3-Dimensional Vector Analysis of 2-Dimensional Ultrasound Diagnostic Images

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***Abstract*—Research work is dedicated to improve diagnostics of appendicitis. Presented algorithm was used for analysis of ultrasound images. The idea of algorithm is based on viewing the picture as combinations of points and vectors. Author of idea and algorithm is Yuriy Yu. Kolesnichenko. Algorithm has been written on Java language. The 3 series of using the algorithm were implemented and presented. Further work is required with an increase in number of analyzed cases for assessment of veracity of obtained results. This idea can be implemented as some portable device for emergency department and surgery department, which would determine the vermiform appendix in discrete form (yes or no) without ultrasound B-mode picture visualization for physician.**

I. Introduction. Topicality of the Theme

The growing of computing power and sophistication of technology bring a new opportunity for Health Care. Big Data analytics as well as various software (different algorithms, artificial neural networks (ANN), machine learning, deep learning, Artificial Intelligence) have some specific goals: provide decision-making capabilities for doctors, find the right path for release medical staff from routine work, create personalized medicine approach, develop new services for patients, estimate return on investment, optimize Health Care processes / care management, etc [1], [2], [3], [4], [5], [6]. One of the most important directions is medical imaging innovation, which have been already transforming radiology for example. Rasu Shrestha, M.D., Chief innovation officer at the University of Pittsburgh Medical Center said at Radiological Society of North America (RSNA 2016, Chicago, SearchHealthIT, TechTarget.com) that any hospital today becomes imaging center, the emergency department, or the hospital in general. More and more projects related to Artificial Intelligence (AI) and machine learning apply to interpretation of medical images. First of all medical imaging innovations aim to enable doctors to better diagnose patients.

There are some image-intensive medical areas, such as cardiology, neurology, oncology departments, emergency room, which need the mainstream imaging workflow. The Healthcare Information and Management Systems Society (HIMSS) Conference 2017 (Orlando) was characterized by significant presence of medical imaging and surge in interest in imaging. This is the sign that medical imaging is becoming important part of mainstream Health Care IT. Louis Frolio, advisory technical education consultant within Dell EMC Education Services described some trends of the new Health Care paradigm [7], which includes: Mobile Health, Personalized Medicine, Telemedicine, Wireless Body Area Network Systems (WBAN), convergence of Big Data and Electronic Health Records (EHR). Health Care paradigm can be designated as broader interdisciplinary concept Smart Space [8], [9], [10]. The medical imaging software is ponderable and significant part of new Health Care paradigm.

Software can be trained to read 2D or 3D images. Different software, AI, machine learning have been used in many complicated cases, for example in oncology to help detect abnormalities in X-rays and MRIs [11]. Opponents of AI in Health Care argued that computers are not always reliable and can cause catastrophic consequences if AI prescribes the wrong decision and wrong diagnosis. Also people are scared of AI, thinking that computers can replace them at work. But if software would receive proven accuracy and safety, it can be trusted and used for patient care.

Scientists are just at the beginning of understanding the biological mechanisms complexity, particularly human optical vision, and what computing power should be used for artificial optical vision equal human. But despite the fact that many of scientific knowledge has come from nature (bionics), scientists should beware “black box” creating software like ANN, especially in such high risk area as medicine [12]. Clearly understandable tools for professionals should be created, which will be irreplaceable for releasing doctors time and improving patient care through reducing human factor impact because of

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errors during overload. Vector analysis can be used without any ANN for image detection on the same manner, more sample images in the library, more accurate detection.

Computer aided detection (CAD) algorithms, which emulates human sensory organs, are well known. Optical symbol recognition software is the most popular from the computer vision series. It uses to convert the scanned paper documents to digital text. Another example is face detection algorithm, which is used for digital cameras and allows to made focus on faces at photo. Or voice, fingerprints and iris recognition algorithms in security and military systems that have been created during second half of previous century [13].

At that time monochrome monitors and computers-mainframes looked like a big cupboard and filled an entire room. During recent period of time computers became personal with color monitors and small size, even pocket size. The need to increase computing power led to return to mainframes and creation of data warehouses. Computers by Moore’s Law becomes twice more powerful each 2 years. Multi-core central processors (CPU) and graphic processors (GPU) allow to elaborate high-performance computing (HPC), but it is still not enough computing power to emulate human brain activity. For example, The Telegraph wrote in 2014 that researchers used the K computer in Japan, the fourth most powerful in the world, to simulate human brain activity. The computer has 705,024 processor cores and 1.4 million GB of RAM (random access memory), but still took 40 minutes to process the data that brain processes just for one second.

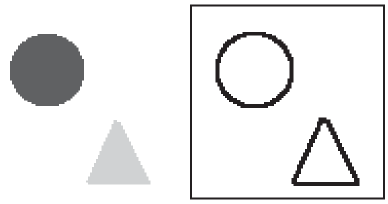
Eliot L. Siegel, professor and vice chair of research informatics at the University of Maryland School of Medicine debated at RSNA 2016 about whether AI will replace radiologists within the next 25 years. Siegel said that whatever preconceived notions people may have, AI currently stands on radiology's doorstep [14]. Computer scientist at the University of Toronto Goffrey Hinton wrote in The New Yorker in 2017 that deep learning is going to do better than radiologists and will replace them during 5-10 years.

II. COMBINATIONS OF POINTS AND VECTORS

One of modern trends in CAD is the convolutional neural network (CNN), a variant of ANN, which becomes very popular in the area of 2-dimensional images detection, particularly medical images as X-ray, CT, etc. CNN works with small areas of image called kernels.

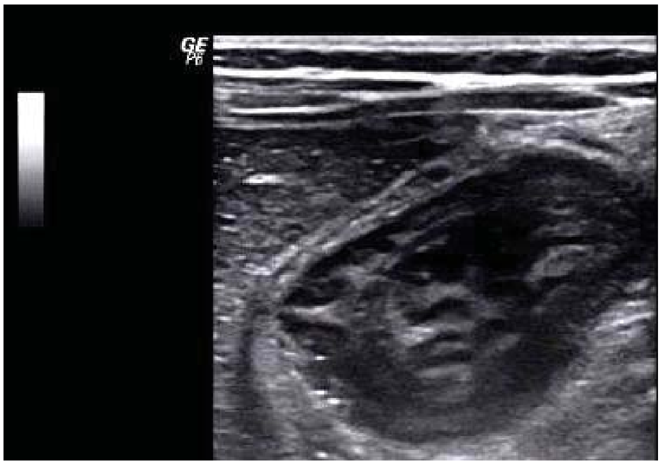
The paradigm “from small to big” doesn’t actually correspond to mechanism of how human detects the picture. Human gets sight of full picture and only then divides picture by fragments and region of interest (ROI). Today scientists don’t fully understand the nature of ANN decision-making process, which is as “black box” – only input and output can be known, and nothing between input and output can be recognized. It is not a short way to see the big thing thru a small eyepiece. The main fact about ANN, which is not properly highlighted, is that the ANN is just a classifier. ANN is only a “top” of the “iceberg” called CAD, and not a necessary part. But a great part of ANN is a mathematical algorithm, such as a vector analysis or other.

The one of CAD steps is an edge detection for further segmentation of the image to ROI. As a rule it is related on widely known Sobel operator algorithm (Sobel-Feldman operator), which is based on colors difference within pixels neighborhood (matrix of pixels) and is used in image processing and computer vision. It looks simple in case of segmentation of images with objects, which are consisted of a homogeneous patterns at the homogeneous background (Fig. 1). But it is very difficult and practically impossible to operate with inhomogeneous images, on that even human eye often cannot accurately recognize the objects (Fig. 2).

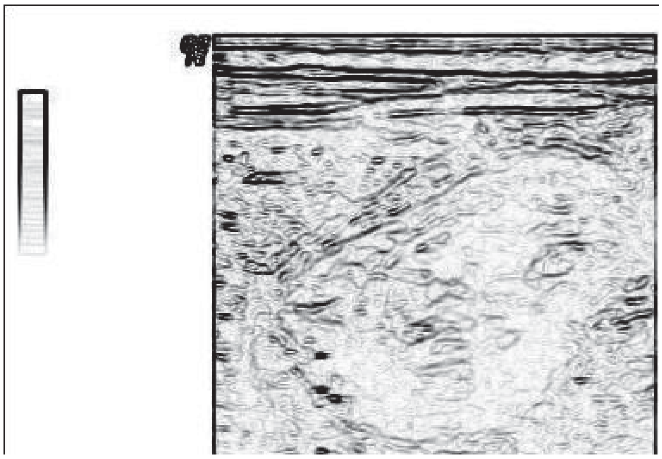


a b

Fig. 1. a – simple objects; b – the same image after Sobel operator



a



b

Fig. 2. a – B-mode ultrasound image of subhepatic intestinal intussusception; b – the same image after Sobel operator

In cases with inhomogeneous images the Sobel operator results in “a pencil art sketch image”, which doesn’t help to find ROI. This situation can be explained by fact that Sobel operator was presented in 1968, when computers had a green monochrome monitors. Modern color monitors appeared only in 1981 or even later.

The right way is to “learn” or program machine to find an equal objects by the sample or ROI from the library. This approach can be called “Supervised Learning” [15]. According to D. Shiffman it is “a strategy that involves a teacher that is smarter than the network itself”. If we talk not about ANN, then it will sounds like a strategy that involves a teacher that is smarter than the CAD algorithm itself.

The idea of presented algorithm in article is based on viewing the picture as combinations of points and vectors. Author of idea and algorithm is Yuriy Yu. Kolesnichenko.

Human can see the same picture without change after picture rotation. The nature of this physiological mechanism still hasn’t been explained. Perhaps visual system uses some starting-points or vectors, while looking on picture. After picture rotation this points or vectors moved. There are still some questions: how does the visual system find vectors again, can human visual system predict all vectors rotations in 2D plane? The basics of modern combinatorics were well described by Witold Lipski in 1982 [16]. Regarding combinatorics, computer doesn’t need to think as human, it just has to calculate faster than human.

III. METHOD

The algorithm has used for the analysis of ultrasound images of ultrasound scanner Esaote MyLab 70, LA523 probe. Represented algorithm has been written on Java language. It calculates possible combinations of points and vectors and compares them.

The data can be shown not only at simple 2D image plane, because combinations cross over and lie on each other as multilayer image. 3D image plane was used, color mode (map) was similarly as in ultrasound images: color duplex mode (gray-scale 2D mode, tissue structure) + color mode (blood flow, tissue movement or elasticity). 3D image plane allows to show data after processing by the algorithm. More intensive color corresponds to more crossing of point or pixel by vectors. It can be called a weight of pixel. Vectors and pixels combinations are not so unique in ultrasound images, thereby the pixel weight is a break point for ROI detection. For better visualization of ROI (an area with bright color) the algorithm smooths weights of pixels in 3x3 matrix to an average empirical threshold (10% of maximum weight of pixel), and draws a colored square border around ROI. Standard deviation (SD) and average values (Avg) were estimated.

IV. CLINICAL SIGNIFICANCE

The idea to collect the set of ultrasound images (sonograms) for development of mathematical algorithm appeared during 24-hour duty in radiology department of Children's Hospital. A lot of routine works were dedicated to diagnose appendicitis (ultrasound investigation of vermiform appendix). Acute appendicitis is more prevalent at younger age, and it is the most frequent case in abdominal surgery practice [17], [18]. The incidence in the pediatric age group is about 4 per 100 [19]. Progression of acute appendicitis to perforation is more rapid in younger child, sometimes occurring within 6 to 12 hours [18].

Acute appendicitis is the most common explanation for the so-called acute abdomen presentation to an emergency department. Unless the condition is treated, appendiceal necrosis ultimately develops, resulting in perforation, abscess formation, and peritonitis. Perforation may occur in up 35% cases [20]. With a classic presentation, the patient is treated with surgery for appendectomy. This is often complicated by surgical removal of a normal appendix in a patient for whom there is another explanation for their symptomatology. Laparotomy resulting in removal of normal, noninflamed appendix is reported in around 26% cases [20].

Surgery may be delayed in some patients with acute appendicitis if the presentation is atypical. This may lead to perforation prior to the surgery. It is a balance between negative laparotomy rate and the perforation rate at surgery, that motivates ultrasound imaging prior to initiating treatment for the patient who presents with acute right lower quadrant pain.

Diagnosis of appendicitis is complicated by the fact that many disorders present with similar clinical picture of an acute condition in the abdomen (gastroenteritis, mesenteric lymphadenitis in children, right ovarian torsion, etc). Abdominal ultrasound has proved to be useful in diagnosing acute appendicitis. It has become the principal imaging study for the diagnostics of appendicitis in children. Before high-resolution ultrasound, no noninvasive imaging technique was available to enable direct visualization of the inflamed vermiform appendix. In 1986, Julien Puylaert described the value of graded compression ultrasound examination of patients suspected of having acute appendicitis. Since then, other investigators have improved the ultrasound examination criteria for diagnostics, firmly establishing the value of ultrasound in assessing patients with equivocal evidence of appendicitis. The size of an appendix can differentiate the normal from the acutely inflamed. In performing ultrasound examination on a patient with suspected appendicitis, the objectives are to identify the patient with acute appendicitis, to identify the patient with-out acute appendicitis, and to identify an alternate explanation for their right lower quadrant pain [20].

The new class of ultrasound devices has appeared such as Bladder Scan or Aorta Scan. These kind of ultrasound devices allow to rapid examination without visualization of ultrasound images. The mathematical algorithm of the device finds the necessary zone of ultrasound scanning and makes measurements without ultrasound medical staff intervention. Bladder Scan measures urinary bladder volume, Aorta Scan measures abdominal aortic diameter. Both ultrasound devices help to make the measurements quickly and diagnose the disease without delay.

The same idea can be implemented for rapid ultrasound examination on a patient with suspected appendicitis. The mathematical algorithm can find the necessary zone of ultrasound scanning and makes measurements without ultrasound medical staff in emergency department or surgery department and without loss of time.

V. Preparing images

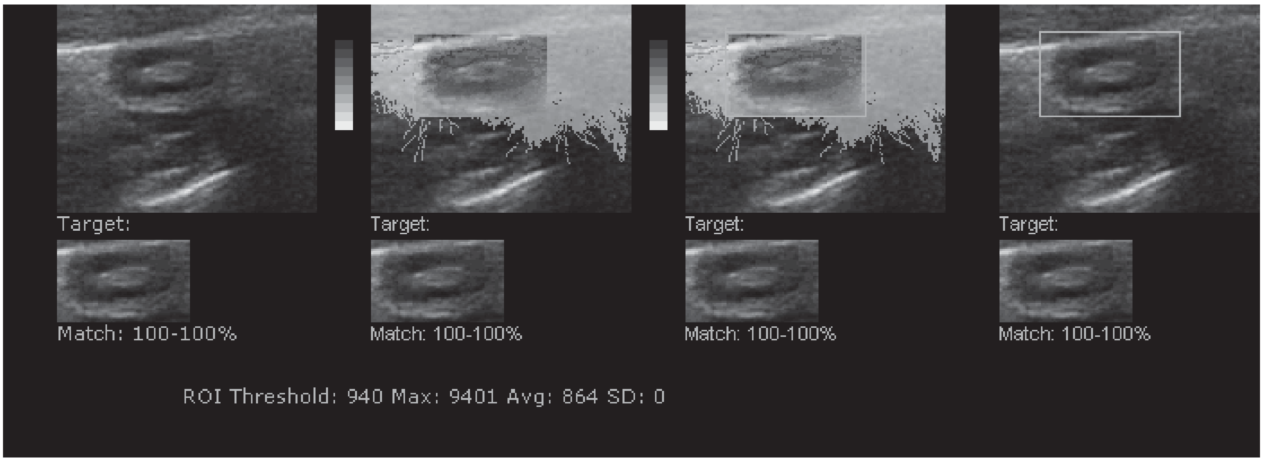
For this study 3 ultrasound images with normal vermiform appendix (source images) were chosen. Cross-sectional area of vermiform appendix was cut from source images into separate images (target images). The source images were complemented by the same images with rotation on 45, 90 and 180 degrees (6 versions of each source image). The aim of the algorithm is to find the target on source images.

By reason of RAM restriction (8 GB) images were cut to less size approximately 150x150 pixels, but nonetheless Java-7 began to terminate the algorithm with an out of memory error. Additional stack algorithm was written for caching the array of data on HDD (hard disk drive), to read and write it partially. For that purpose 600 GB of HDD was used. This restriction greatly slows down the algorithm. Comparing of two images took about 8-12 hours at Yorkfield CPU core which was used. This algorithm approximately needs 120 GB RAM or more for work without caching on HDD with even such small images. Several variants (filters) of vector creating / computing were written. 2 most representative filters: colors dependent and colors independent were chosen.

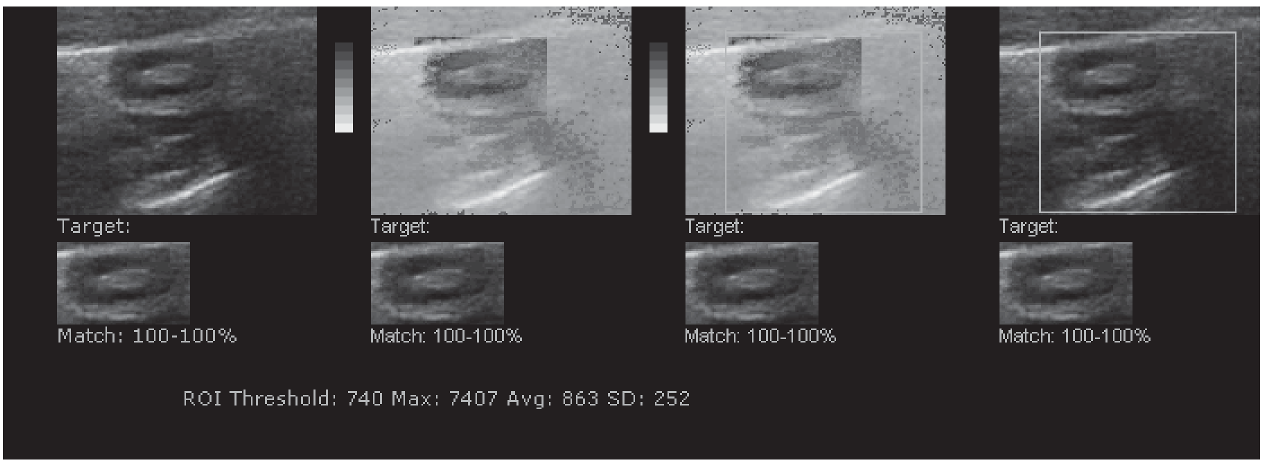
It is important to mention that some manufacturers of the ultrasound scanners by default set a compression of an image data like a JPEG/MPEG that is the problem for vector analysis because of pixel “noise”. Images from ultrasound scanner in this study were converted to PNG. The resulting images created by algorithm were also in PNG format.

VI. Results

The 3 series of using the algorithm were implemented: original source-target series (example at Fig. 3, Fig. 4); original source-target series with 45, 90 and 180 degrees clockwise or counterclockwise rotation (example at Fig. 5); cross-comparison series (example at Fig. 6). Colors dependent filter in most cases has smaller ROI than colors independent filter that can be hypothetically explained by higher detection accuracy of colors dependent filter. Colors independent filter in most cases has bigger ROI than colors dependent filter in most cases that can be hypothetically explained by higher detection sensitivity of colors independent filter. Also colors independent filter is faster.

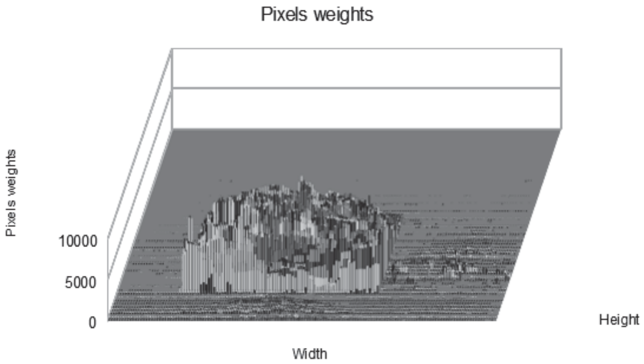


Case A

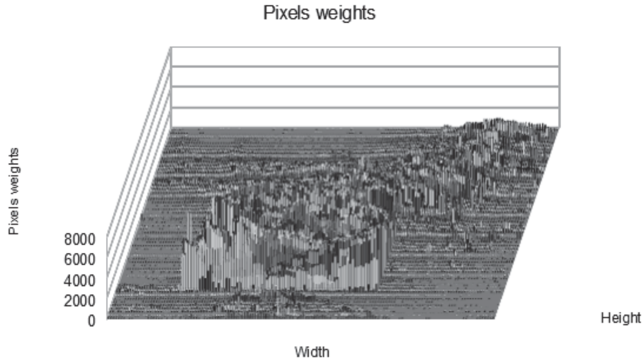


Case B

Fig. 3. Ultrasound image with normal vermiform appendix. Original source-target series: case A – colors dependent filter, case B – colors independent filter. Set of 4 stages of image analysis, from left to right: B-mode found pixels (2D vector analysis); B-mode plus vectors weights color mode (3D vector analysis); 3D vector analysis plus ROI; 2D vector analysis plus ROI.

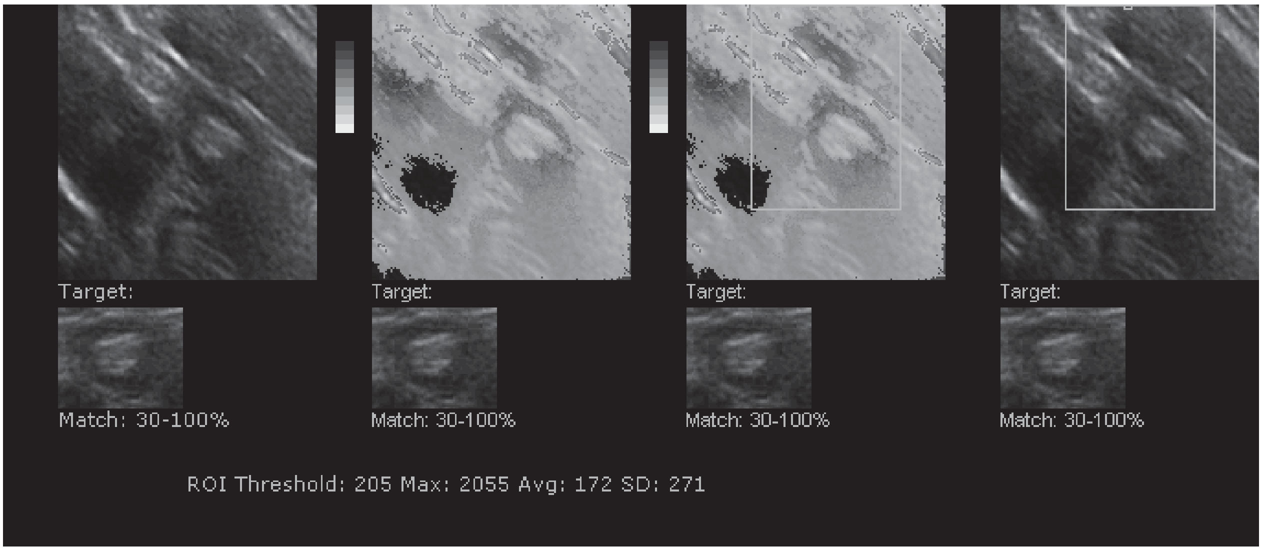


Case A

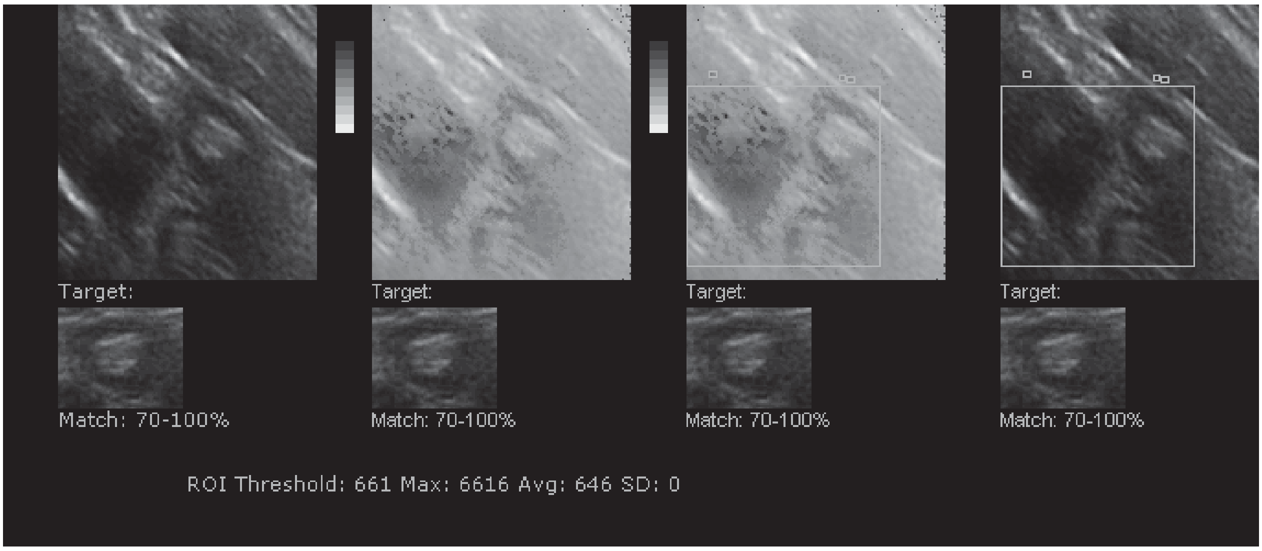


Case B

Fig. 4. Original source-target series (same images as at Fig.3): case A – 3D histogram of pixels weights (for colors dependent filter); case B – 3D histogram of pixels weights (for colors independent filter)



Case C



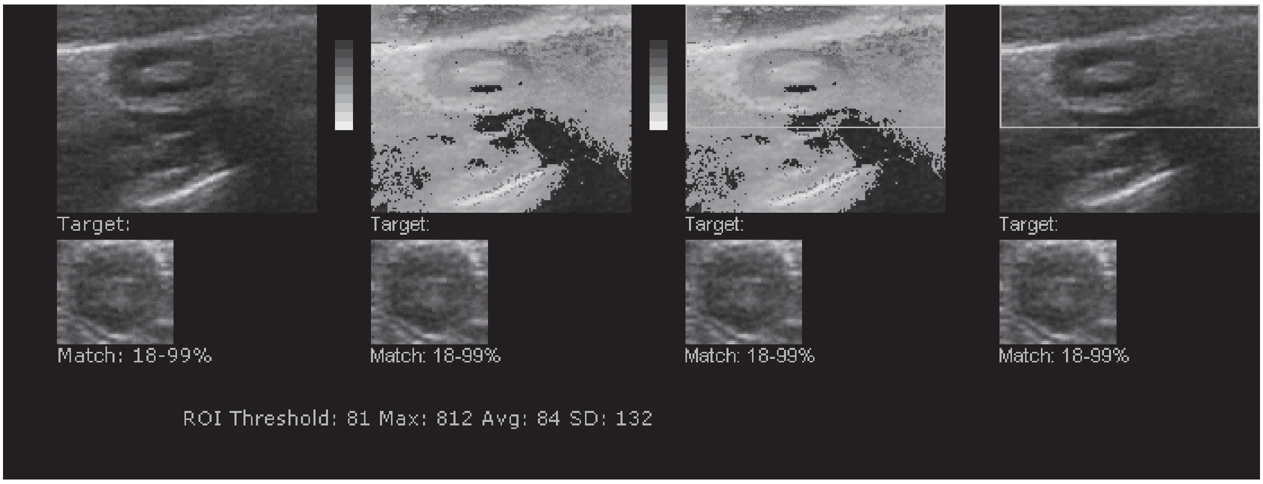
Case D

Fig. 5. Ultrasound image with normal vermiform appendix. Original source-target series with 45 degree clockwise rotation (CW): case C – colors dependent filter; case D – colors independent filter. Set of 4 stages of image analysis, from left to right: B-mode found pixels (2D vector analysis); B-mode plus vectors weights color mode (3D vector analysis); 3D vector analysis plus ROI; 2D vector analysis plus ROI.

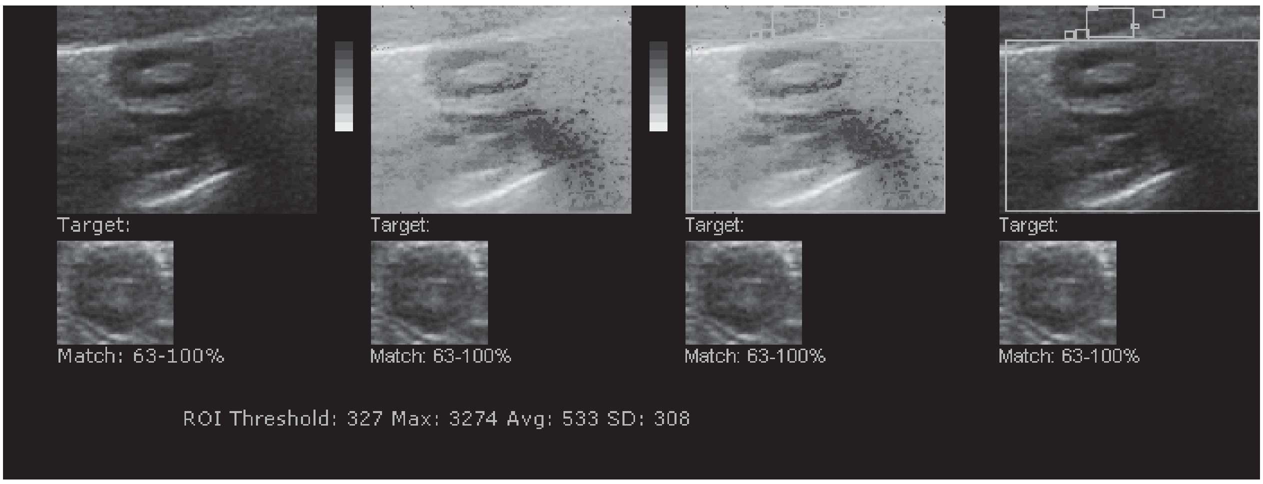
At the resulting images the percentage values are presented thru the dash. The first number represents the percentage of matching vectors combinations, and the second number represents the percentage of target image pixels from target vectors, which were found on source. The real percentage of matching vectors combinations on source image can be more than 100%.

For the understanding of relation of 2D resulting images and 3D histogram drawn in Open Office Calc should be considered that at digital 2D images 0 coordinate starts from left upper corner, but at represented 3D histogram 0 point is in the left lower (front) corner. So at 3D histogram can be seen the 2D plane of source image which fallen forward. At 2D source images peaks of 3D histogram correspond by red color gradation, higher peak – more intensive gradation of red color.

Represented files were converted to gray-scale colors due to the requirements of publication. Original files have the color gradient legend corresponded to layers of images in red color gradation, ROI color frame and text are green. 3D histograms, that are presented at Fig. 4, originally were drawn in Open Office Calc and originally in color.



Case E



Case F

Fig. 6. Ultrasound image with normal vermiform appendix. Cross-comparison series: case E – colors dependent filter, case F – colors independent filter. Set of 4 stages of image analysis, from left to right: B-mode found pixels (2D vector analysis); B-mode plus vectors weights color mode (3D vector analysis); 3D vector analysis plus ROI; 2D vector analysis plus ROI.

VII. Conclusion

This algorithm possibly can be used at the level of PACS-RIS (Picture Archiving and Communication System – Radiology Information System) and for diagnostic ultrasound scanners in radiology departments of hospitals, or even for such task as tracking the movable ventricular and atrial walls of heart during ultrasound examination, if equipment of PACS-RIS or scanners would have enough computing power.

The most probable variant is to use such algorithm at the level of global (inter-hospital) Cloud Big Data center with supercomputer as a part of search engine where physician could upload a diagnostic image and receive the most relevant results from the digital Cloud library, or as a part of server side (for example as a layer of ANN) of network / mobile application.

Possibility and cost-effectiveness of work in GPU environment (parallel computing) is unclear, because the total cost of motherboard with indicated capacity of RAM is equal to cost of GPU.

While computing power is growing, the new opportunity for Health Care is appeared to release medical staff from routine work and save the time in conditions of urgent diseases complications. The way to use for Health Care different algorithms, ANN, machine learning / deep learning, AI has just started. Presented algorithm concerns human visual system. Many questions, problems and challenges wait scientists on this way to create an artificial human visual system model that will be able to image processing, video processing as it does human visual system with recognition and understanding of images by brain. The answers lie in area of bionics approaches.

It is not clear yet the computing power equivalent of brain to process and recognize images. Moore's Law confirms the concernment that the atomic essence of modern computing technology will reach its power limit soon, and sciences cannot even close in to the capability of nature to processing information. There are some attempts in the world to develop fundamentally new computers, for example, biocomputer or quantum computer. It is important to notice that biological objects can be compared with quantum computers, because quanta of sunlight lie in essence of entire chain of biological evolution. Definitely the only quantum computer with higher computing power will allow to create completely autonomous, without operator, equipment for Health Care.

But today doctors should use any algorithm carefully, “black box” instead clear decision-making process can lead to mistakes. Presented in this article mathematical algorithm based on 3-dimensional vector analysis can be used without any ANN or any “black box” for detection of ultrasound 2-dimensional images of diagnostic scanner.

Further work on presented algorithm is required with an increase in the number of analyzed cases for evaluation of the veracity of obtained results. It is also necessary to evaluate the needed capacity of computing power for this kind of algorithm in clinical practice.

The idea refers to product that can be a portable device for emergency department and surgery department, which would determine the vermiform appendix in discrete form (yes or no) without ultrasound B-mode picture visualization for physician. This vermiform appendix case study is just an example of applying of the algorithm.

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