Efficient Bone Detector and Geometric Descriptor for X-ray Imaging

Jakub Romanowski, Marcin Korytkowski, Rafał Scherer *Member, IEEE*
Institute of Computational Intelligence, Czestochowa University of Technology
ul. Armii Krajowej 36, 42-200 Czestochowa, Poland
Email: {jakub.romanowski, marcin.korytkowski, rafal.scherer}@iisi.pcz.pl

***Abstract*—Detection of bone area in X-ray images and methods of comparing such images on the basis on their content is still an issue which can be substantially improved. In this paper we present a new method of efficient bone identification and its description by a collection of simple geometrical shapes. The idea of this kind of bones description was to developed a method that could reduce the amount of data to minimum. The solution enables fast comparison of X-ray images by checking small amount of data. This kind of geometric description of bone area is designed to create a robust bone descriptor which will be used as image pattern for image comparison method. The assumption is to create a descriptor of X-ray digital image content, mining them in large databases and search and compare X-ray images on the basis of their content. The achievement of the objectives was possible through the use of an edge detection method modified by the authors. Application of our method of edge detection gives much more satisfactory results and possibilities to further process medical images than commonly used methods of edge detection.**

I. Introduction

Digital X-ray image processing is an important area of medical computer science and there exist many methods of bone detection, description and comparison. Part of the research refers to bone detection algorithms basing on the bone structure (bone density) [6]. Such algorithms examine a kind of tissues contained in X-ray images. Soft tissue and bone tissue are separated most frequently by the dual-energy X-ray absorptiometry (DEXA) [19]. A large set of algorithms developed in this area allows to perform very interesting operations on X-ray image. It gives a possibility to generate a lot of important information which are contained in X-ray images.

Despite of developing many algorithms, there is a need to develop methods which will generate the minimal amount of data to describe digital X-ray images. At the same time, there is a demand for efficient algorithms, which will be able to detect objects and compare them with those from other X-ray images. Digital images are often processed in the form of a matrix of pixels with the size of rows and columns equal to image pixel count in width and height. Image resolution can be very high and such data amount in the form of huge sets of pixels does not allow performing fast and efficient search and comparison based on the image content. Complex calculations of such huge images are time consuming and the dimensionality of data should be reduced by designing a descriptor of X-ray images. Descriptors allow to fast compare and retrieve images in large databases. This paper proposes a method of bone description with use of basic geometrical shapes such as squares, triangles or rectangles. The geometric shapes are the basis for the proposed here bone descriptor, which would allow storing small data amount concerning bones comparing to the whole image pixel set.

Describing bones by geometric shapes is much more useful than local interest point descriptors obtained by e.g. the SURF [2][7] or the SIFT [11] algorithms. Our research has shown that the methods based on keypoints are able to compare images mainly in the same scale and the insignificant image rotation. Greater changes of image subjects or their rotation on the image cause the subject will be not recognized in relation to the original pattern. Additionally, keypoints are generated in a very large number and sometimes in excess. This problem is noticeable in X-ray images where substantially redundant data do not carry any relevant information. In this case, an alternative for keypoint-based methods are shape adjustment methods. Shape adjustment methods consist in matching the shapes of contour of the bone to a predetermined pattern of bone shape [8][17]. It is a time consuming method and is not universal because it can be applied only to a specified types of bones. There are also some soft computing approaches [4][5][13][14] to image classification.

Our approach to bone description is a very versatile method with a possibility to apply to a larger amount of bone types. This approach is not related to fitting shapes nor contains excessive number of keypoints being often incorrect information. The proposed method allows to represent bone area as geometric shapes in the form of coordinates of points of vertices of the figure. It is possible to partition selected geometrical area into sub-geometric areas. This sub-area regions allow to determine bone type or to recognize a kind of bone damage such as e.g. bone fracture. Our method is not based on bone edge shape fitting to the predefined patterns. Geometric wireframe of bone is generated automatically on the basis of the previously detected edges. Our approach consists in developing a new framework of methods for geometric bone description. Such a framework has not been presented in the literature. We used an edge detection method developed in [16].

In our method, similar bone areas are described by a similar set of geometrical shapes. This kind of bone descriptor allows to precisely hash data from the form of geometric shapes group to the text form. The goal is to create a possibility to search bones in images basis on text form of their description in large data sets.

978-1-4799-7560-0/15 $31.00 © 2015 IEEE
DOI 10.1109/SSCI.2015.191

IEEE computer society

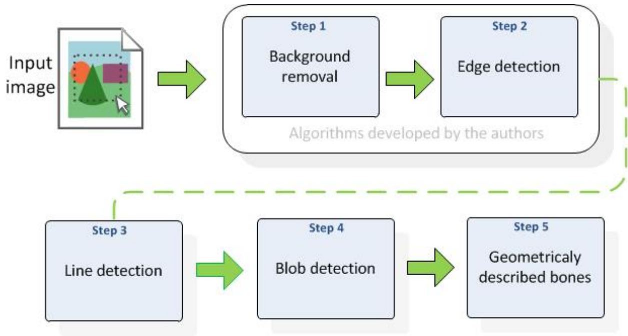

Fig. 1. Block diagram of the proposed method.

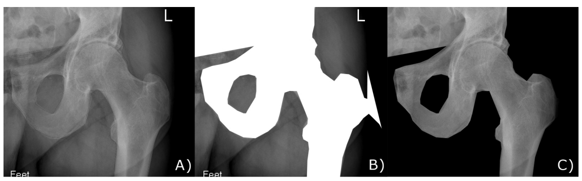

Fig. 2. Tissue division model. A) presents original X-ray image, B) and C) soft-tissue and bone-tissue respectively.

A. Outline of the Proposed Approach

Block diagram (Fig. 1) of the proposed solution consists of several sub-algorithms. Image processing is carried out in five successive stages. Two first of them are the background removal algorithm and the improved edge detection algorithm described in [16].

B. Background Removal

One of the most popular method of background removal in digital X-ray images is a family of algorithms based on two X-ray images taken with two different radiation levels named DEXA (Dual-Energy X-ray Absorptiometry) [3][19][20]. It allows to separate soft-tissues and bone-tissues based on radiation level and tissues permeability. Unfortunately this method requires two X-ray images. The method developed by the authors allows to determine accurate edges of bones area. Bones area edges are detected by prior elimination of soft tissues areas which are unusable for this kind of image processing. Often soft-tissue areas have similar brightness as bone areas. It is visible for human eye but for the image processing methods it was necessary to develop a special algorithm which will allow to distinguish two kinds of tissues. Fig. 2 presents tissue division model on three layers. Fig. 2 A) presents original X-ray image, Fig. 2 B) and C) soft-tissues and bone-tissue respectively. To achieve expected results there are used properties of bone brightness which are treated as protected pixel value and it will represent probable bone areas. Protected value is some kind of pattern of brightness of bone area. Pixels which are represented by this value are not processed in the specific stages of image processing. That kind of operations gives a possibility to create a mask of soft-tissues areas. The protected value can range from 0 to 255 that is the full grayscale space.

C. Edge Detection

The basis of commonly used edge detection methods is a family of second derivative operators, e.g. the Sobel Operator, the Roberts Operator, the Prewitt Operator, the Canny Operator [12] or the Laplace Operator [18]. The following formula describes the Laplace operator which is the second order derivative in x axis direction. It gives a possibility to detect vertical edges in images [15]. The x and y in the Laplace operator formula are pixel coordinates and f is a function which returns value of pixel (x, y).

$$\delta^2 x = \nabla\Delta(x, y) = f(x+1, y) - 2f(x, y) + f(x-1, y) \quad (1)$$

The above mentioned methods are based on some kind of filters used to detect edges. These filters work in two axis directions of the processed image. Calculations are processed on image sub-areas and consist in summing pixels values from each cell of the filter mask. The results of calculations is appearance indicator of edge in processed image area. The edge detection masks act as a second derivative calculated on a selected pixels area. An exemplary Laplace operator of second derivative in X axis direction can take the form [18]

$$\begin{bmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad (2)$$

Construction of the second derivative filter in y axis direction is based on reversion of horizontal values of matrix (second derivative in x axis direction) to vertical values in derivative in y axis direction. This construction of two kinds of filters in edge detection mask allows to detect vertical and horizontal edges in the image. The Laplace operator of second derivative in Y axis direction can be presented as [18]

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & -2 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad (3)$$

Finally, the filter formula for x and y axis direction [18] is

$$\nabla^2 = \delta^2 x + \delta^2 y \quad (4)$$

and the sum of two filters can be written as [18]

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (5)$$

As these operations are time consuming and they hardly detect almost invisible edges we decided to apply a different kind of the filter. The filter proposed by the authors significantly accelerates image calculations and increases the accuracy of the edge detection. In the image processing edges less visible for human eye are also important as they often represent borders between bone tissue and soft tissue. This is a common situation in the case of incorrectly taken image (overexposed). Commonly used image processing filters are based on computing single pixels values what is time consuming and requires many calculations. To reduce calculations of single pixels we decided to use the integral image [2] concept as a counterpart of single pixel. Integral image is applied as each edge detection filter cell. Previously used filter cell in the form of one pixel has been replaced by cell in the form of pixel set from specific area. By using the integral image algorithm, it is possible to rapidly calculate average value of pixel set in a selected image

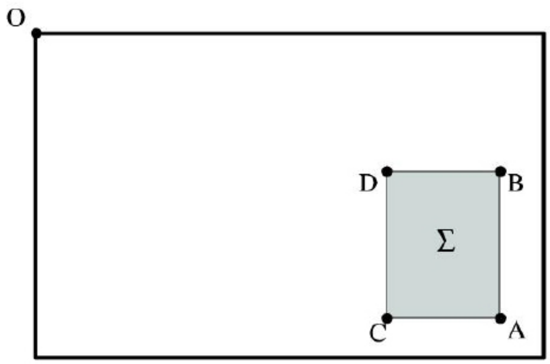

Fig. 3. Area presented by the integral image [2][7].

area. Image is calculated once at the beginning of the integral image algorithm. In result it is possible to obtain average value of whole image pixels. Single pixel value in the processed image is represented by sum of pixels on his left and above them. Integral image pre-calculation can be described [2] as

$$I_{\sum}(x) = \sum_{i=0}^{i \leq x} \sum_{j=0}^{j \leq y} I(i,j), \tag{6}$$

where $I_{\sum}(x)$ is integral image once calculated whole image pixels sum with beginning in start point in $(0;0)$ and the end on last coordinate of image $(x;y)$. Application of the integral image algorithm allows to obtain the average value of pixels area through the use of simple addiction operation of four variables. The average value of pixels in the selected image area can be described by $\sum = A - B - C + D$ [2] and it is presented in Fig. 3. Calculations speed and rapid operation of the integral image is an appropriate justification for using it as basis of the modification of edge detection filter proposed in the paper. Developing filter mask with this kind of filter cells gives the possibility to detect less visible edges or gradients in the image.

D. Line Detection

To detect lines in the image, the Hough line detection algorithm was used with previously detected edges by the method proposed in [16]. At this stage of image processing, line detection is not used to detect lines of bone edges. It is used to fill bone area by lines which link detected edges with selected distance. It gives more clear and more visible bones area. The Hough transform which is basis of line detection relies on discovering collinear points. Parameters describing lines create the Hough space, and commonly used ones are: radius vector σ and angle θ and it is described [1][9] as

$$\sigma = xcos(\theta) + ysin(\theta). \tag{7}$$

A line from Cartesian space, is represented by a point in the Hough space. A point from the Cartesian space in the Hough space is a sine curve. Sine wave in the Hough space passing through a common point corresponds to point on the same line in the Cartesian space [10][21].

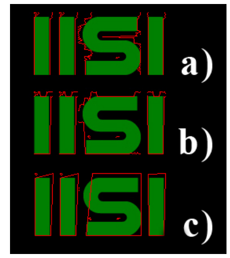

Fig. 4. Edges and important vertexes of detected blobs a) left/right edge detection b) top/bottom edge detection c) blob vertexes.

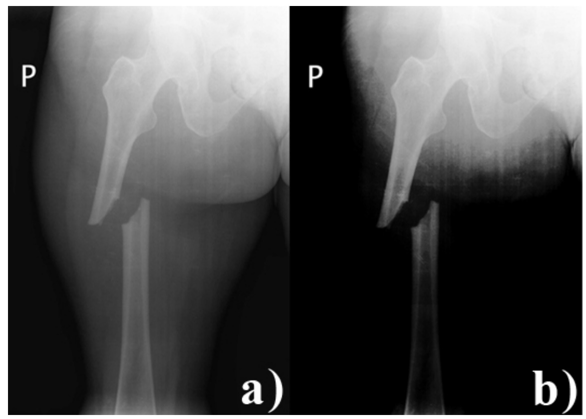

Fig. 5. Results b) of the background removal algorithm on the input image a).

E. Coherent Areas Detection - Geometric Description

Coherent areas detection is carried out in a manner analogous to most algorithms used for blob detection. The stage of blob detection comes down to the division of the image into segments with the background prepared in the previous step. Background preparation is filling possible background area by black color. Blobs are determined on the basis of some values such as center of gravity of the area, color value and edges of an object. The first step is to determine blobs on the basis of top and bottom border detection. This kind of edge detection is used to determine important vertexes of the detected blob in such way that the edges are maximally fitted to the edges of processed objects. Fig. 4 shows effects of blob edge detection from left and right side a) and from top and bottom b). Additionally, there are presented blob areas by establishing the most important edges vertexes of potential blob area (c)). Such operations were used to detect bone areas in X-ray images by the presented method.

II. Background Extraction and Edge Detection

To approximate results of the proposed algorithms of background removal and edge detection we present two figures which present image processing results. Fig. 5 shows background removal algorithm results and Fig. 6 shows differences between edge detection algorithm developed by the authors and edge detection algorithms based on commonly used edge detection filters. Fig. 5 presents the final result of background removal algorithm which was developed by the authors in their previous works. The X-ray image was selected intentionally as

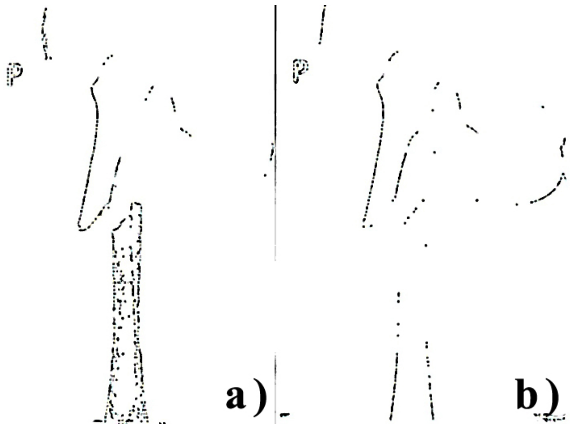

Fig. 6. Results of a) our edge detection method b) commonly used edge detection filters.

an example of deeply overexposed image. Overexposed area is visible in top-right quarter, yet the goal was achieved and the main part of the bone and fracture area was extracted. This form of image is basis for an edge detection algorithm focused mainly on bones area without soft-tissues. Results of the proposed method of edge detection from Fig. 5 a) are presented in Fig. 6 a) and it is the edge detection algorithm based on filters developed by authors. Fig. 6 b) presents results of image processing with use of commonly used edge detection filters. Comparison of these two methods shows the effectiveness of our method and it shows amount of correctly detected edges of bones area. Colors in Fig. 6 were inverted in order to improve the visibility of the results of edge detection.

III. Hough Line Detection

Lines detected with use of the Hough line detection algorithm were processed in image from Fig. 6 a) as the next step of the whole solution. Density and quality of obtained edges in Fig. 6 a) causes that this image is basis for next steps of processing. Such edges of bones density allows to fill area of bone by lines in one specified color. Lines are generated with use of lines detection algorithm and it can be generated in predetermined distances from each other (min. 1 pixel) and may have specific length (min. 1 pixel). This is to create a distinctive area of a single color that can be treated as kind of bone area mask. On the basis of the pseudo bone mask there are generated blobs representing regions of interest. The use of the line detection algorithm with our method of edges detection gives definitely better results than with use of the commonly used methods of edge detection. Image processing results with use of line detection are presented in Fig. 7. Results with use of our edge detection algorithm are presented in Fig. 7 a) and with use of commonly used edges detection algorithms are shown in Fig. 7 b). Determining blobs on the basis of the only edges detection gives unsatisfactory results. The use of the line detection gives more concentrated area of pixels and it gives better results of correct blob areas detection.

IV. Blob Area Detection

Bringing an image into a form of black background and green pseudo-bone areas in the previous step of the algorithm,

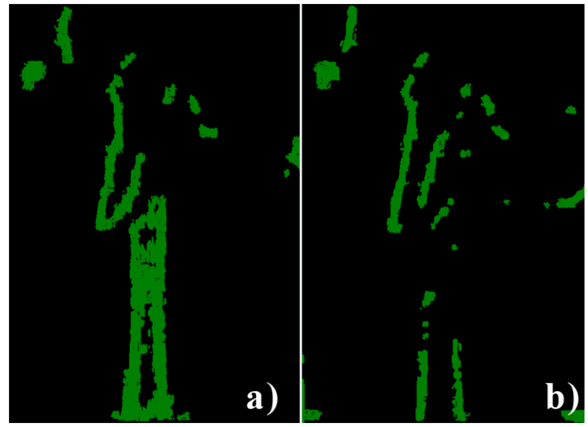

Fig. 7. Lines detection with basis on a) our edge detection method b) commonly used edges detection methods.

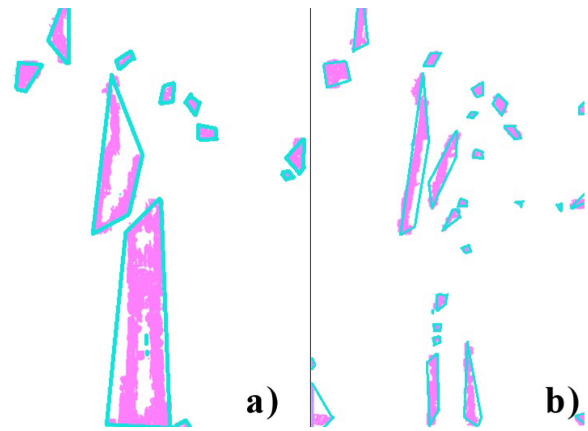

Fig. 8. Results of detection of consistent areas described by polygons by a) developed by us edges detection method b) commonly used edges detection filter.

strongly favours the detection of blobs. Blobs are defined mainly on the basis of coherent areas specified by green pixels and its pixels neighbourhood. Blob edges are equivalent to the edges of the bones area. In relation to methods of edge detection this method gives a more general description of the bone area that contains a very small quantity of data. As a result a set of points of the bone edge is represented as coordinates of a geometric figure. Coordinates of bone area are specified using most significant vertices of blob. It gives a new possibility to store information about the bones in the image, much simpler and faster in further processing than popular methods of edge detection. This method reduces the huge amount of data as all the bone edges pixels to only a few vertices data. Fig. 8 presents results of blob areas detection described by vertices of polygons. Image presented in Fig. 8 is in inverted values of colors in order to improve visibility of results of image processing. In the following results description we focus only on image from Fig. 8 a) because of the best result of blob detection. To select most suitable areas of bones there can be determined threshold value of their areas. Key areas of bone may be represented by blobs that contain enough number of pixels in the area. In Fig. 8 a) there are presented ten blobs with various amount of pixels in each of them. Two

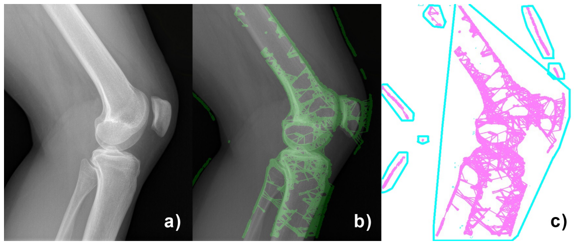

Fig. 9. Results of high-quality X-ray processing a) original X-ray b) line detection c) geometric bone area description.

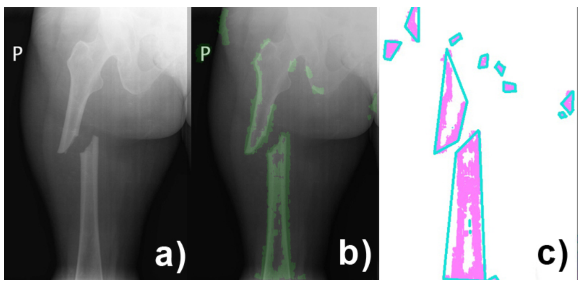

Fig. 10. Results of low-quality X-ray processing (overexposed) a) original X-ray b) lines detection c) geometrical bone area description.

biggest blobs are characterized by a much larger pixel amount in each of their area in reference to other eight blobs. This case presents a clear position of choice of the key areas based on the number of pixels in the blobs. In this way we can choose the most relevant information from the image and reduce the amount of data to be further processed to minimum. As a result of the proposed method, bone regions can be described and stored as the coordinates of simple geometric figures. It gives a possibility to compare images basing on the generated from them geometric figures.

V. Experimental Results

Our experiments were performed on a set of X-ray images of varying quality. We showed only a part of experiments as examples. Part of images was taken digitally and the second part was a subject of a processing from analog to digital form. The first group of images gives much better results in bone area detection. Images in this group do not have areas of substantially different brightness. An example of processing an image from this group is presented in Fig. 9. In Fig. 10 there are presented final processing results for an image from the second group. All of images are processed by the same algorithm steps. Both the Fig. 9 and Fig. 10 present three most important algorithm steps: a) original image, b) an image with detected lines, c) an image with detected most significant bone areas. Our experiments have shown that in handing major cases there is a possibility to describe the bone area using the characteristic geometric shape. For images containing areas of varying brightness it is possible to execute the geometric description of the most significant components of bone. This allows to obtain the information even from damaged X-ray images.

VI. Conclusions

The research has shown that it is possible to detect and then to describe the bone area using simple data of key vertices in these areas. It gives a possibility to compare images basing on the generated from them geometric shapes. The result can only be achieved through the use of the all steps of the algorithm. The study also showed significantly better results in detected areas of bones using a modified edge detection method in pre-processing stage.

At the stage of detecting blobs, research have shown the highest efficiency of one of the three blob detection method. Method specifying the blob edges from left to right side of the image and from top to bottom do not work properly in the field of bone area detection. Only the method based on detection of the most important vertices results in an innovation in description of the bones in digital X-ray images. The development of set of algorithms presented in this paper allows to create of new method of comparing medical X-ray images.

Once processed image is represented by a small set of coordinates of points (x, y) it is very easy to further process and compare with other images. Comparing images on the basis of simple geometrical shapes is much more faster than commonly used methods of digital X-ray images comparing.

Acknowledgment

This work was supported by the Polish National Science Centre (NCN) within project number DEC-2011/01/D/ST6/06957.

References

[1] D. Antolovic, "Review of the Hough Transform Method, With an Implementation of the Fast Hough Variant for Line Detection," *Technical Report*, TR663, 2011.

[2] H. Bay, A. Ess, T. Tuytelaars, L. Van Gool, "SURF: Speeded Up Robust Features," *Computer Vision and Image Understanding*, 2008.

[3] A. Bayar, S. Sarikaya, S. Keser, S. Ozdolap, I. Tuncay, A. Ege, "Regional bone density changes in anterior cruciate ligament dificient kness: A DEXA study," *Knee*, 2008.

[4] K. Cpałka, L. Rutkowski, "A New Method for Designing and Reduction of Neuro-Fuzzy Systems," *Proceedings of the 2006 IEEE International Conference on Fuzzy Systems (IEEE World Congress on Computational Intelligence)*, Vancouver, BC, Canada, pp. 8510-8516, 2006.

[5] K. Cpałka, "On evolutionary designing and learning of flexible neuro-fuzzy structures for nonlinear classification," *Nonlinear Analysis Series A: Theory, Methods and Applications, Elsevier* vol.71, issue 12, pp. e1659-e1672, 2009.

[6] I.D. Cullum, P.J. Cullum, J.P. Ryder, "X-ray dual-photon absorptiometry: a new method for the measurement of bone density," *British Journal of Radiology*, vol. 62, pp. 587-592, 1989.

[7] Ch. Evans, "Notes on the OpenSURF Library," `http://cs.bris.ac.uk/Publications` , 2009.

[8] W.A. Hoff, R.D. Komistek, D.A. Dennis, S. Walker, E. Northcut, K. Spargo, "Pose estimation of artificial knee implants in fluoroscopy images using a template matching technique," *Applications of Computer Vision*, 1996.

[9] J. Illingworth, J. Kittler, "A Survey of the Hough Transform," *Computer Vision, Graphics, and Image Processing*, 1988.

[10] V.F.F. Leavers, "Shape Detection in Computer Vision Using the Hough Transform," *Springer-Verlag New York*, Inc. Secaucus, NJ, USA, 1992.

[11] D.G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints," *International Journal of Computer Vision*, 2004.

[12] R. Maini, H. Aggarwal, “Study and Comparison of Various Image Edge Detection Techniques,” *International Journal of Image Processing*, 2009.

[13] R. Nowicki, A. Pokropińska, “Information Criterions Applied to Neuro-Fuzzy Architectures Design,” *Lecture Notes in Artificial Intelligence*, vol. 3070, pp. 332-337, 2004.

[14] R. Nowicki, L. Rutkowski, “Soft Techniques for Bayesian Classification,” *Neural Networks and Soft Computing, Advances in Soft Computing, L. Rutkowski, J. Kacprzyk (Eds.)*, Springer Physica-Verlag, pp. 537-544, 2003.

[15] R.B. Paris, ”The discrete analogue of Laplaces method”, *Computers & Mathematics with Applications*, 2011.

[16] J. Romanowski, T. Nowak, P. Najgebauer, S. Litwiński, “Improved X-ray Edge Detection Based on Background Extraction Algorithm,” *Artificial Intelligence and Soft Computing*, pp. 309-319, 2013.

[17] J. Schreiber, R. Schubert, V. Kuhn, “Femur Detection in Radiographs using Teplate-based Registration,” *Bildverarbeitung für die Medizin*, 2006.

[18] D.C. Shubhangi, S. Raghavendra, P. Chinchansoor, S. Hiremath, “Edge Detection of Femur Bones in X-ray images - A comparative study of Edge Detectors,” *International Journal of Computer Applications*, 2012.

[19] G.J. Whitma, L.T. Niklason, M. Pandit, L.C. Oliver, EH. Atkins, O. Kinnard, A.H. Alexander, M.K. Weiss, K. Sunku, E.S. Schulze, R.E. Greene, “Dual-Energy Digital Substraction Chest Radiography: Technical Considerations,” *Curr Problems in Diagnostic Radiology*, 2002.

[20] S. Yamamoto, J. McWilliams, C. Arellano, W. Marfori, W. Cheng, T. Mcnamara, W.J. Quinones-Baldrich, S.G. Ruehm, “Dual-energy CT angiography of pelvic and lower extremity articles: dual-energy bones substraction versus manual bone substraction,” *Clinical Radiology*, 2010.

[21] W. Żorski, ”Image segmentation method based on Hough transform”, *Institute for Automation and Robotics, Department of Cybernetics. Military Technical Academy*, in Polish, 2000.