Improving Aorta segmentation from phase contrast MRI using adaptive velocity-dependent weighting on the deep learning output for magnitude and phase images

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***Abstract*— Phase contrast MRI can provide a comprehensive analysis for the hemodynamic changes in the aorta which is useful for the diagnosis of several aortic diseases. However, an initial step of accurate segmentation of the aorta is necessary, which is usually a time-consuming and subjective step. Several methods have been proposed to automate this step using classical segmentation methods and recently deep learning models. Most of the current models combine the magnitude and phase images equally across all time phases which hinder the potential advantage that the frames of higher velocity might have more useful information compared to the low velocity frames. In this work, we propose a novel adaptive combination model that combines the output probability maps of both the magnitude and phase models based on an initial velocity estimation as a surrogate for the confidence level in the velocity images. We applied our model on the 2D-PC images of 215 patients and our results shows an accuracy of 87% for the magnitude images, 68% for the velocity images, 87.1% for the combined images, and 89.1% for our proposed combination model.**

***Clinical Relevance*— This work improves the accuracy of automatic aorta segmentation which is likely to improve the quantifications output extracted from the flow images.**

1. Introduction

Flow imaging has potential in visualizing and quantifying many cardiovascular applications. [1] It also has a role in diagnosing of pulmonary hypertension, by its' noninvasive ability to determine pressure measurements. [2] And could assist in complex intracardiac flow patterns which are associated with several valve diseases and heart failure. [1]

2D Phase Contrast (PC) MRI is used for blood flow analysis and was first introduced in 1980s. In the 1990s, 4D flow MRI was introduced as an extension for (PC) MRI. 4D flow MRI consists of three dimensional orthogonal velocity encoding with time as the fourth dimension. 4D flow velocity volume is useful in blood flow quantification through calculating hemodynamic parameters such as blood pressure gradients, wall shear stress and kinetic energy loss. Also, 4D flow is used in turbulent flow analysis. [3] Three dimensional phase encoding used in 4D flow results in longer acquisition time for 4D flow compared to 2D PC MRI, in some cases a 4D flow scan could exceed 30 minutes. [4]

Phase data of 2D (PC) MRI is calculated by subtracting two sets of images (stationary and flowing), resulting in residual signals formed from the motion nuclei's which have different phase values between each successive planes. [5] Phase images are considered as a reliable mapping for flow velocity through slice-selective (PC) MRI. [6]

One of the applications of (PC) MRI is analysis of aorta blood flow, the flow calculations depend on raw pixel values – that lie inside the aorta region- from both magnitude and phase images in addition to other parameters, for example, velocity encoding parameter VENC. [7] During acquisition, VENC value controls velocity encoding range. Thus, an aliasing artifact will be cased for an area with velocity values outside the velocity encoding range.

Aorta segmentation in phase contrast MR images is a necessary step for accurate quantification of the flow dynamics [7]. However, this is usually a subjective and very time-consuming step [8]. Recently, automatic segmentation has gain popularity in the medical imaging field especially with the latest development of deep learning models [9]. Several deep learning models have been applied to segment the aorta from the flow images[7], [10]. However, most of these models combine the magnitude and phase equally before being fed to the utilized models. In this work, we propose an adaptive combination weight between the two images to take advantage from the relative quality of each of the two images across all the time phases. Since this quality is likely to depend on the flow velocity in each phase, we propose to use a rough velocity estimate to control the proposed combination weight.

2. Methods

A. Datasets

The study was approved by the Research Ethics Committee, Faculty of Medicine at Cairo University. Flow images of 215 patients were used. The acquired images were in the axial view of the aorta with the following parameters: FOV, 256×256, in-plane resolution, 1.25×1.25, venc, 150-300 (cm/s), Number of frames, 20-30. The aorta area was manually segmented from the images by two expert radiologist of 5-10 years of experience. Dataset was split to 120 for training, 30 for validation and 65 for testing.

B. Preprocessing

It is an essential step to map DICOM images to the correct intensity ranges using slope and intercept extracted from

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DICOM metadata. After normalization, magnitude images are between (0,255) and phase images (-π, π). Data cleaning was performed to exclude images with VENC artifacts from the dataset or any other artifact types. Data augmentation parameters were used such as random rotations, zooming, horizontal and vertical shifting and flipping, Augmentation parameters' values were determined using superposition to reproduce the highest possible segmentation results on magnitude images, since untested augmentation parameters values could lead to affecting image field of view.

C. Training

Training each model involves first, data augmentation (rotation, zooming, panning, horizontal and vertical flips), using batch size of 16 and using Adam optimizer. We proposed a custom loss function for dice evaluation and used it to optimize the weights of the models. We trained each model for 500 epochs on a PC with 16GB RAM, GPU NVIDIA GTX 1080 Ti.

D. Evaluation

1) Dice Coefficient

For each frame dice coefficient is calculated using the formula:

$$Dice = \frac{2 * |X \cap Y|}{|X| + |Y|} \tag{1}$$

Let X and Y be two sets, $|X \cap Y|$ indicates the number of intersected elements. While the denominator term represents the summation of elements count for each set. To compare patients' segmentation performance, we will calculate average dice coefficient over all distinct frames with count (n) as following:

$$Average\ Dice = \sum_{0}^{n}(Dice) \tag{2}$$

2) Flow Curve Comparison

Segmentation is used to compute blood flow curve during cardiac cycle. Since 2D PC MRI is considered a reliable mapping for flow velocity through slice-selective (PC) MRI [6]. It is used in many crucial assessments such as regurgitation analysis [11].

A. Magnitude Model

For segmentation, we built our own U-Net architectures based on the one used in [7]. This architecture has residual connections blocks which lead to a significant accuracy improvement. This model will be trained and evaluated only using magnitude (Anatomy model).

B. Phase Model

To further study the possible velocity effect on image quality and consequently on the learning process and segmentation accuracy. An independent segmentation model was built using the same architecture as magnitude model. This model segments the aorta using only phase data. Eventually, we will use this model to segment aorta based on flow velocity information. This velocity-driven segmentation will then be used to improve magnitude model results.

C. Velocity Range Estimation

Previous systems used a magnitude – phase combination on input level. For example, in [10], a multiplication based combination was proposed. Our approach relies on building two pipelines (magnitude and phase), so no input-level combination was needed. Since 2D PC MRI has only one velocity component V_z, the proposed system works on 2D images assuming all phase images during the cardiac cycle are independent, thus, we proposed an adaptive temporal correction system.

Velocity range estimation is a rough estimate for the average blood velocity for a phase frame using magnitude segmentation model output. A frame at time t can have a velocity range between $(-VENC, VENC)$. The average velocity can be calculated as follows:

$$V = S * P_t * ASF \tag{3}$$

$$ASF = \frac{10\ \pi\ R}{VENC} \tag{4}$$

$$Average\ Velocity = (\textstyle\sum_{(i=0)}^{N} (V))/(N) \tag{5}$$

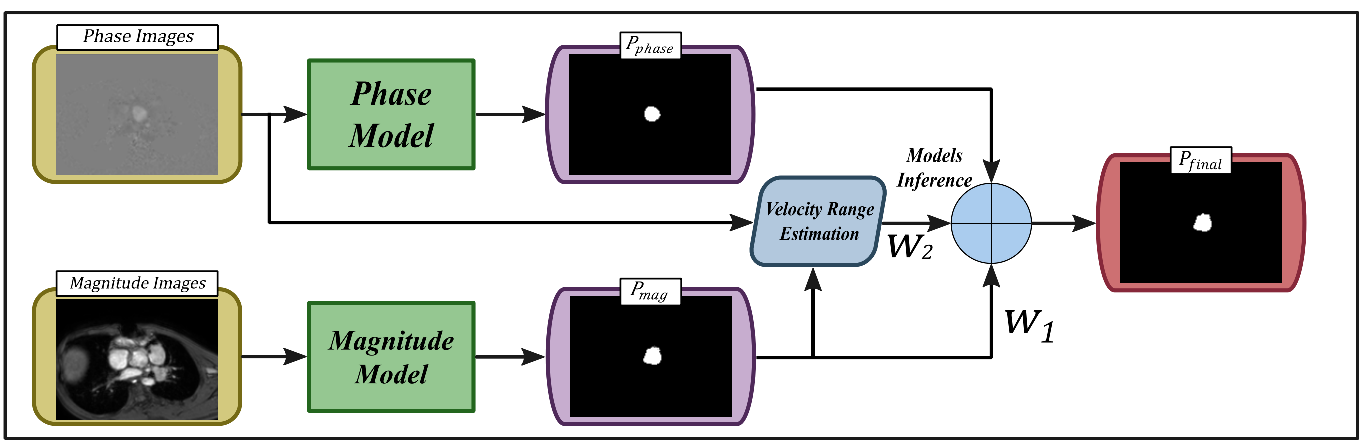

Figure 1. Flow Diagram of the Proposed System

For (Eq.3) V is the velocity map resulting of multiplying S (ground truth mask) by Pt (the corresponding phase image at time t) and by a *ASF* (velocity scaling factor). (Eq.4) implies the definition of scaling factor ASF, using reconstruction constant R and the velocity encoding parameter VENC. Finally to calculate average velocity we use (Eq.5), which takes the average of the velocity map V on all flow (non-background) pixels (N). For a patient we need to calculate the flow for each frame at time interval t and then plot flow values with time which is known by physicians as flow curve.

D. Probability weighting

Based on the previous step different phases were divided into five velocity groups based on each phase. The output masks of the magnitude and phase models are then combined as a weighted average to obtain the final mask using the following equation:

$$P_{final} = \omega_1 P_{mag} + \omega_2 P_{phase} \qquad (6)$$

Where P_{final} is the inferred mask probability, $\omega_{1,2}$ are the assigned weights and P_{mag}, P_{phase} are probability masks obtained from each model. Then, $\omega_{1,2}$ are optimized for each velocity group. Masks were evaluated using the dice score to calculate the similarity with the manually segmented masks. Figure.1 shows a flow chart for the proposed workflow.

E. Deep learning Ensemble

A more generic extension was made to search for weights' optimal values. Using a fully connected neural network to ensemble the models' probability masks into one final mask.

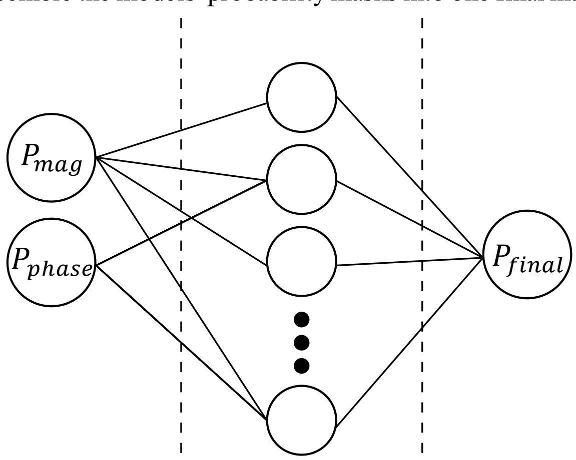

Figure 2. Deep Learning Ensemble Concept

3. Results

Table 1 shows the average Dice score when using the conventional combination (Multiplication) and when adopting the proposed weights showing an improvement of 2.1% in the overall average score.

Model	***Average Dice***
Magnitude Model	0.87
Phase Model	0.68
Combined (Multiplication)	0.87
Proposed System (Inferred)	0.89

Table 1. Dice Evaluation on test set using Magnitude, Phase, Multiplication (Literature) and our Proposed Model

A. Velocity Effect

Figure.3 illustrates the correlation between the blood flow computed for every frame from ground truth masks and from magnitude model, we set the color map to the dice coefficient. It's clear that for magnitude model, the higher velocity of the frame the better dice coefficient. This emphasizes the velocity change effect on segmentation results. And the possibility of using phase data to enhance magnitude model results.

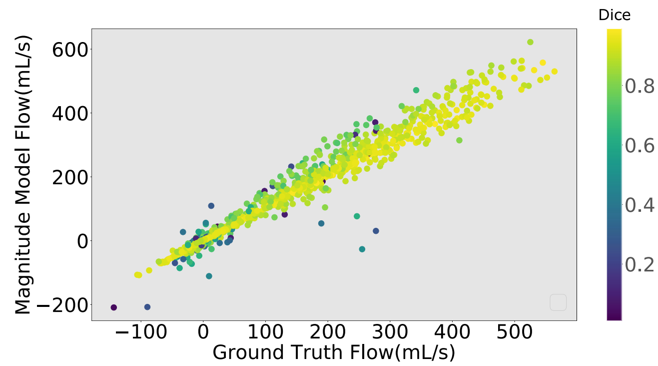

Figure 3. Showing (Ground Truth Flow vs Magnitude Model Flow), emphasizes the correlation between amount of flow inside the anatomy images with deep learning segmentation performance

B. Probability Weighting

In order to perform an optimal combination between magnitude and phase probability masks, we needed to make a grid for ω_1 *and* ω_2, maximum average dice value for the test set was at $(\omega_1 = 1, \omega_2 = 0.5)$. Moreover, we built another grid for ω_2 as it's the one correlated to phase images directly. Figure.4 shows the effect of changing ω_2 on the final dice score on five different velocity intervals.

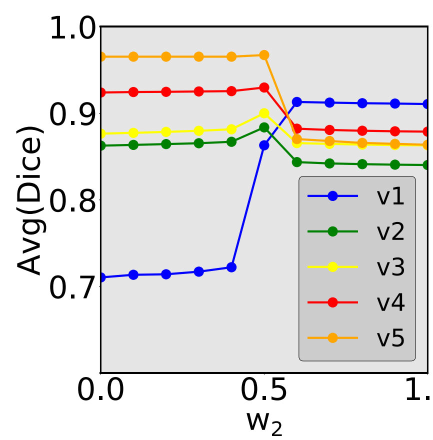

Figure 4. ω_2 Grid results using velocity ranges and showing an optimum point at w2 = 0.5

C. Flow Curve Comparison

Random samples were used from test set to validate the improvement of flow curves by using the proposed system. Figures (5, 6) show this improvement on a specific patient 2D PC MRI data during the cardiac cycle.

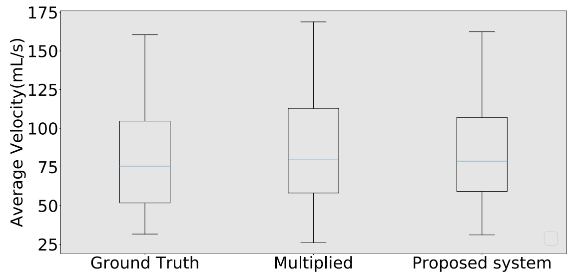

Figure 5. A Box Plot Comparison for average velocity of a patient, using Ground Truth, Multiplication (Literature) model and proposed model

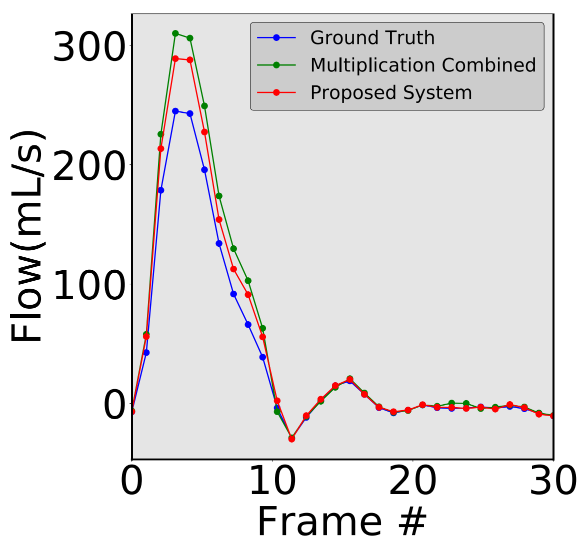

Figure 6. Sample of flow curve for a patient, using Ground Truth, Multiplication (Literature) model and proposed model

4. Discussion & conclusion

In conclusion, the dynamic nature of flow images controls the output images quality across the different phases. Thus, a fixed combination model between the magnitude and phase images is not expected to give the best possible output, through equally weighting of velocity at different time steps. Our results show that changing the combination factor across different phases can lead to better segmentation output (increased by ~2%). Also, Deep learning Ensemble enhanced the segmentation output (increased by ~1%). Velocity information could lead to improvements in magnitude based segmentation. A rough estimate for each frame velocity can be calculated and used as a surrogate for the phase image quality and thus a higher weight for the phase image information can be applied.

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