to neighboring pixels in horizontal, vertical and both diagonal directions.

IV. COVARIANCE OF NEIGHBORING PIXELS

To detect small foreign objects of undefined shape, the following approach is proposed:

1. Filtering the whole image according to (1) both by rows and columns to obtain matrix $\boldsymbol{B}$.
2. Perform fragmenting of the image based on expected object size S: process fragments
   $F_{11} = (b_{ij}), i = \overline{1, S}, j = \overline{1, S}$,
   $F_{12} = (b_{ij}), i = \overline{1 + S/2, S + S/2}, j = \overline{1, S}$,…,
   $F_{21} = (b_{ij}), i = \overline{1, S}, j = \overline{1 + S/2, S + S/2}$,…
3. Form vector $\boldsymbol{x}$ from each fragment F_{mn} as defined in (2), and calculate the following property:
   $$C^1_{mn} = C_1 + C_{S-1} + C_S + C_{S+1} . \quad (4)$$
4. If the calculated value for the fragment C^1_{mn} exceeds the set threshold T^1 , it is considered to contain the foreign object.
5. If the result in p.4 for any of fragments F_{mn} is positive, image is considered to contain the foreign object.

Threshold T^1 can be chosen on the basis of processing image(s) for which it is known in advance that they do not contain any foreign objects, e.g. it can be set to value

$$T^1 = \alpha \max(C^1_{mn}) , \quad (5)$$

where α is a chosen sensitivity parameter.

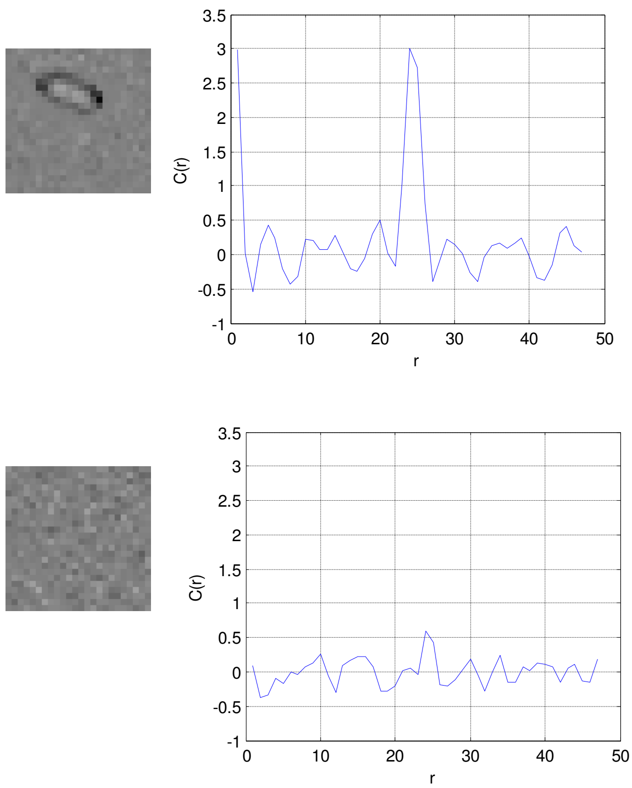


Fig. 3. Covariance-based function defined by (3), calculated for image fragments containing and not containing foreign object.

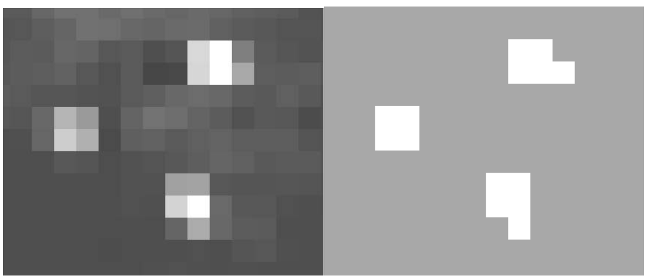


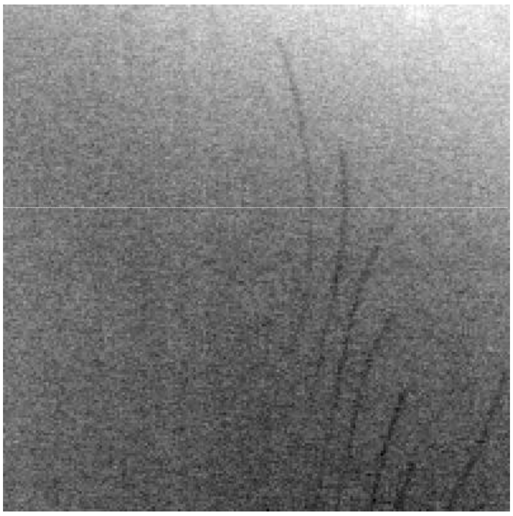
Fig. 4. Left: covariance image obtained from fragment illustrated in Fig. 1a using the property (4); right: binary image obtained using thresholding.

Results of calculations of properties C^1_{mn} can be presented as a covariance image (pixels of this image illustrate values of property C^1_{mn} obtained for fragments of image $\boldsymbol{B}$) revealing fragments with higher covariance property values (see Fig. 4). It may be noticed that each foreign object is revealed in several overlapping sub-fragments of the initial image.

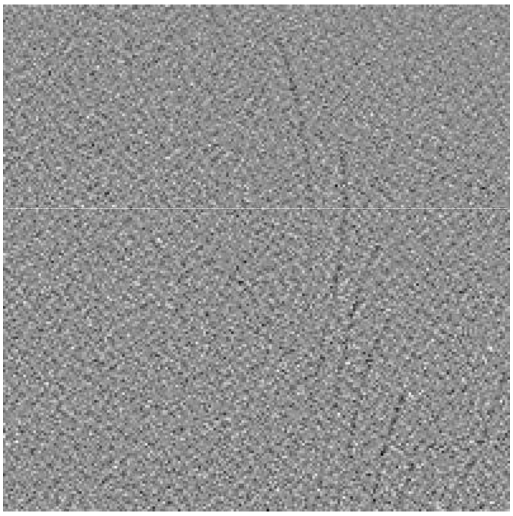
V. COVARIANCE OF PIXELS IN THIN OBJECTS

Similar approach can be used to detect thin objects with small dimension over one particular direction. An example of such task is detection of fishbones in fish fillets, illustrated in Fig. 5. In this case, signal to noise ratio of the image is significantly lower and it may be noticed from line profiles that simple thresholding of filtered image cannot be used to detect fishbones.

a)



b)



c)

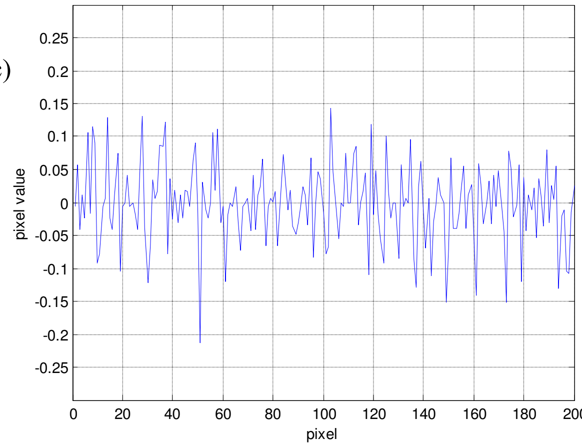


Fig. 5. a) Fragment of image with fishbones; b) the same fragment after filtering based on (1); profile of line marked in b).

The proposed approach for detection of such objects is similar to the one described above in section IV except for the different properties to be used to reveal the particular type of object. For example, to detect vertical fragment of a fishbone, it is proposed to use function (3) with the increased parameter O=5 and calculate the following property:

$$C^1_{mn} = C_S + C_{2S} + C_{3S} + C_{4S}\,. \qquad (6)$$

The corresponding covariance image obtained for this property from image fragment presented in Fig. 5 is shown in Fig. 6. It may be noticed that despite the very low signal-to-noise ratio obstructing observation of the objects in line profiles, it can be reliably detected using the proposed covariance-based property.

Similar as in the application case described in section IV, calculation of only several coefficients related to covariance properties of the image and specific to the application task is needed to perform detection. In addition, this involves only calculation of dot products of vectors that can be effectively implemented with modern processors. Therefore the proposed approach can be effectively implemented for real-time operation.

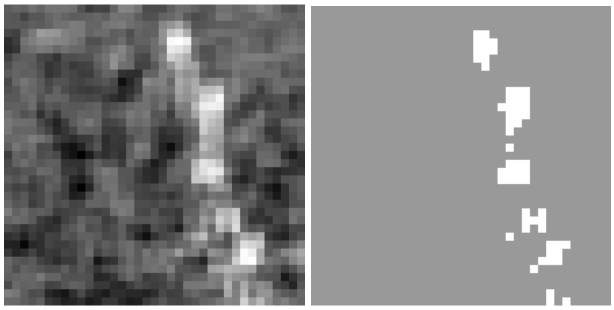


Fig. 6. Left: covariance image obtained from fragment illustrated in Fig. 5 using the property (6); right: binary image obtained using thresholding.

VI. CONCLUSIONS

1. The proposed object detection method can be successfully used to detect small objects of specific shape in grayscale images with very low signal-to-noise ratio when there is a difficulty to notice them even for a human observer.
2. Different covariance-based properties can be used to detect compact objects in grayscale (e.g. X-ray) images if the simpler characteristics are inapplicable due to high noise level in acquired images. A set of used properties can be adjusted to application task (features of objects to be detected).
3. Proposed approach is based on 1D median filtering and calculation of coefficients revealing covariance properties of pixels in image fragments. Both operations are suited for real-time applications as they can be implemented by regular easy-to-optimize procedures with predictable execution time independent from the image contents.

Algorithms implementing the proposed approach were developed and successfully used in the European FP6 project MODULINSPEX for detection of foreign objects in food by processing the X-ray images in real time mode needed for the conveyor-based systems.

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