Echocardiographic Epicardial Adipose Tissue Quantification: Challenges and Insights

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SoBigData++

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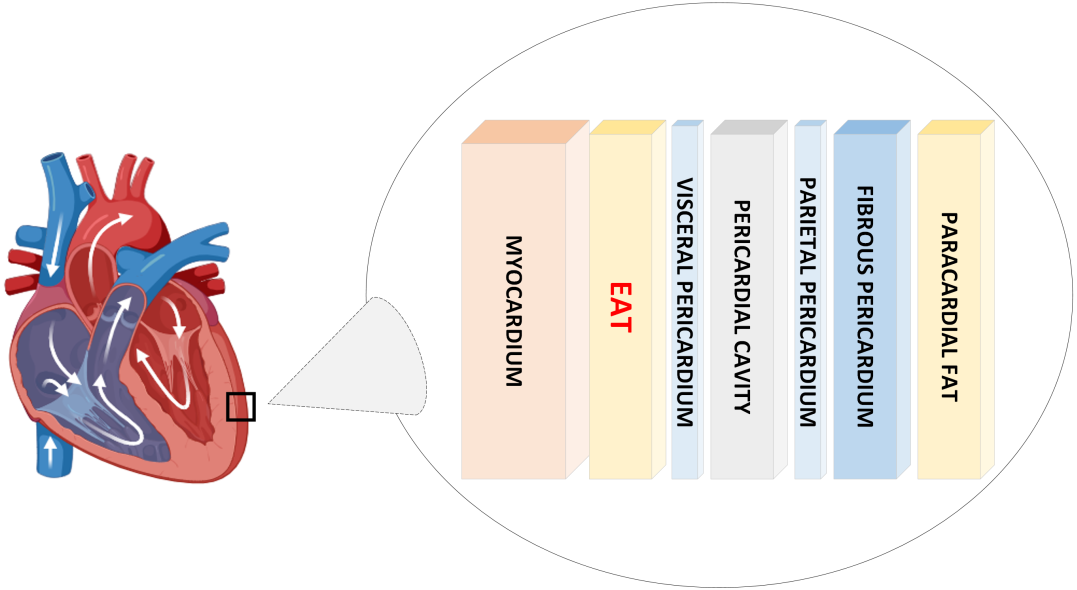
Context: Epicardial Adipose Tissue



- The Epicardial Adipose Tissue (EAT) is located between the Myocardium and the Pericardium.
- It is a thin layer of visceral fat.

Context: Cardiovascular diseases

- Cardiovascular diseases (CVD) represent a formidable challenge for current medicine.
- **EAT thickness** is a very important indicator of cardiovascular health.
- By automatically measuring EAT thickness during Echogardiogram (ECG), we can aid medical personnel with related diagnosis.

Task: Determine EAT thickness from ECGs

Context: Pervasive Computing

- Our goal aligns with the goal of pervasive computing in healthcare
- Aim for real-time, on-demand medical systems
- Possibly integrate with cloud services

Proposed Workflow

- This is our proposed workflow for EAT thickness determination.
- Yellow-tinted steps require human practitioners.
- Blue-tinted steps are automated.

ECG Acquisition

- ECG Acquisition is done by medical personnel.
- For our analysis, we employed a dataset consisting of 152 echocardiograms videos captured under consistent clinical conditions.

Dataset

- We used a dataset consisting of 152 echocardiogram videos captured under consistent clinical conditions

- The dataset is enriched with tabular data on biometric indicators

Frames Extraction

- We need to capture a single definitive frame that offers the most accurate representation of EAT.
- We need to target the telesystolic phase of the cardiac cycle, where the heart is almost void of blood, to get the clearest picture possible.
- In order to do this, we selected one frame per second for each video (20 seconds each)

Frames Extraction (2)

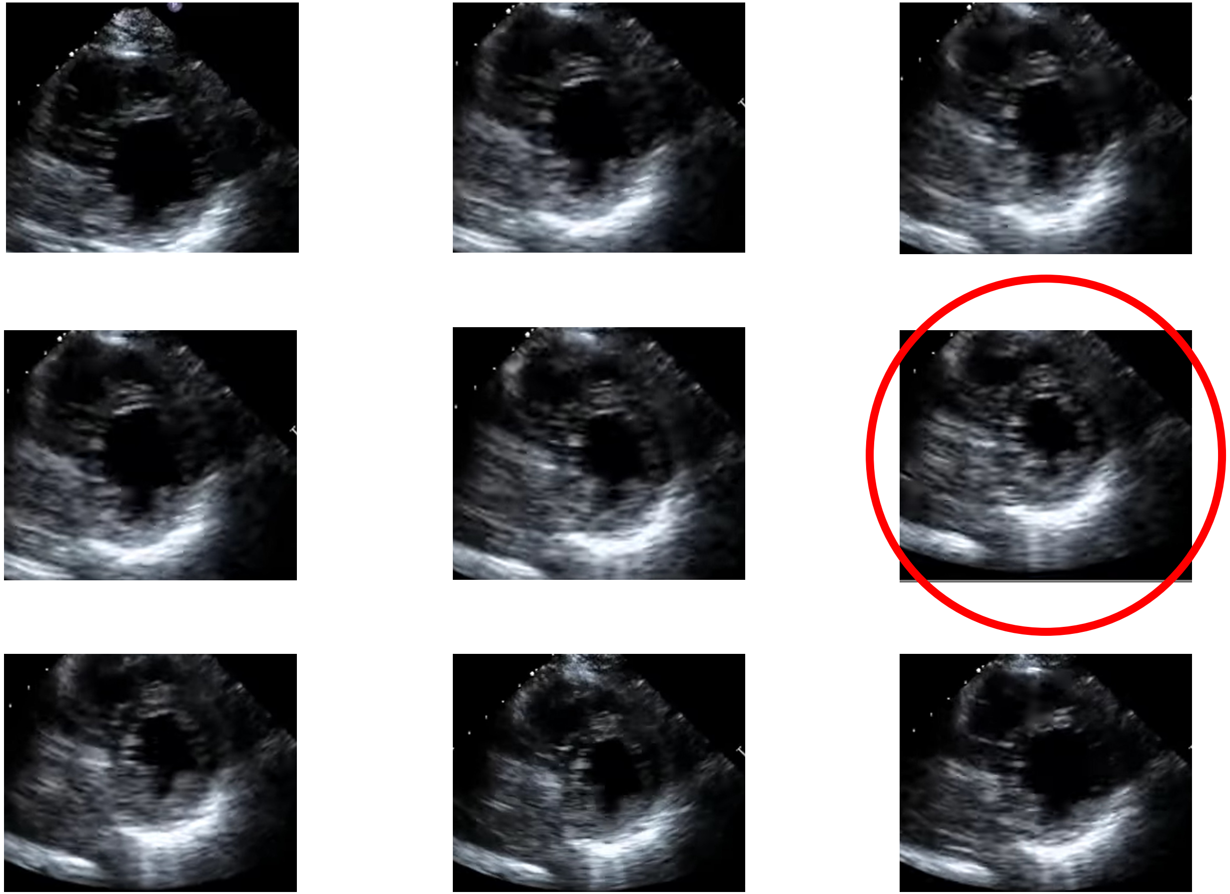
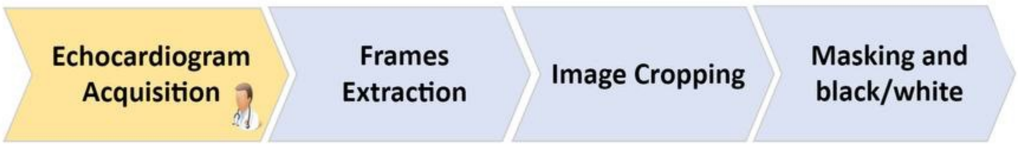


Image Cropping

- We crop the image to focus on the location of the EAT.
- The exact position might change for different videos, but the general position remains the same.
- We crop the image to remove superflous details.

Masking and black/white



- We mask the image in black and white to remove other noise from the gray scale.

EAT Borders Detection

- We now want to detect the borders of the EAT. It is the space enclosed between the two distinct bright lines.

- We experimented with a variety of automatic line detection methods.

EAT Borders Detection (2)

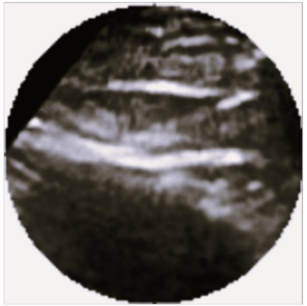
We tried several line detection algorithms (see references).

However, for different reasons, none of them was able to accurately detect the boundary lines of EAT.

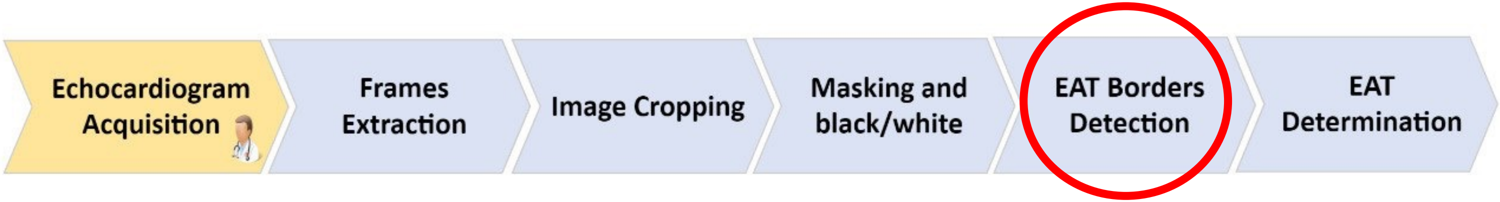
Contrary to our expectations, none of the employed methods yielded satisfactory results for EAT boundaries. The general algorithms for line identification could not be applied to this domain.

EAT Determination

- Being unable to detect the borders, we are also unable to determine EAT thickness.



What went wrong?



- Despite our best efforts, we were not able to automate this step.
- [1] could identify the edges but showed inconsistent performance.
- [2] often missed key points necessary for identification.
- [3] detected an excess of corner points.
- [4] found many irrelevant line fragments.

What can we learn?

- Applying line detection algorithms to medical imaging is not as straightforward as it seems.
- We might need an ad-hoc approach to solve this problem.
- Our stringent quality constraints on the images to select resulted in many images getting discarded for low quality. We might need to be more flexible when selecting specific frames.

What can we keep?

- The idea of applying automated techniques for diagnosis by exploiting non-invasive tests like ECG remains valid.
- It works towards a broader pervasive vision of medical diagnosis via ad-hoc, always available cloud services.
- However, we might need to be more flexible when selecting frames, develop ad-hoc detection algorithms, or incorporate medical experts in the research loop.

References

- [1] N. Kanopoulos, N. Vasanthavada, and R. L. Baker, “Design of an image edge detection filter using the sobel operator,” IEEE Journal of solid-state circuits, vol. 23, no. 2, pp. 358–367, 1988
- [2] K. G. Derpanis, “The harris corner detector,” York University, vol. 2, pp. 1–2, 2004.
- [3] C. S. Kenney, M. Zuliani, and B. Manjunath, “An axiomatic approach to corner detection,” in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05), IEEE, vol. 1, 2005, pp. 191–197
- [4] C. Galamhos, J. Matas, and J. Kittler, “Progressive probabilistic hough transform for line detection,” in Proceedings. 1999 IEEE computer society conference on computer vision and pattern recognition

Thank you for your attention

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