OBJECT LOCALISATION IN FETAL ULTRASOUND IMAGES USING INVARIANT FEATURES

UNIVERSITY OF OXFORD

Christopher P. Bridge, J. Alison Noble

Institute of Biomedical Engineering, University of Oxford, UK

ABSTRACT

We combine image representations based on the monogenic signal with a rotation-invariant sliding window detection framework to perform object localisation in 2D fetal ultrasound images, where invariance to factors such as image contrast and object orientation is desirable.

INTRODUCTION

Detection of anatomical features ('objects') in medical imagery is a common problem. In fetal ultrasound imagery, we encounter a number of complicating factors, e.g. variable contrast levels, imaging artefacts such as speckle, shadowing and enhancement, and unknown orientation of objects relative to the probe.

We combine the monogenic signal, with its proven robustness to the speckle artefact and contrast variation, with rotation invariant detection methodologies in order to overcome these problems.

ORIENTED FEATURES FROM THE MONOGENIC SIGNAL

If we retain the filter orientation of the monogenic filters[1] ($q_{even}(\mathbf{x})$, $q_{odd}(\mathbf{x})$) we can define oriented image representations based on the popular feature symmetry/asymmetry measures[2]:

- ***Signed feature symmetry*** - a scalar feature that picks out symmetric areas of the image, and distinguishes between *peaks* (positive) and *troughs* (negative).

$$S(\mathbf{x}) = \frac{\lfloor |q_{even}(\mathbf{x})| - \|q_{odd}(\mathbf{x})\| - T \rfloor}{M(\mathbf{x})} \cdot \operatorname{sgn}(q_{even}(\mathbf{x}))$$

- ***Oriented feature asymmetry*** - 2D vector-valued measure giving the *magnitude* and *direction* of image boundaries.

$$A(\mathbf{x}) = \frac{\lfloor \|q_{odd}(\mathbf{x})\| - |q_{even}(\mathbf{x})| - T \rfloor}{M(\mathbf{x})} \cdot \frac{q_{odd}(\mathbf{x})}{\|q_{odd}(\mathbf{x})\|}$$

- ***Monogenic odd filter*** **-** the 2D vector-valued response to the odd filter, $q_{odd}(\mathbf{x})$, is itself a rich descriptor of an image.

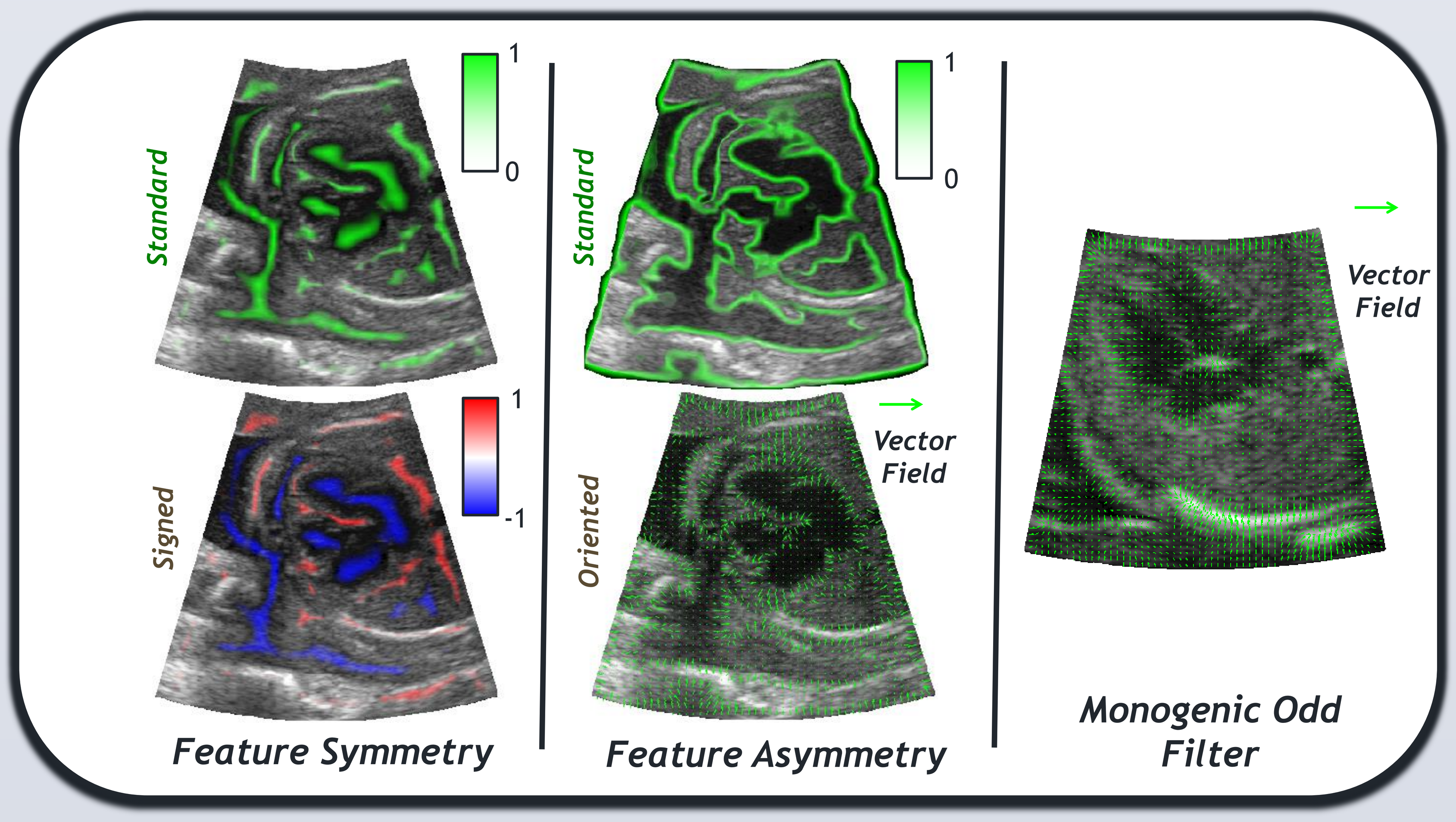

Fig. 1 - The image representations used in our experiments

ROTATION INVARIANT OBJECT DETECTION

We use a sliding-window object detector using a set of complex-valued, rotation invariant basis functions (Fig. 2) on circular image windows[3]. The basis functions are separable into a radial and rotational part:

$$u_{j,k}(r,\theta) = p_j(r)e^{ik\theta}$$

When convolved with an image window, the magnitude of the resulting value is rotation invariant.

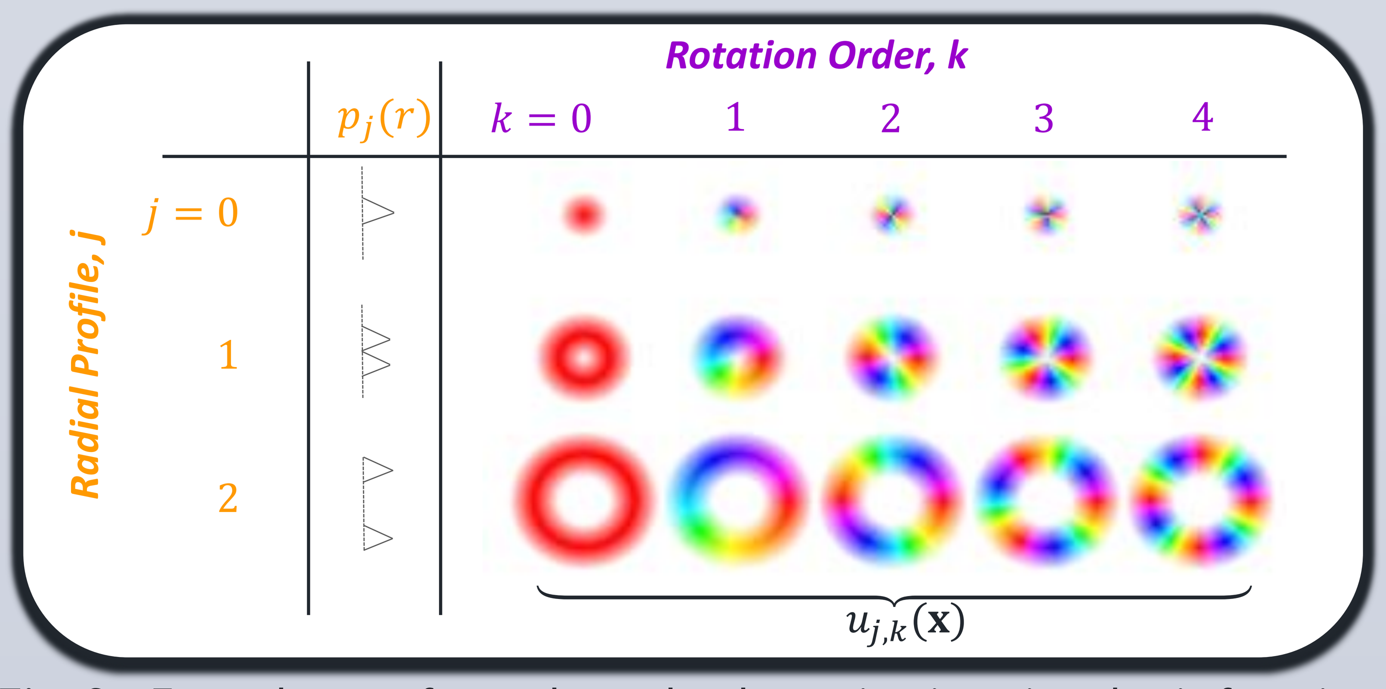

Fig. 2 - Example set of complex-valued rotation invariant basis functions. Saturation gives the magnitude and hue gives the argument of the complex value

FOURIER ORIENTATION HISTOGRAMS

2D vector-valued representations can be described using a magnitude-weighted orientation histogram (much like the standard HOG method) represented by its low-order Fourier series coefficients[3] rather than discrete bins. A new image 'channel' is created for each Fourier coefficient, and is described using the basis functions.

FULL DETECTION METHODOLOGY

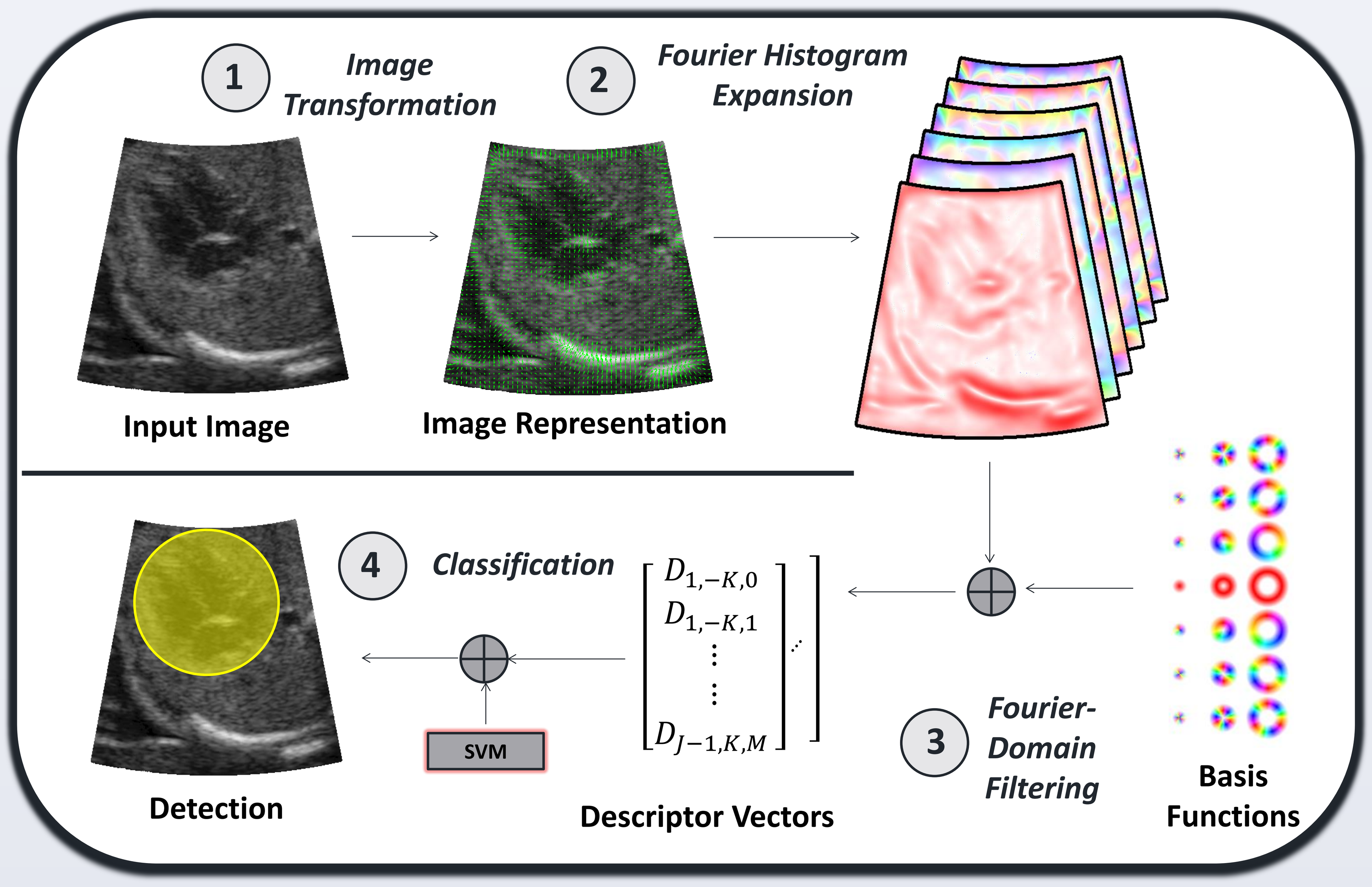

Fig. 3 - Flowchart representation of the detection methodology

EXPERIMENTS

We tested our approach on a dataset of 63 videos containing four-chamber views of the fetal heart in a range of orientations. We created a set of 630 positive (heart) and 630 negative (background) windows and trained a support vector machine on the feature vectors extracted from these windows.

We tested the monogenic-based measures (above) and compared them to standard intensity and gradient features. We performed a cross-validation with 7 sets of 90 frames. In the test frames, evaluation was performed using two measures:

- ***Classification accuracy*** - proportion of images where the detected heart centre was less than heart centre was $r/3$, where r is the heart radius.
- ***Localisation error*** - average distance between the detected and true heart centres, normalised by the heart radius, r.

Feature	INT	GRAD	MGOF	SFS	OFA
Best Classification Accuracy	0.87	0.82	**0.88**	0.84	0.82
Best Localisation Error	0.30	0.37	**0.21**	0.26	0.24

Table 1 - Selected results for intensity (INT), gradient (GRAD), monogenic odd filter (MGOF), signed feature symmetry (SFS) and oriented feature asymmetry (OFA). Values for each feature are the best results over a range of basis function parameters

CONCLUSIONS

Reasonable detection performance (87%) can be achieved using intensity features within a rotation invariant detection framework, and this gives an simple and efficient rough detector. The monogenic odd filters give similar detection performance (88%) but a lower localisation error (0.21 compared to 0.30) due to its ability to capture the structural information in the image. The gradient feature was particularly ineffective, possibly because of the effect of the speckle artefact.

REFERENCES

1. M. Felsberg and G. Sommer, "The monogenic signal", *IEEE Trans. Signal Process.*, vol. 49, no. 12, pp. 3136-3144, 2001
2. P. Kovesi, "Symmetry and asymmetry from local phase", in *Tenth Australian Joint Conference on Artificial Intelligence*,1997, vol. 190, pp. 2-4
3. K. Liu, H. Skibbe, et al., "Rotation-invariant HOG descriptors using Fourier analysis in polar and spherical coordinates", *IJCV*, vol. 106, no. 3, pp. 342-364, 2014.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Christina Aye and Prof. Paul Leeson of the Oxford Cardiovascular Clinical Research Facility, John Radcliffe Hospital, Oxford for the data used in experiments. Christopher Bridge acknowledges the support of the UK Engineering and Physical Sciences Research Council (EPSRC) Doctoral Training Award and the Institution of Engineering and Technology (IET) Travel Awards programme.

CONTACT (✉)

christopher.bridge@eng.ox.ac.uk
alison.noble@eng.ox.ac.uk

The Institution of Engineering and Technology