Automatic Detection of Cardiomyopathy in Cardiac Left Ventricle Ultrasound Images

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***Abstract*— This paper presents development of an automatic diagnostic tool based on machine learning that analyses cardiac ultrasound images of patients with cardiomyopathy in several views (4 chamber apical, 2 chamber apical and M mode view). The main aim of the developed tool is to perform automatic left ventricle (LV) segmentation and to extract relevant parameters in order to estimate the severeness of cardiomyopathy in patients. Dataset included 1809 images with apical view and 53 images with M view from real patients collected at three Clinical Centers in UK and Serbia. Separate methodologies have been implemented for analyzing apical and M mode view, including U-net for segmentation, after which parameters such as left ventricular length (LVL), internal dimension (LVID), posterior wall thickness (LVPW) and interventricular septum thickness (IVS) are calculated, both in systole and diastole. The tool has also been implemented on the platform with a user-friendly interface, which allows these two modules to be used either separately or combined. In order to validate the model and compare the results between gold standard and developed methodology, two cardiology specialists have independently manually annotated LV and measured relevant parameters. The results show that the model achieves dice coefficient of 92.091% for segmentation and average root mean square error (RMSE) of 0.3052cm for parameter extraction in apical view images and average RMSE of 1.3548cm for parameter extraction in M mode view. Fully automatic detection of cardiomyopathy in cardiac LV ultrasound images can help clinicians in supporting diagnostic decision making and prescribing adequate therapy.**

I. Introduction

Ultrasound echocardiography has the highest priority in use among medical images that are used to describe and visualize the left ventricular (LV) for the purpose of evaluation of cardiac ventricles [1]. For example, dilated cardiomyopathy is described in ultrasound images as a large left ventricle that loses the capability to pump blood to the rest of the body. [2]. This condition can lead to heart damage and death, and therefore requires a quick and accurate diagnosis. For setting up the diagnosis ultrasound device is used. An ultrasound probe that passes over the heart area creates an ultrasound image that can be displayed at different angles and in different typical views, such as apical 4-chamber, apical 2-chamber, M-mode, etc. On one hand, apical view (separately in diastole and systole phases are necessary to estimate Left Ventricular Length, Diastolic, 2D - LVLd [cm] and Left Ventricular Length, Systolic, 2D – LVLs [cm] (subscript *d* and *s* correspond to diastole and systole phases) [3]. On the other hand, M-mode is crucial in estimating Interventricular Septum Thickness, Diastolic, M-mode - IVSd [cm], LV Internal Dimension, Diastolic, M-mode - LVIDd [cm], Left Ventricular Posterior Wall Thickness, Diastolic, M-mode - LVPWd [cm], Interventricular Septum Thickness, Systolic, M-mode - IVSs [cm], LV Internal Dimension, Systolic, M-mode - LVIDs [cm], Left Ventricular Posterior Wall Thickness, Systolic, M-mode - LVPWs [cm] [3].

However, due to less clearly defined borders in image, automatic LV segmentation using 2D echocardiographic images is a very challenging task. It is common practice that an experienced cardiologist manually extracts a region of interest (ROI), but this is a time-consuming and error-prone task [4]. For this reason, this research deals with the problem of left ventricular segmentation on ultrasound images using the dataset from patients with cardiomyopathy and automatic extraction of parameters that are needed to assess the patient's condition. These methods can be used to develop automated diagnostic tools that can help doctors in making accurate decisions and diagnoses.

A. Related work

Some of the main problems in developing an algorithm for automatic LV segmentation are specific characteristics of ultrasound images such as low signal-to-noise ratio, weak echoes, more than one anatomical structure in the image, etc. [1]. As a result, many authors have attempted to solve the segmentation problem using a variety of approaches, including active shape, active contours, layout methods, and machine learning methods [5, 6, 7, 8]. The literature shows that these approaches are not so sensitive to the initial conditions, and their main limitations are the image conditions. In contrast, deformable templates are robust to image conditions, however, they are very sensitive to initialization conditions [9].

In order to overcome some of the shortcomings of the mentioned traditional methods, we will consider deep neural networks. In terms of image segmentation, Oktay et al. [10] presented the usage of neural networks in 3D left ventricular segmentation. Oktay et al. solved the problem of small training data by regularizing training with an anatomical 3D model of the heart, which was made based on a large database of manually annotated heart magnetic resonance imaging. Carneiro et al. [4] used the deep learning method which decouples the rigid and nonrigid classifiers, in order to perform LV segmentation in echocardiographic images using a 4-chamber view and get valuable results. Zyuzin et al. [11] implemented U-net to segment LV using 2D 4-chamber view echocardiography images. Also, usage of pre-trained U-net was proposed by some authors such as Smistad et al. [8]. They propose pre-trained U-net and the Kalman filter, then compare the obtained results. The results showed that the Dice coefficient of Kalman filter and U-net were similar, but Hausdorff distance of the proposed U-net method was remarkably better. On the other hand, the application of U-net in the LV segmentation on images of patients with cardiomyopathy cannot be found in the literature, so it cannot be said that previously proposed methods in literature will successfully segment LV in images, mainly because of the asymmetrical pattern of LV hypertrophy which is present in patients with cardiomyopathy.

On the other side, regarding the automatic segmentation and extraction of relevant parameters on using M-mode view, with the exception of two papers, no research has dealt with the automatic detection of LV borders on M-mode images. Unser et al. propose a method for automatic extraction of myocardial borders in M-mode echocardiograms by using several step processing algorithms - preprocessing for noise reduction, then enhancement of border characteristics using adequate filters and final extraction of borders by searching for optimal paths along the time axis [12]. However, they analyze typical M-mode echocardiograms from healthy persons, as well as they do not report the number of patients nor some statistical measures such as accuracy, false positive rate, true negative rate etc. The second, more recent paper, proposes a semiautomatic contour detection in M-mode images [13]. Their model starts with a manual candidate contour after which each candidate contour is moved towards the desired borders, behaving as active contours. Active contours method is known to be not so effective in the presence of higher level of noise, and it is uncertain how this approach would behave if the images are tested on patients and contain larger amount of noise.

With all this said, it is clear that there is a need for a fully automatic LV segmentation and automatic extraction of the parameters of interest. A fully automatic LV segmentation system has the potential to streamline the clinical work-flow and reduce the inter-user variability.

II. Materials and Methodology

A. Datasets

During 2019 and 2020, we collected data from 12 patients in the Institute of Cardiovascular Diseases, Vojvodina – Sremska Kamenica (ICVDV) and from 6 patients in Newcastle University and Newcastle upon Tyne Hospitals NHS Foundation Trust (UNEW). In total, for the 2D image ultrasound apical view we had 1809 recordings. The set of 1602 images was randomly split into two subsets, for training and validation (1360 for training and 242 for validation) and the remaining 207 images were used as a testing set (without data augmentation). In order to increase the number of images for training, data augmentation was performed using mirroring effect in the training and validation phases. Validation data were used for fine-tuning the hyperparameters and for providing an unbiased evaluation of a trained model. It should be underlined that sets for validation and testing are different. The testing set includes only unseen real images, there are no artificially augmented images. In addition, 53 patients were collected from Clinical Centre Kragujevac, Serbia (CCKG), with manually extracted discussed parameters of interest for the purposes of setting ground truth for comparison with the automated way. As a result, 53 images with M-mode view were available as training dataset in automatic extraction of parameters for this view. For all sets, image resolution was 1016 x 708 pixels and all the images were in DICOM format. The ethics committee gave consent for research, as well as the research participants were informed about the study and approved the data uses.

In order to account for the inter-observer variability, two expert radiologists blindly completed LV manual segmentations. When using the automatic segmentation process, the results were compared with the mean of the segmentation output by experts. Since the inter-observer variability was shown to be statistically significant in manual segmentation, automatic segmentation emerges as the solution to reduce the variability.

B. Proposed methods

Methodology will be divided in two sections – section on methods used to analyze apical view and section on methods used to analyze M-mode view. Full workflow is shown in Fig. 1. DICOM image format is used as the input to the system. User friendly application will have the possibility for the user – doctor or a researcher to choose which view is represented by the image and should be further analyzed. Three possibilities are given – 4-chamber, 2-chamber, or M-mode (Figure 1). Proposed tool will further analyze the images depending on the view:

1. Apical 4-chamber/ Apical 2-chamber view analysis will include segmentation of the LV using U-net previously trained and calculating bordering rectangle, based on which parameters LVLd[cm] and LVLs[cm] A4C/A2C will be calculated. User should define if the view represents the systolic or diastolic phase.
2. M-mode view analysis will include bordering of the characteristic areas of LV – septum in diastole phase, diameter in diastole, LV wall in diastole, septum in systole, diameter in systole and LV wall in systole. Based on these areas, parameters IVSd[cm], IVSs[cm], LVIDd[cm], LVIDs[cm], LVPWd[cm], LVPWs[cm]

will be calculated. User should define that the view is M-mode.

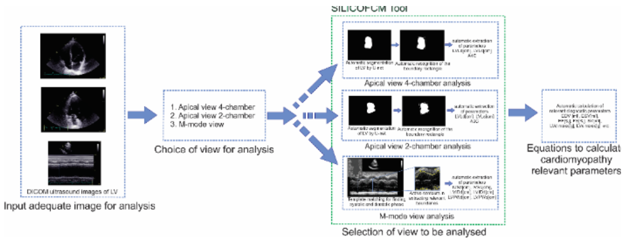

Figure. 1. Workflow of the proposed methodology

Diving more into analysis of 4-chamber view and 2-chamber view analysis, it was mentioned that U-net is used to segment LV in ultrasound images. Standard U-net neural network architecture for segmentation was used. This architecture has proven to be applicable to various medical image segmentation issues [1, 14]. Proposed U-net included two 3x3 convolutional layers and 2x2 max pooling in contraction path and consecutive 2x2 up-conv and two 3x3 convolutional layers in expansion path. In order to recover some of the fine-grained features cross-over connections are used. After removing scale and patient data from the image, resulting images 708 x 708 pixels size. Input to the network were images 128×128 pixels size, meaning that both original input, as well as target mask images, were resized to this size. We have also tried analysis with higher resolution (256 x 256), but it was an overdemanding task for the computer and the results did not get any improvement. Additionally, as only one region in the image is the region of interest, a reduction in image resolution is justified. Also, ultrasound images that were used as masks were binarized. The training was performed for 10 epochs, using early stopping, with a regularization factor of 0.05 and learning rate of 0.001. The final output is a binary segmented image of LV. For the performance evaluation of the algorithm, we have used the dice coefficient D [15]. After segmentation, output image is forwarded to the system for drawing the bordering rectangle. The output result corresponds to the longer side length, which has a meaning of LVLd[cm] and LVLs[cm] A4C will. The same methodology is applied for the way 2-chamber view, except the final outputs are LVLd[cm] and LVLs[cm] A2C.

As far as the methodology for M-mode analysis is concerned, we firstly used adaptive histogram equalization called contrast limited adaptive histogram equalization to improve the image contrast. After this template matching will be introduced. It should be emphasized that for every new dataset, the template should be extracted manually just once for that dataset – that specific ultrasound device. After this, no further manual action is required. Found area matching the template will be extracted on the analyzed image and Canny edge detection will be performed subsequently. Output values after binarization are IVSd[cm], IVSs[cm], LVIDd[cm], LVIDs[cm], LVPWd[cm], LVPWs[cm]. Due to great deal of noise present in ultrasound images, the same described procedure is repeated for upper half of the image and lower half of image. This was found to reduce mean square error between the manually extracted values and those automatically determined by the algorithm.

In addition, in order to convert the extracted parameters from unit pixels to the unit cm, it was required to extract from DICOM info data the information about the conversion scale. In the available images, DICOM tags (0018,602C) Physical Delta X and (0018,602E) Physical Delta Y contained the adequate values.

Hardware components that were used for the purposes of this research are: a GPU Nvidia GeForce GTX960M, an Intel (R) Core (TM) i7-6700HQ CPU @2.60GHz and 8GB of RAM. Implementation of the algorithms was done in the Python 3.7.4 environment with Tensorflow 1.15.

III. Results and Discussion

The results have shown that proposed U-net deep convolutional neural network can learn to segment heart left ventricle in ultrasound images. In cases where external additional areas are recognized (Figure. 2a), they are easily removed in a fine-tuning stage (Figure. 2b). This was achieved by using kernel of size 3x3 for erosion in the images, which in return improved the accuracy by 0.52%.

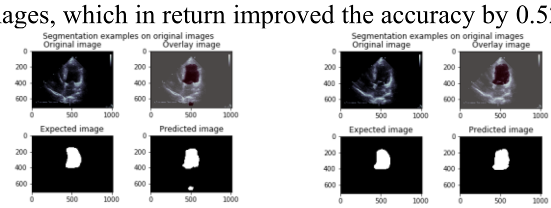

Figure. 2. Segmentation results performed by U-net and using manual annotation a) before fine tuning b) after fine tuning using erosion

Loss function with its falling trend during training and validation is shown in Figure. 3, while the accuracy during training and validation data were increasing up to 93.67% and 88.36% respectively (Figure. 4).

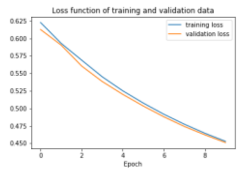

Figure. 3. Loss function during training and validation

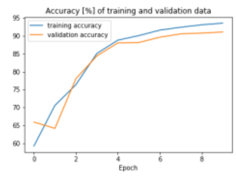

Figure. 4. Accuracy during training and validation

For the comparison between manual segmentation and automatic segmentation by U-net, dice similarity coefficient was calculated. Test accuracy on 128x128 images was 90.32%, test accuracy on 1016x708 images without kernel was 91.57%, and test accuracy on 1016x708 images with kernel was 92.091%. The runtime of the training process was 96.08 ± 2.81s per epoch, but this may be reduced by optimizing the network architecture and computation graph, as well as by using better hardware configuration.

In addition to that, automatic extraction of LVLd[cm] and LVLs[cm] A4C has shown to perform well, with root mean square error of 0.3052cm for all parameters, combined datasets. Although there could be some improvements, it can be concluded the results are promising and can further be tested on other available datasets. Results for automatic extraction of parameters on Apical view images in the form of mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) are presented in Table 1.

TABLE I.
RESULTS FOR AUTOMATIC EXTRACTION OF PARAMETERS ON APICAL VIEW ULTRASOUND IMAGES

Parameter name	ICVDV			UNEW		
	MAE	MSE	RMSE	MAE	MSE	RMSE
LVLd[cm] A4C	0.1897	0.0459	0.2143	0.2442	0.0815	0.2855
LVLs[cm] A4C	0.2820	0.1124	0.3352	0.5180	0.2683	0.5180
LVLd[cm] A2C	0.0627	0.0088	0.0939	0.5314	0.7532	0.8679
LVLs[cm] A2C	0.2443	0.0823	0.2869	0.0340	0.0012	0.0340

On the other hand, further automatic extraction of the parameters IVSd[cm], IVSs[cm], LVIDd[cm], LVIDs[cm], LVPWd[cm], LVPWs[cm] are reported in Table 2 in the form of mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) for available dataset.

TABLE II.
RESULTS FOR AUTOMATIC EXTRACTION OF PARAMETERS ON M MODE VIEW ULTRASOUND IMAGES

Parameter name	CCKG		
	MAE	MSE	RMSE
IVSd[cm]	0.8921	1.3754	1.1728
IVSs[cm]	2.1119	5.6667	2.3805
LVIDd[cm]	1.0543	2.2327	1.4942
LVIDs[cm]	1.4824	3.1217	1.7668
LVPWd[cm]	0.4679	0.3660	0.6050
LVPWs[cm]	0.6062	0.5030	0.7093

IV. CONCLUSIONS

Due to the characteristics of cardiomyopathy such as the specific shape and size of the LV, previous work dealing with the application of deep neural networks could not be compared with the results presented in this paper. The proposed method with U-net has been shown to segment LV successfully in a fully automatic manner. Even when it comes to different imaging conditions or the usage of a small training dataset, the method was shown to be robust. Extraction of the parameters was accomplished with a small mean square error. For parameter ex-traction in apical view images, the average mean square error (MSE) is 0.2305cm and for parameter extraction in M mode view, the average MSE is 1.1025cm. In future, the model will be further improved by integrating the modules on the plat-form and connect these segmentation and parameter extraction modules with parametric model of the left ventricle enabling automatic 3D left ventricle geometry creation based on ultrasound images.

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