CUDA parallel programming technology application for analysis of big biomedical data based on computation of effectiveness features

N Yu Ilyasova¹,², V A Shikhevich¹ and A S Shirokanev¹,²

¹Samara National Research University, Moskovskoe Shosse 34A, Samara, Russia, 443086
²Image Processing Systems Institute of RAS - Branch of the FSRC "Crystallography and Photonics" RAS, Molodogvardejskaya street 151, Samara, Russia, 443001

e-mail: Ilyasova.nata@gmail.com, alexandrshirokanev@gmail.com

Abstract. This paper proposes the technology for large biomedical data analysis based on CUDA computation. The technology was used to analyze a large set of fundus images used for diabetic retinopathy automatic diagnostics. A high-performance algorithm that calculates effective textural characteristics for medical image analysis has been developed. During the automatic image diagnostics, the following classes were distinguished: thin vessels, thick vessels, exudates and a healthy area. The study of the mentioned algorithm efficiency was conducted with 500x500-1000x1000 pixels images using a square 12x12 dimension window. The acceleration relationship between the developed algorithm and various data sizes was demonstrated. The study showed that the algorithm effectiveness can be affected by certain characteristics of the image, e.g. its clarity, shape of exudate zone, variability of blood vessels, and optic disc location.

1. Introduction

A few years ago, a breakthrough in medicine occurred when the technologies for medical data analysis started to be introduced in the advanced countries. Nowadays medical data is being actively processed in various medical devices. Some international scientific projects are demonstrating artificial intelligence in medicine. The main task of the medical data automatic analysis is to use the automated methods for data processing and analyzing in order to reduce physician’s working time and human errors during medical examinations or procedures.

A large amount of medical database makes it difficult for a physician to analyze the data. Many important details of the examination are skipped before the final diagnosis and treatment. Medical database includes a large amount of unstructured information, such as: photos, videos, one-dimensional signals and patients’ data [1]. The amount of unstructured information is growing exponentially year after year. Many scientific projects highlight the analysis of unstructured information to be their main task. Usually there is a great amount of information that should to be processed quickly enough. The intellectual analysis of fundus images for pathology detection can be seen as a special case of such analysis.
Today, diabetes mellitus is considered to be the most dangerous and common endocrine disease in the world. In diabetes, the blood vessels of the retina change and this leads to disruption in oxygenation in retinal vessels. This disease can lead to diabetic retinopathy (DRP). In DRP, all parts of the retina are affected, but the changes in its central area in the form of diabetic macular edema lead to the most rapid and irreversible reduction in vision [2]. Macular edema is characterized by retinal thickening or the presence of "solid" exudates. Figure 1 is an example of a healthy retina and the retina with pathology.

There are several ways of treating diabetic macular edema, but laser coagulation is considered to be the “gold standard” [3,4]. Its effectiveness was confirmed during the large-scale study (ETDRS, 1987) [4]. The essence of laser coagulation is in application of dosed micro-burns - laser coagulants - on the area of retinal edema. The coagulates are imposed either one by one or in a series arranged in the form of a regular pattern or with a preliminary planning of its location followed by the plan superimposing on the retina in real time [5]. Optimal location of coagulates is preferable, it implies their location in edema at the maximum distances from each other excluding their penetration into the blood vessels.

The papers [7-8, 12] present studies on the application of digital technologies or image processing methods for analyzing fundus images to identify pathologies and their features. The works [9-11] present the information technology that makes it possible to fill in automatically the given edema areas with coagulates, the vessels net location being different in it. Currently, the urgent task is to accelerate this technology.

2. Technology for large biomedical data analysis

The proposed technology for analyzing biomedical data is based on the selection of effective textural features and includes several steps (Figure 2), such as: sampling; classification of sample elements; discriminant analysis and selection of effective signs [9, 13-14]. Earlier, textural features had shown good results for the recognition and further diagnostics of biomedical images [6]. Experimentally selected parameters can be used for image segmentation [14]. For the analysis of diagnostics effectiveness a sample is formed by the fragmentation of a full-scale fundus image. Sampling is used to select the size of the fragmentation window. The optimal size will be used for image segmentation.

The algorithm for textural features calculation for a large number of pictures has an excessively high computational complexity. Within this technology the use of a high performance algorithm is based on CUDA technology. For the purpose of classification the generated feature set will be used. The most effective textural features are selected due to discriminant analysis.

The proposed technology makes it possible to evaluate efficiency of high performance algorithm with different sampling parameters and size of the target fragment image.

At the initial stage the selection of fragments of certain sizes, their fragmentation and expert segmentation performed by a physician were carried out for further formation of training and test samples. The analysis of image fragments showed that they were well distinguished by their textural properties. The textural features were well proven for biomedical images recognition and further diagnosis [6, 12]. The well-known MaZda library was used, it made it possible to calculate up to 300 different textural features of one colour channel [15]. The evaluation of the effectiveness of the obtained set of features was carried out by discriminant analysis [16-18]. The purpose of it was to
select from the massive amount of signs a subset of the most informative ones that provided the minimum clustering error. At the same time, it was necessary to determine the best mask size for the system to process the image and automatically select areas of interest during laser coagulation.

Figure 2. Technology of effective features formation for a large amount of biomedical image analysis.

As a result of discriminant analysis for each object sampling the best features were determined by the criterion of separability. To assess the quality of separability, the clustering error was calculated for each set of features and different sizes of the fragmentation window. The formation of the sets of features was carried out through the selection of the best ones considering their individual criteria of separability. Within the framework of discriminant analysis, clustering using the K-means method was applied, and the Euclidean distance [19] was used as a measure of similarity. The required minimum size of the fragmentation window and the measure of similarity were chosen by the minimum clustering error criterion.

3. Existing software using GPU-CUDA.

A wide variety of software has been developed around the world for the use of CUDA in the medical industry. AxRecon is a solution for image recovery followed by image reconstruction using CUDA in computer tomography [20]. ELEKS helps a medical device to reduce the time of the patient’s assessment, accelerating the software for post-processing an MRI scanner using CUDA [21]. ELEKS realizes parallel one-time vector decomposition on an MRI scanner and reduces the time to 155x. EGSnrc is a well-known Monte-Carlo simulation package for coupled electron-photon transport, which is widely used in medical physics applications [22]. EGSnrc works with CUDA to accelerate and archives the acceleration factor up to 20x - 40x. Aetina M3N970M-MN is a 4-D ultrasonic equipment using CUDA kernels to perform advanced 3D visualization of ultrasonic data using the latest phase shift harmonics images [23].

4. Development of the high-performance algorithm for computing textural features

The fundus objects classification by their textural features is used for the purpose of the fundus image segmentation, i.e. to highlight zones with the disease, which are used for final diagnosis. The procedure of the sample elements classification, being the fragments of the fundus image is shown in Figure 3. Figure 4 is an example of the fundus image segmentation with different measures of similarity. At the first stage, the adjacency matrix, histogram and gradient field should be calculated; the calculation of these parameters takes an unacceptably long time. The algorithm for histogram and gradient features as well as for Haralik features calculation has a high computational complexity. Among all 300 features calculated by the MaZda [6, 24-26] program the most effective five were
selected according to different colour channels: Perc.10%, G_Skewness, G_S(5,0)Entropy, B_Perc.99% and B_GrVariance [9].

The step-by-step description of the algorithm is as follows:
1. The pixel of interest is selected and put at the center of a 12 x 12-pixel region. It was experimentally proven that for this window size, the clustering error would be admissible [14];
2. The above features are calculated for the selected area;
3. The distances to the centers of each class are calculated. The Euclidean and Makhalanobis distances are used as a similarity measure [14];
4. The analyzed pixel is assigned to the nearest center;
5. These steps are performed for each pixel, only pixels found at the center of regions that extend beyond the image boundaries are excluded from consideration.

In this paper, we aim to accelerate the existing algorithm using a parallel programming technology CUDA.

The parallel option for the textural features calculation is very specific, as it requires calculating of mathematical objects that seem to be complex for a video card (adjacency matrix, histogram and gradient field); it should also take into account the relationship between atomic tasks, which depend on these specified mathematical objects. The computation of features for each pixel area is the most resource-consuming part of the algorithm. This part is transferred to the graphics device. Since the GPU-CUDA computational model is representable in the form of an array (one-, two-, or three-dimensional), the superimposing of the model to this algorithm won't cause any difficulties. The calculation of features is performed in accordance with their color images. The original image is represented as a three-dimensional array, where the first level is responsible for the channel, while the second and third levels for the x and y coordinates, respectively. Each channel possesses its own calculated textural features. The GPU-CUDA computational model is set as a two-dimensional grid, the size of which coincides with the image size. See Figure 5 for the CUDA parallel algorithm.

The step-by-step description of the new algorithm is as follows:
1. Arrays of the original and the resultant image are copied in the graphic processing device;
2. The working thread extracts a pixel from the original image array and builds a 12x12 region;
3. Features for the selected region are calculated;
4. The analyzed pixel is assigned to the nearest center;
5. Step 1-4 are reiterated for each pixel, only pixels found at the center of regions that extend beyond the image boundaries are excluded from consideration.

6. The information thus derived is written into an output image array:

![Original and segmented images](image1)

**Figure 4.** Original and segmented images (Euclidean distance, Mahalanobis distance).

![Operation scheme of a separate thread](image2)

**Figure 5.** Operation scheme of a separate thread using the proposed high-performance algorithm.

The resulting array is copied back to the CPU execution, where a segmented image is created from it.

The algorithm uses mostly local memory. CUDA adjacency matrix calculation is carried out on the basis of complex implementation that works with the matrix in rows because a single thread does not fit a large matrix in the local memory.

5. **Results of experimental study**

For detailed study, the fragments of images were extracted from full-scale images of the patients’ fundus subjected to fragmentation and followed by the formation of sampling. The sampling is a
certain amount of data expressed in MB. Figure 6 shows the results of the effectiveness of the proposed algorithm depending on the amount of data (MB) for 4 different images of the fundus of real patients. The NVIDIA videocard was used to accelerate the studies.

Figure 6. Results of algorithm acceleration for the samples generated from four fundus images.

The results in Figure 6 demonstrate maximum efficiency at 148 MB data volume. Despite the independent character of the tasks, linear acceleration due to the data volume increasing is not observed as the picture clarity, shape of the exudate zone, variability of the vessels and location of the visual disk effect the computational complexity. 202 MB is the optimal amount of data with maximum average acceleration. In case of the large size only the first experiment (Figure 1a) demonstrates high algorithm efficiency at large data volumes. Such a result is noticed because the first image had the smallest proportion of exudates presented in the image compared to other images subjected to the research.

6. Conclusion
The present study proposed the technology for analyzing large amount of biomedical data, based on CUDA parallel programming. Five the most effective textural features were used for the fundus image classification. The study was conducted on four real patients’ images. At some data volumes the suggested algorithm allows to achieve 19-fold acceleration. The fundus images have great variability in the shape of the exudate zone, blood vessels and optic disc location; it affects the algorithm computational complexity in calculating features. The study showed that the proposed algorithm ensured optimal operation on various fundus images when processing data of 202 MB.

7. References
[1] Ilyasova N Yu, Kupriyanov A, Paringer R and Kirsh D 2018 Particular use of BIG DATA in medical diagnostic tasks Pattern Recognition and Image Analysis 28(1) 114-121
[2] Kutimova E Yu and Kutimova V G 2016 Diabetic retinopathy. The role of outpatient clinics in early diagnosis. Tratment. Forecasts Medicine 21(2) 573-577
[3] Doga A V 2014 Modern aspects of diagnosis and treatment of diabetic macular edema FSBI Interdisciplinary Scientific and Technical Complex "Eye Microsurgery" them. 4 51-59
[4] Astahov Yu S 2009 Modern approaches to the treatment of diabetic macular edema Ophthalmological statements 2(4) 59-69
[5] Kernt M 2012 Navigated focal retinal laser therapy using the NAVILAS® system for diabetic macula edema Ophthalmology 109 692-700
[6] HeiShun Yu 2016 Using texture analyses of contrast enhanced CT to assess hepatic fibrosis *European Journal of Radiology* **85**(3) 511-517

[7] Khorin P A, Ilyasova N Yu and Paringer R A 2018 Onformative feature selection based on the Zernike polynomial coefficients for various pathologies of the human eye cornea *Computer Optics* **42**(1) 159-166 DOI: 10.18287/2412-6179-2018-42-1-159-166

[8] Ilyasova N Yu 2014 Estimating the geometric features of a 3d vascular structure *Computer Optics* **38**(3) 529-538

[9] Ilyasova N, Paringer R, Shirokanev A, Kupriyanov A and Ushakova N 2017 A smart feature selection technique for object localization in ocular fundus images with the aid of color subspaces *Procedia Engineering* **201** 736-745

[10] Ilyasova N Yu 2017 Coagulate map formation algorithms for laser eye treatment *IEEE Xplore* 1-5

[11] Shirokanev A S, Kirsh D V, Ilyasova N Yu and Kupriyanov A V 2018 Investigation of algorithms for coagulate arrangement in fundus images *Computer Optics* **42**(4) 712-721 DOI: 10.18287/2412-6179-2018-42-4-712-721

[12] Ilyasova N Yu 2013 Methods for digital analysis of human vascular system. Literature review *Computer Optics* **37**(4) 517-541

[13] Ilyasova N Yu 2016 Regions of interest in a fundus image selection technique using the discriminative analysis methods *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)* **9972** 408-417

[14] Ilyasova N Yu 2017 Intelligent feature selection technique for segmentation of fundus images *IEEE Xplore. Seventh International Conference on Innovative Computing Technology* 138-143

[15] Strzelecki M 2013 A software tool for automatic classification and segmentation of 2D/3D medical images *Nuclear Instruments & Methods in Physics Research Section A: Accelerators. Spectrometers. Detectors and Associated Equipment* **702** 137-140

[16] Ilyasova N Yu 2015 The Discriminant Analysis Application to Refine the Diagnostic Features of Blood Vessels Images *Optical Memory & Neural Networks (Information Optics)* **24**(4) 309-313

[17] Ilyasova N Yu 2014 Formation of features for improving the quality of medical diagnosis based on discriminant analysis method *Computer Optics* **38**(4) 751-756

[18] Ilyasova N Yu and Paringer R A 2015 The study of the effectiveness of signs for the diagnosis of vascular pathology *Publishing House of the Samara Scientific Center of the Russian Academy of Sciences* **17**(2) 1015-1020

[19] Fukunaga K 1979 *Introduction to statistical pattern recognition theory* (Science) p 270

[20] Acceleware Enters the Imaging Market with the Launch of the AxRecon™ Image Reconstruction Solution 2008 URL: http://www.acceleware.com/node/529

[21] Accelerated image processing for healthcare 1991 URL: http://eleks.com/pdf/accelerated-image-processing-for-healthcare.pdf

[22] Lippuner J A and Elbakri I A 2011 GPU implementation of EGSnrc's Monte Carlo photon transport for imaging applications *Phys Med Biol.* **56**(22) 56-62

[23] Aetina M3N970M-MN 2017 URL: http://www.innodisk.com

[24] Gentillon H 2016 Parametr set for computer-assisted texture analysis of fetal brain *BMC Research Notes* **25**(9) 496

[25] Acharya U R 2012 An integrated index for the identification of diabetic retinopathy stages using texture parameters *Journal of Medical Systems* **36**(3) 2011-2020

[26] Hajek M 2002 Texture Analysis for Magnetic Resonance Imaging *Dialogues in Clinical Neuroscience* **4**(4) 235-242

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