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On the use of motion-based frame rejection in temporal averaging denoising for segmentation of echocardiographic image sequences



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- Semi-automatic segmentation of the left ventricular wall in short-axis echocardiographic images
- Pre-processing: temporal averaging for image denoising.
 - Motion estimation is used to detect and reject frames that do not correlate well with the set of images being averaged.
 - Segmentation: histogram-based thresholding, region labeling, and neighborhood operations
- Main contributions are :
 - to reduce the algorithm's computational load without significantly reducing the segmentation quality with two approaches.
 - First: motion detection is performed by taking the pixel-by-pixel difference between frames - five frames with stronger motion are removed from the image set
 - -Second: temporal averaging without frame rejection using smaller window size

Motion quantification using image subtraction



temporally-adjacent frames



pixel-by-pixel difference between the two frames



Smaller window size

	image quality - # of images	CCCª	<i>PE (%)</i> ^b	<i>ES (%)</i> ^b	EPE ^c	Proc. Time ^d
Optic flow [10]	good - 10	0.95	3.52 ± 1.24	9.47 ± 2.02	1.04 <epe<1.21< td=""><td></td></epe<1.21<>	
	medium - 10	0.90	11.96 ± 3.38	16.49 ± 2.15	2.01 <epe<2.61< td=""><td>20 min</td></epe<2.61<>	20 min
	low - 5	0.68	21.98 ± 7.04	35.50 ± 7.27	5.04 <epe<5.95< td=""><td></td></epe<5.95<>	
Pixel-by-pixel subtraction	good - 10	0.94	6.15 ±2.56	11.38 ± 3.05	1.14 <epe<1.41< td=""><td></td></epe<1.41<>	
	medium - 10	0.90	12.71 <u>+</u> 4.36	13.32 <u>+</u> 3.99	2.61 <epe<2.91< td=""><td>10 min</td></epe<2.91<>	10 min
	low - 5	0.67	23.65 ± 8.36	36.32 <u>+</u> 8.32	5.91 <epe<6.95< td=""><td></td></epe<6.95<>	
Small sliding window	good - 10	0.93	6.40 ± 2.60	11.98±3.19	1.25 <epe<1.52< td=""><td></td></epe<1.52<>	
	medium - 10	0.88	14.36 ± 3.95	14.01 ± 4.02	2.97 <epe<3.99< td=""><td>6 min</td></epe<3.99<>	6 min
	low - 5	0.63	24.99 ± 8.55	36.02 ± 9.08	6.08 <epe<7.11< td=""><td></td></epe<7.11<>	
de Andrade et al. [7]	good - 20	0.98	2.49 ± 2.46	9,62 ± 7,9	-	-
Klingler et al. [3]	-	0.93	-	-	-	-
Coppini et al. [12]	500	-	-	-	0.53 <epe<0.77< td=""><td>-</td></epe<0.77<>	-

Table 1 – Quantitative comparison between the three proposed approaches and other methods from the literature

^a mean value; ^b mean \pm standard deviation; ^c dynamic range; ^d processing time for a sequence of 90 images (81 contours).

- A set of 25 short-axis echocardiographic images from 13 patients was used to evaluate the performance of the proposed algorithms.
- four metrics were applied: cross-correlation coefficient (CCC), percent error (PE), error sum (ES), and edge-positioning error (EPE).

Results

Left ventricular wall contours for good quality

from left to right: (a) manually-segmented; (b) optic flow method; (c) image subtraction method; (d) small sliding window method. Bottom row presents a superposition over the manually-segmented contour.

images.



Conclusions

- the proposed methods are capable of providing LV-wall contour estimates with a high degree of accuracy, especially for good and medium quality images.
- The results show that it is possible to eliminate the computationally-intense process of calculating the optic flow matrix by using a smaller sliding window for temporal averaging, at the expense of a small reduction in segmentation precision.