

Abstract

Ultrasound imaging of the fetal heart is vital for the antenatal diagnosis of congenital heart disease. To maximise the likelihood of detecting abnormalities, it is desirable to visualise several complementary views; however this is time-consuming and requires experienced sonographers. We present initial work towards a method for automated detection of viewing plane within ultrasound videos, arguing that such a method needs to make use of motion cues within the video.

Background

Congenital heart disease (CHD) is a term applied to a large number of structural defects of the heart that can develop *in utero*. Together, such defects are estimated to contribute to 42% of infant deaths reported to the World Health Organisation².

Antenatal screening for such problems is conducted during routine ultrasound scans, which typically include visualisation only of the ‘four-chamber’ viewing plane of the heart (Fig. 1). Using this view, the form and function of the atria, ventricles, and atrioventricular valves can be assessed for abnormalities such as septal defects, bradycardia/tachycardia, and hypoplastic left heart syndrome.

However the four-chamber view alone is insufficient to detect certain other types of CHD¹, especially conotruncal anomalies (those involving the major vessels entering and leaving the heart). Consequently, recent guidelines recommend visualisation of several additional planes in which the outflow tracts and vessels can be inspected². Extending scans to incorporate these views places further pressure on sonographers, both in terms of the time required to perform a satisfactory scan, and the level of training and experience needed.



Fig. 1 – *Left* A four-chamber view of the healthy fetal heart, *Right* A right ventricular outflow tract view showing the pulmonary artery

Aims

The aims of this project are therefore to utilise machine learning and image analysis techniques in order to detect automatically the viewing plane of the heart from a video taken as the probe ‘sweeps’ through the heart. This could allow:

- Automatic quality control of videos captured
- Storage of key frames or timestamp metadata for efficient review

The problem is complicated by a number of factors:

- Low resolution of ultrasound imagery
- Image artefacts – speckle, shadows and enhancement
- Different fetal lie – resulting in unknown reflections and rotations
- Heart motion – resulting in gross shape changes throughout the cardiac cycle
- Computational load – high frame rate video data

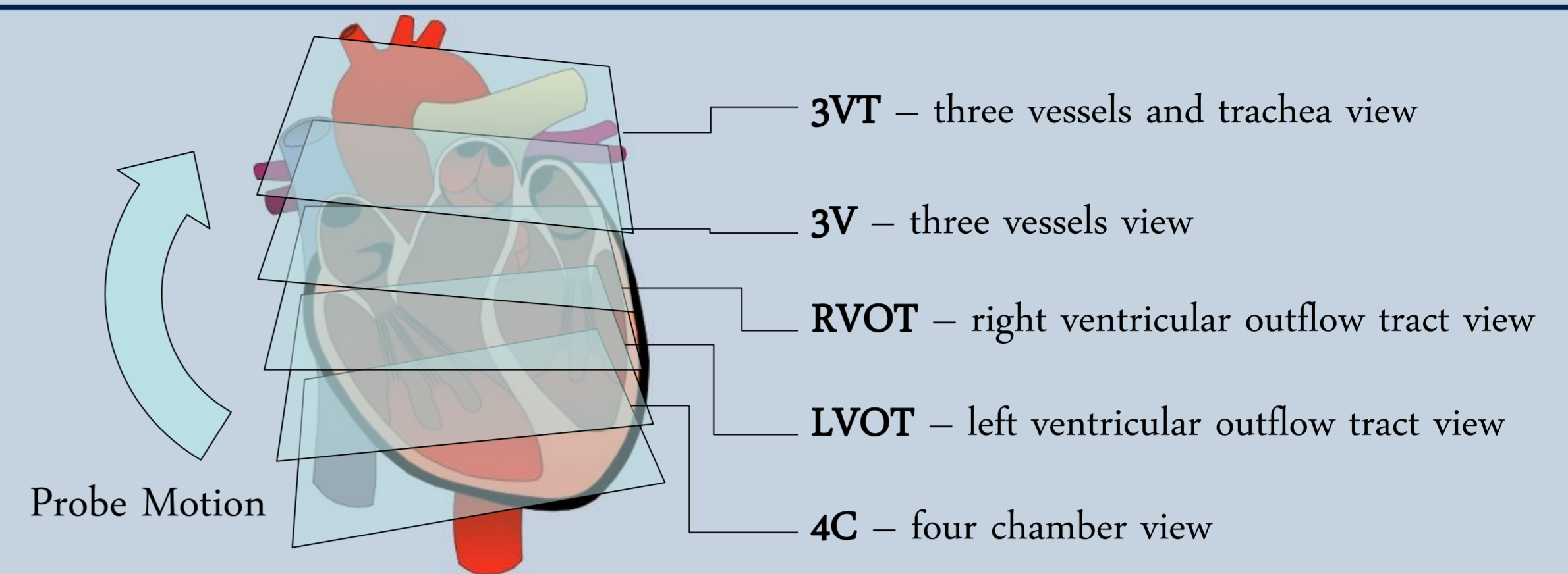


Fig. 2 – The viewing planes of the fetal heart

Approach

We propose the use of densely-estimated motion fields (‘optical flow’) in order to analyse the motion cues that are vital to understanding images with poor resolution and artefacts. We hope to combine these with appearance-based methods for recognition.

Since intensity-based techniques for motion estimation tend to give poor results in the domain of ultrasound, we are investigating other approaches. In particular, methods that replace the classical assumption of constant brightness with the assumption of constant local phase vectors along flow lines have proven successful in ultrasound cardiac imaging³ (see Fig. 3).

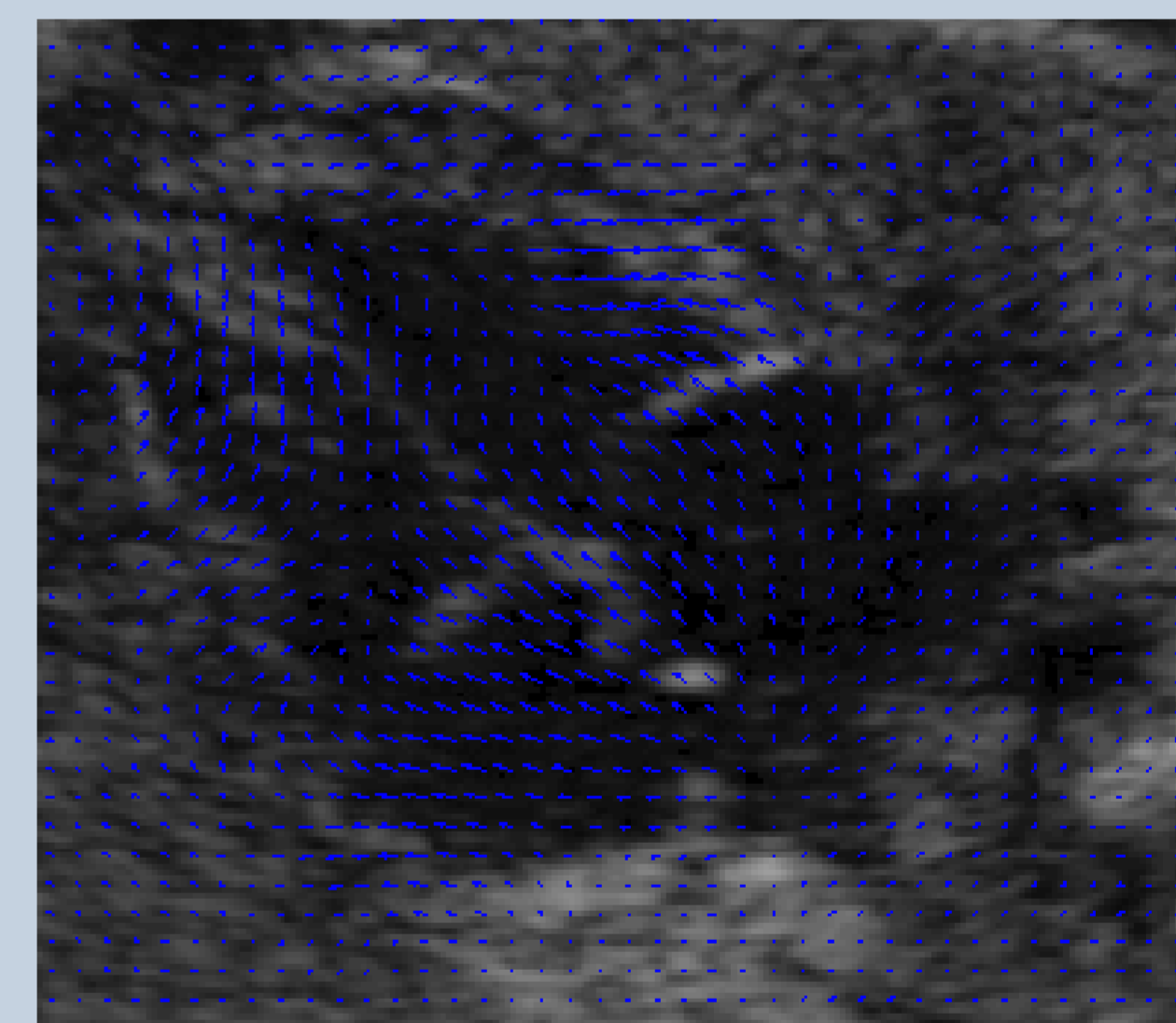


Fig. 3 – Motion estimate within a four-chamber view during systole, using the method of Alessandrini *et al*³

Once the motion fields have been estimated, we will investigate methods for recognition based on this motion, drawing inspiration particularly from histogram-based methods such as histogram of optical flow (HOF) descriptors.

References

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3. Alessandrini, M. et al. Myocardial Motion Estimation from Medical Images using the Monogenic Signal. *IEEE Transactions on Image Processing*, 22(3):1084-1095, 2013

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