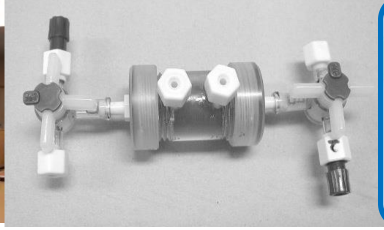
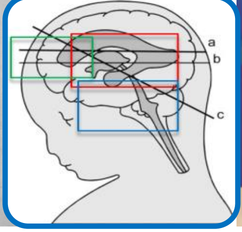
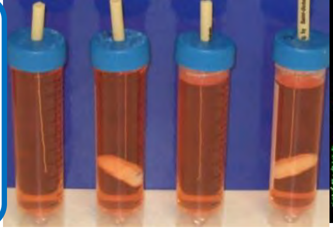
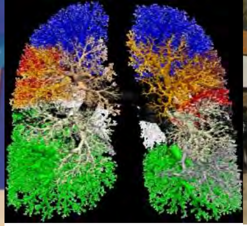
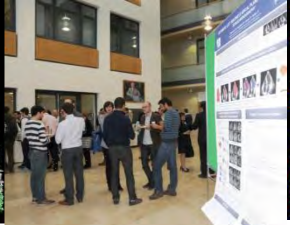
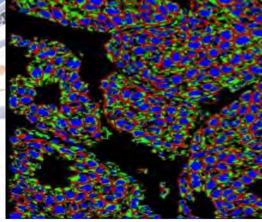




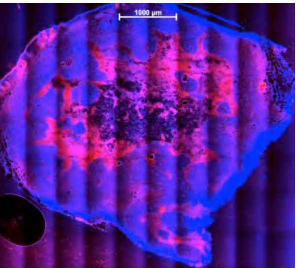





Ultrasound Image Analysis Of Fetal Heads and Brains

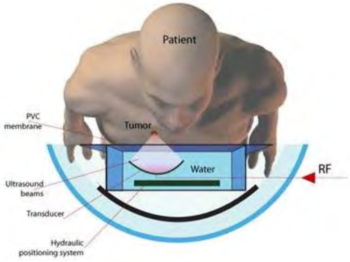
Professor Alison Noble

Institute of Biomedical Engineering, University of Oxford, UK

March 8, 2016






My research has been shaped by the engineering challenges posed by healthcare need…..

Collaborators define the protocols (input) and diagnostic criteria (output) for analytics we develop

INTERGROWTH-21st Study

International biometry charts for optimal fetal growth to improve pregnancy care worldwide – a reference of care; Lancet 2014a-c


Articles

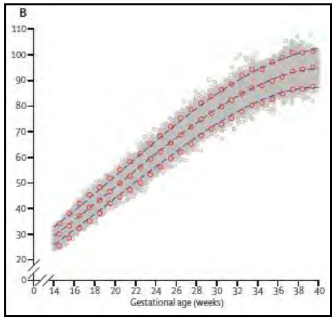
The likeness of fetal growth and newborn size across non-isolated populations in the INTERGROWTH-21st Project: the Fetal Growth Longitudinal Study and Newborn Cross-Sectional Study

Articles

International standards for newborn weight, length, and head circumference by gestational age and sex: the Newborn Cross-Sectional Study of the INTERGROWTH-21st Project

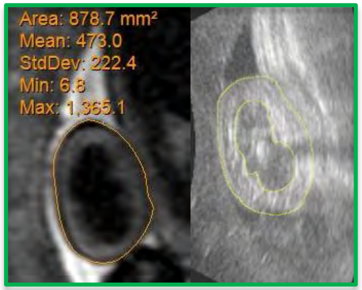
Articles

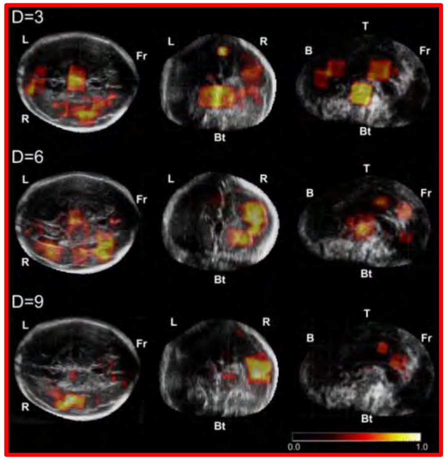
International standards for fetal growth based on serial ultrasound measurements: the Fetal Growth Longitudinal Study of the INTERGROWTH-21st Project



Perinatal Monitoring – Womb-to-Cot Imaging

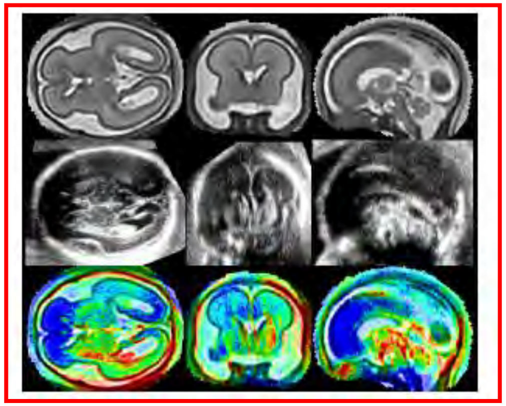
MR-US fetal limb fat correlated



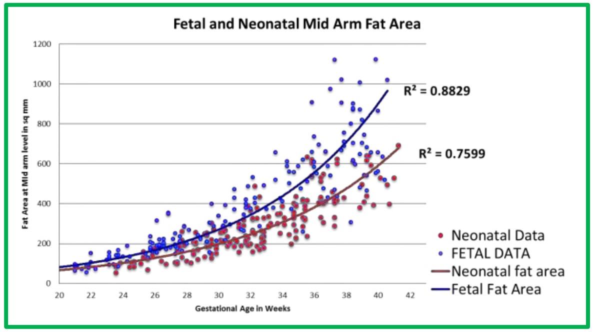


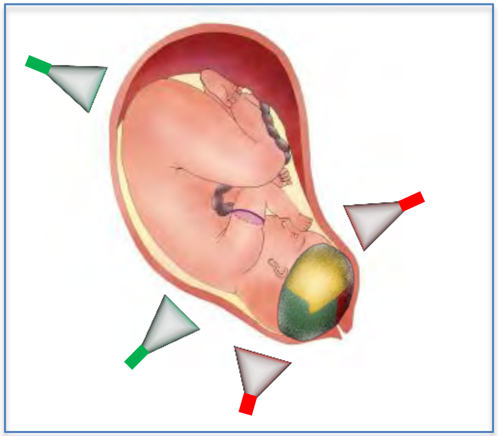
3D sonographic patterns predict GA better than biometry

MR-US fetal neuroimage alignment

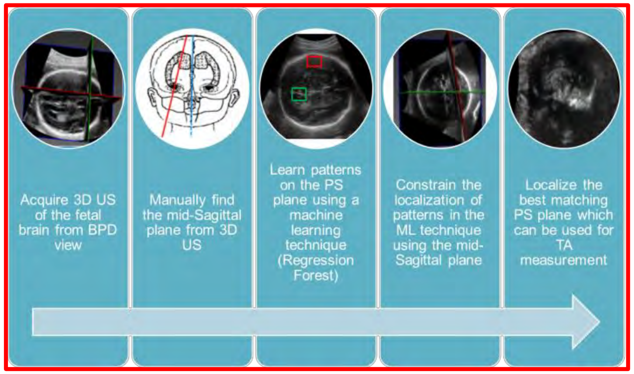


Womb-to-cot nutritional assessment: US fetal-neonatal limb fat correlated





Womb-to-cot neurosonography: Automatically finding 2D fetal planes in 3D volumes for correlation with 2D neonatal brain scans



Automatic fetal limb measurement reliable across GA

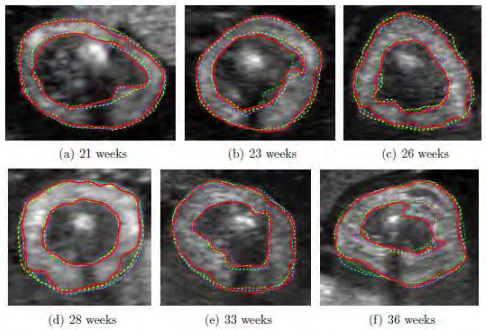
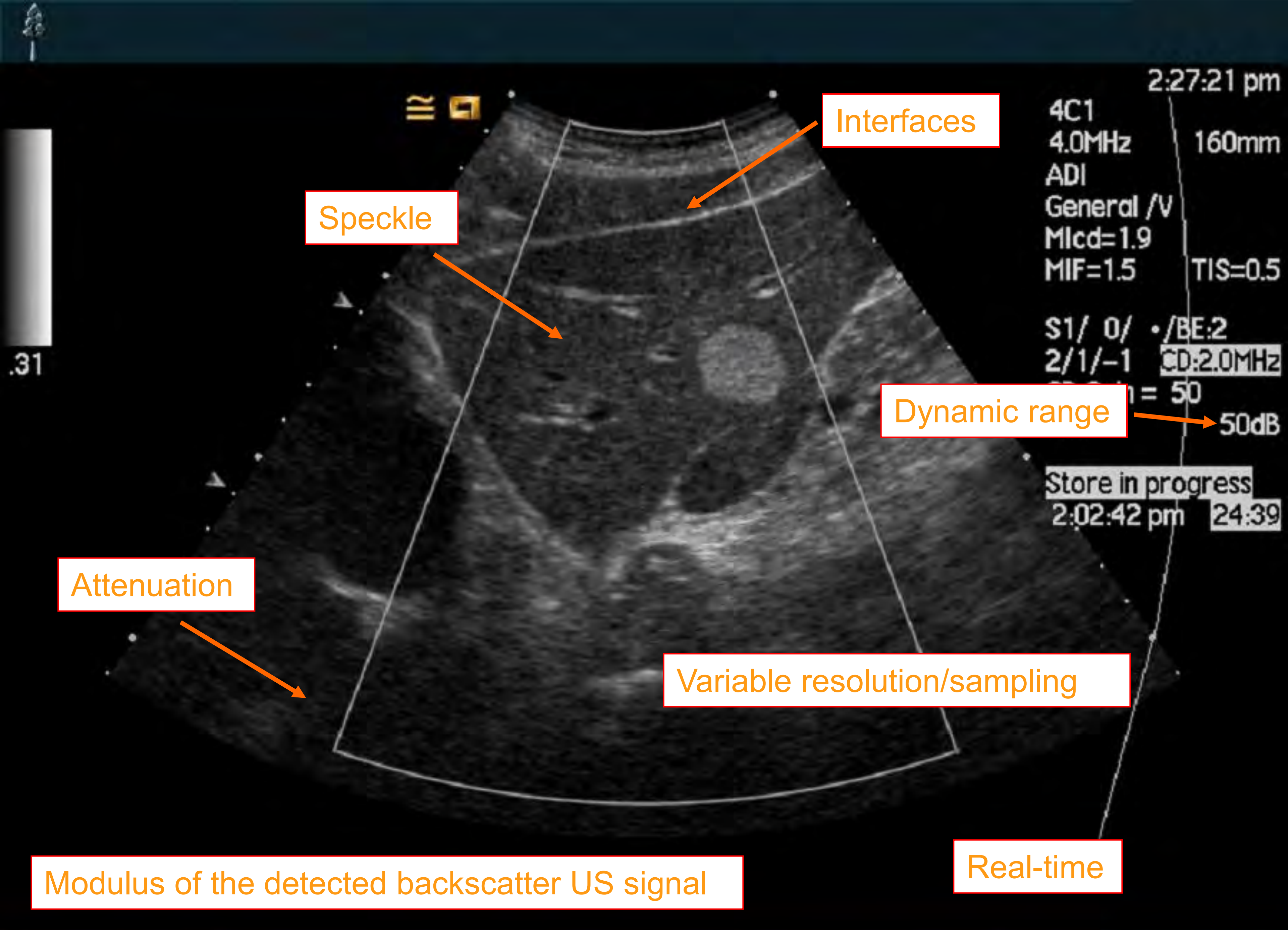


Figure 16: Segmentation results across gestational ages. Manual segmentations are displayed in dashed lines. (Expert 1: green and yellow lines; Expert 2: magenta and cyan lines). Continuous red lines show the proposed segmentation results.

3D fetal shape analysis for womb-to-cot assessment of syndromes

IBME The Institute of Biomedical Engineering Professor Alison Noble and team


Interfaces
Speckle
Dynamic range
Attenuation
Variable resolution/sampling
Real-time
Modulus of the detected backscatter US signal
2:27:21 pm
4C1
4.0MHz
160mm
ADI
General /V
MIcd=1.9
MIF=1.5
TIS=0.5
S1/ 0/ •/BE:2
2/1/-1
CD:2.0MHz
50dB
Store in progress
2:02:42 pm
24:39
.31


M11131 /
V7-3/OB Gen/FPS32D/13.0cm/HGen./MI0.95/TIb0.2/15-02-2013 15:18:23
[2D] G34/110dB/PER8/P90/HAR/FSI 3
SNR
P
0
5
10

INTERGROWTH-21st Study


Articles

The likeness of fetal growth and newborn size across non-isolated populations in the INTERGROWTH-21st Project: the Fetal Growth Longitudinal Study and Newborn Cross-Sectional Study

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International biometry charts for optimal fetal growth to improve pregnancy care worldwide – a reference of care; Lancet 2014a-c

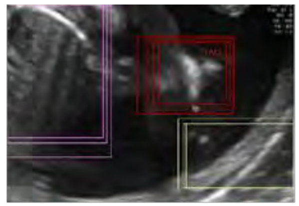
8TB carefully quality assured longitudinal data on 5000 healthy pregnancies from 8 sites (incl. 3D/2D ultrasound)

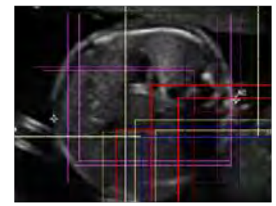
BILL & MELINDA GATES *foundation*

Guided Random Forests for Identification of Key Fetal Anatomy and Image Categorization in Ultrasound

Designing fetal structure detection algorithms for real world data








Head: Green box | Femur: Yellow box | Face: Red box | Spine: blue box | Magenta: blue box | Heart: light blue box

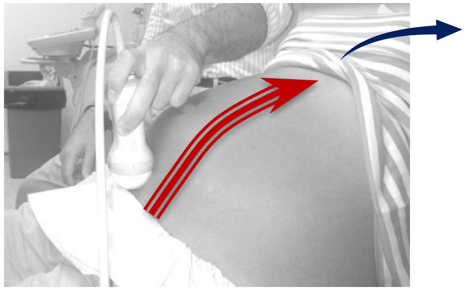
(Yaqub et al MICCAI 2015)

Detecting key events in ultrasound videos

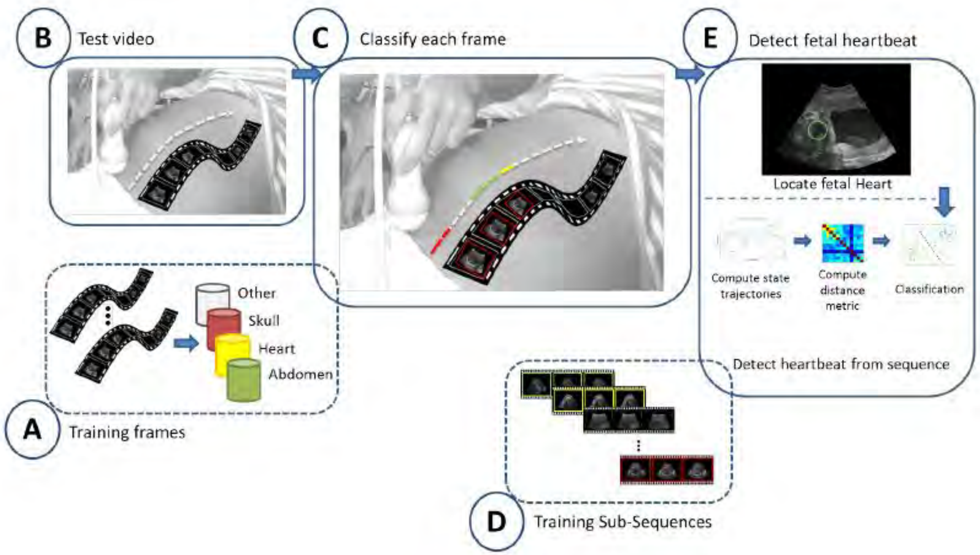
?

Normal Position

Breech Presentation



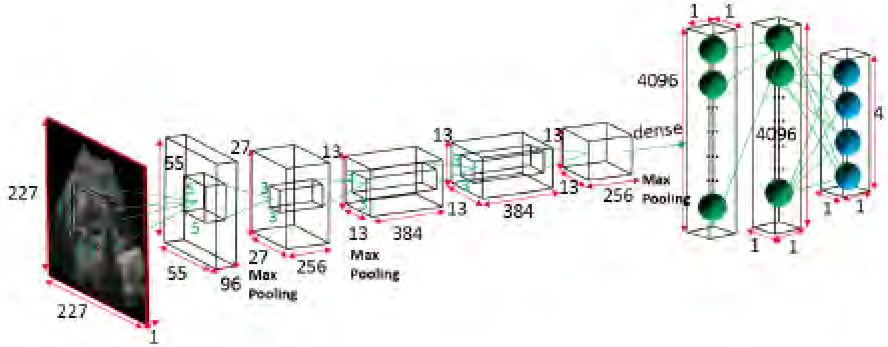
(Maraci, Napolitino, Papageorghiou and Noble, ISUOG 2013, MLMI 2014)

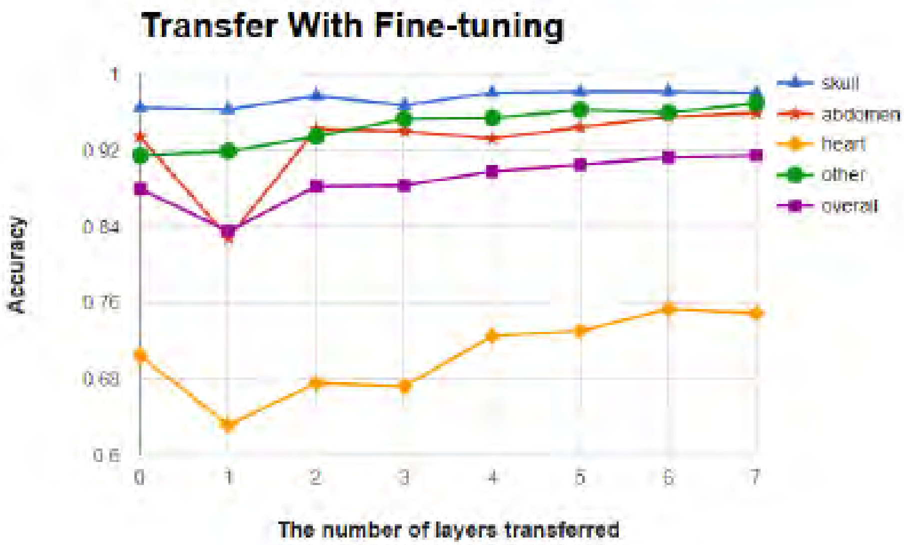


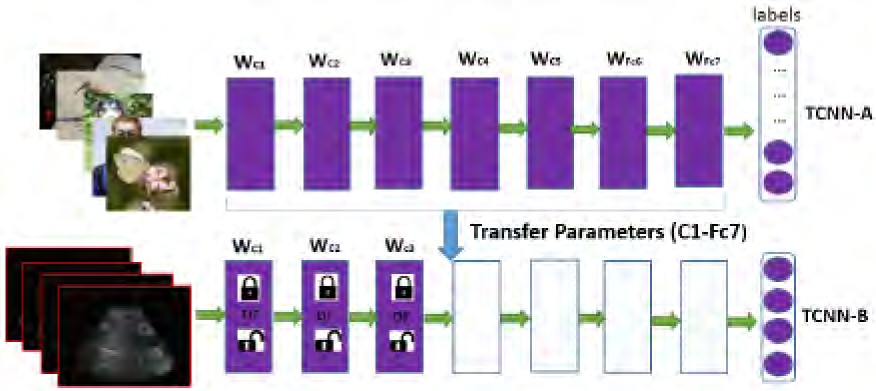
Detecting Key Structures in Ultrasound Videos

Current detection of skull, heart, abdomen and "other" frames is 92% accurate

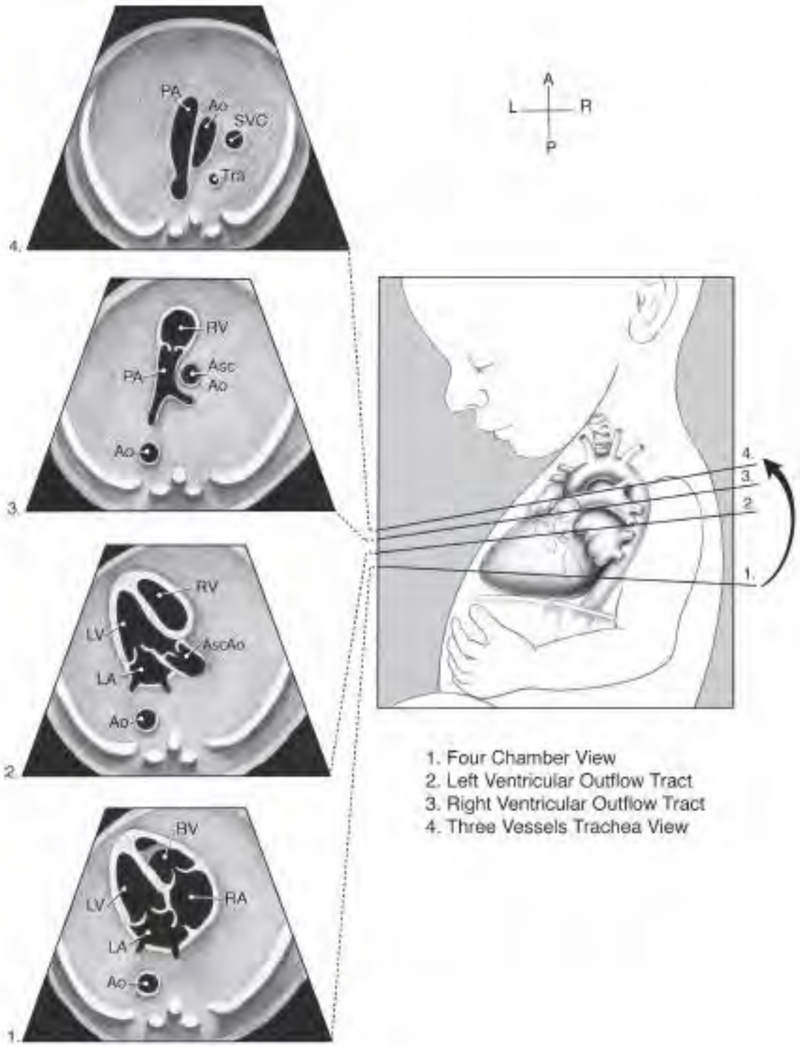
(Maraci, Napolitino, Papageorghiou and Noble, IEEE ISBI 2015; Maraci, Bridge, Papageorghiou, Noble, journal submission 2015)







(Gao et al IEEE ISBI 2016 (to appear))



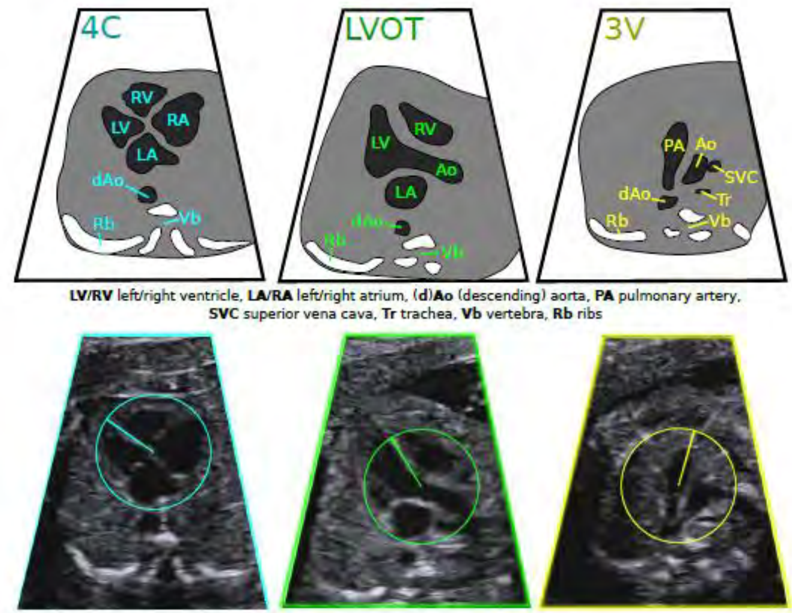
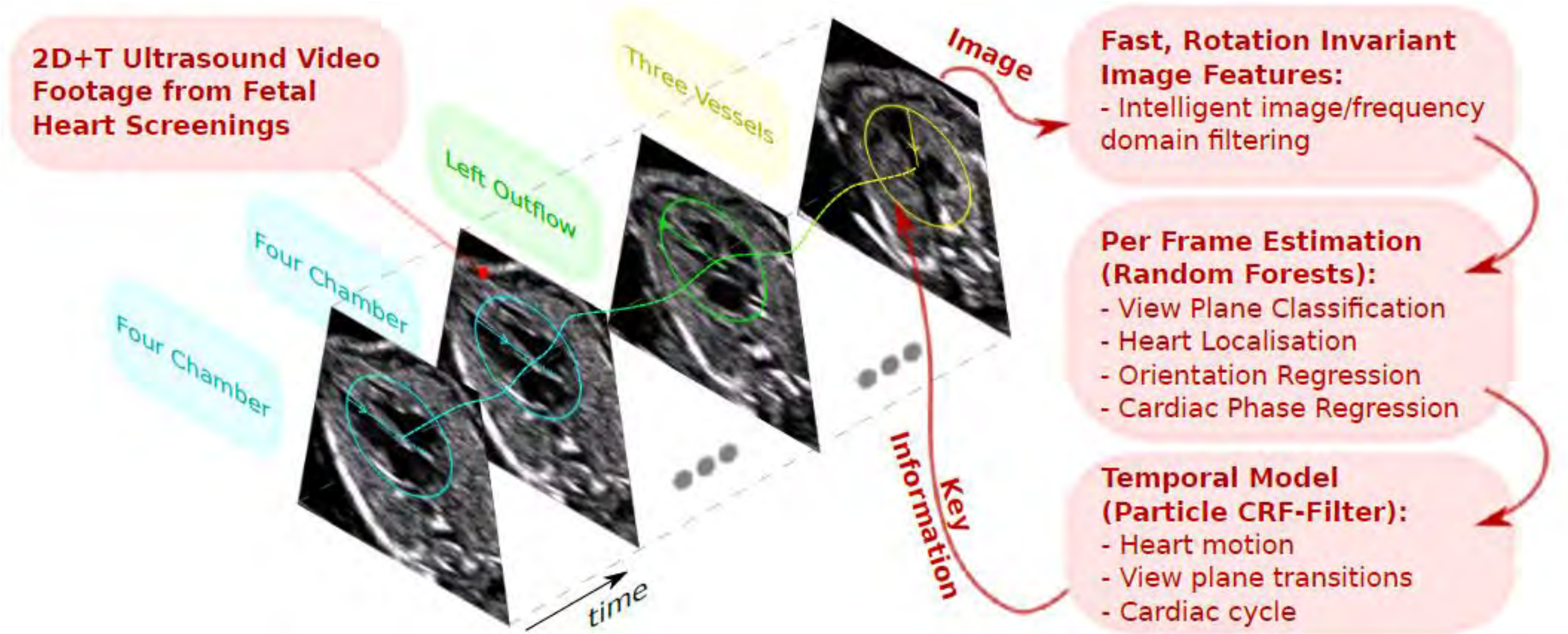


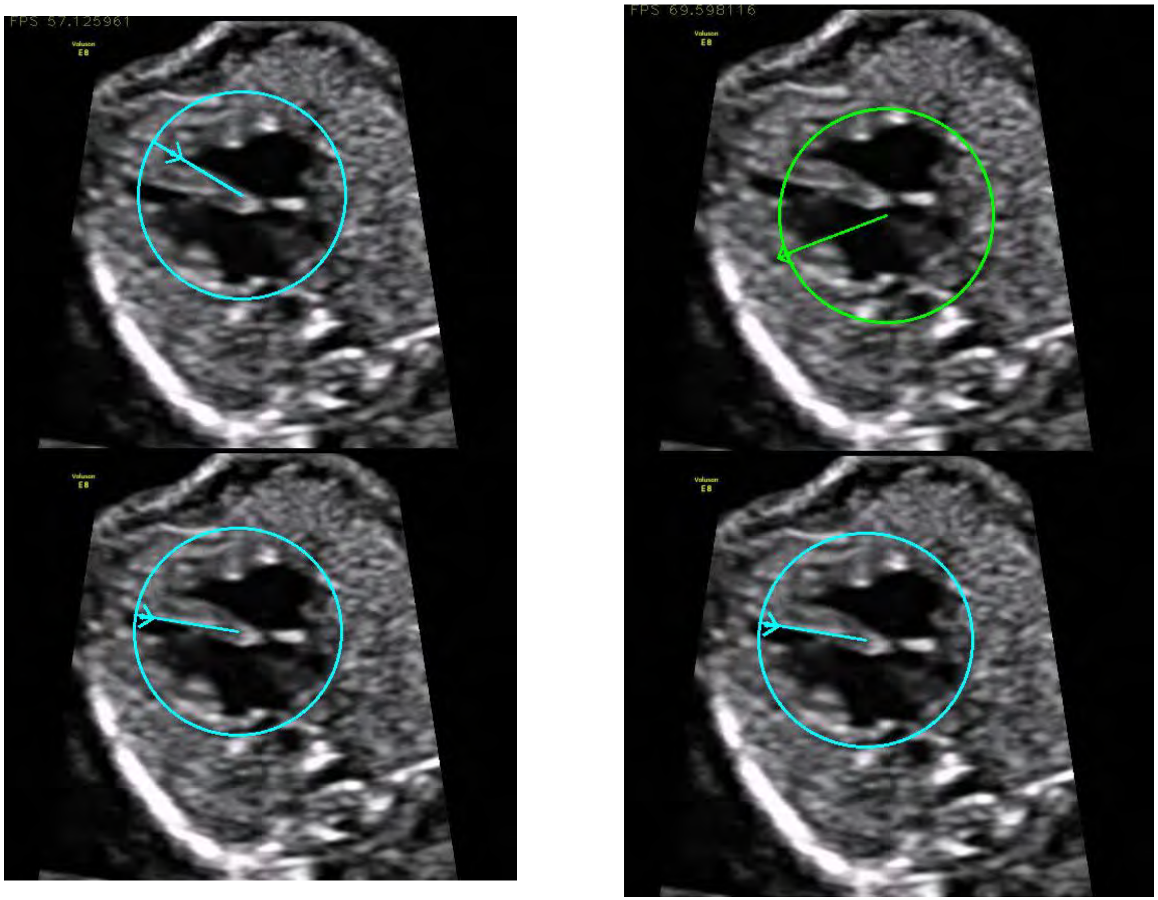
Figure 1: Definition of the three viewing planes and their annotations. *Top row* schematics showing the anatomic structures visible within the fetal abdomen in each view. *Bottom row* example image and annotation.

(Bridge et al, submitted for publication 2016)

Describing fetal heart videos



(Bridge et al, submitted for publication 2016)

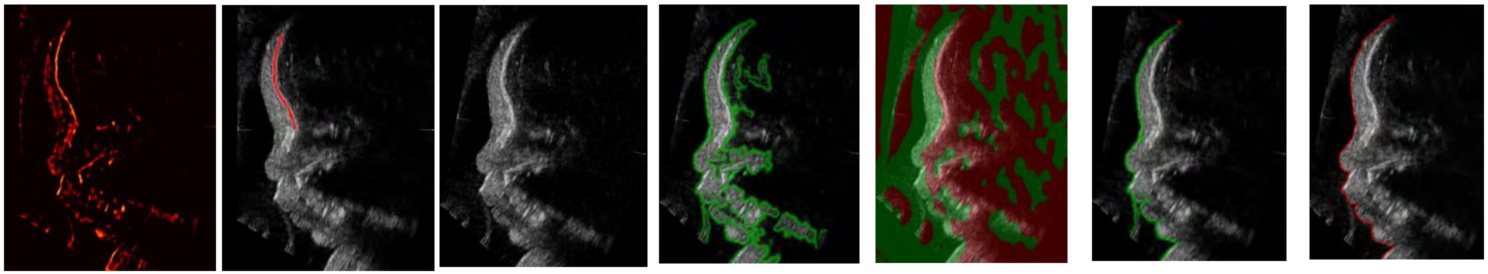


“state” description – heart location, view label, heart orientation and current cardiac phase.

Translate into a state estimation problem

Current solution uses a conditional random field (CRF) filter for state estimation.

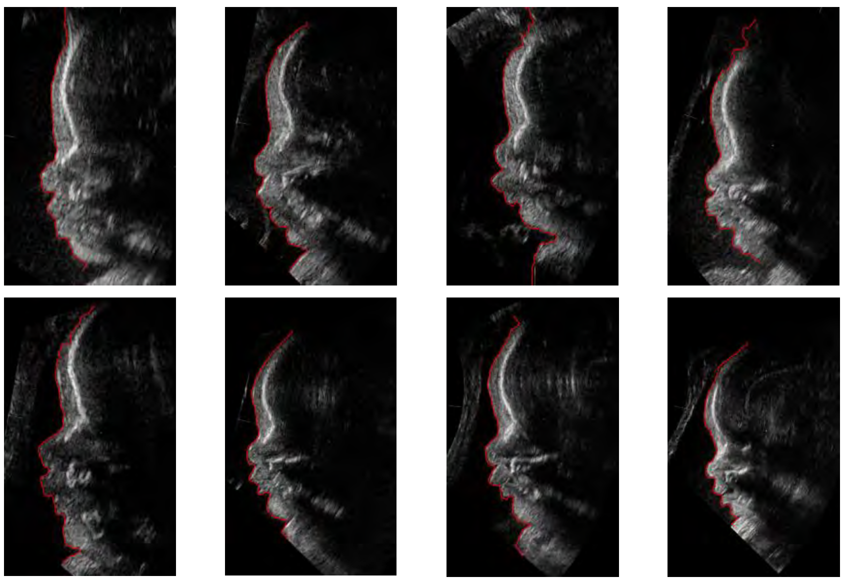
(Bridge et al, submitted for publication 2016)



a b c d e f g

Figure 1 Segmentation of the mid-line fetal profile from a single slice of a 3D ultrasound volume

a) Feature Symmetry (FS) identifies high intensity ridges.
b) A combination of Local Energy and the delineated ridges enables skull segmentation (red curve).
c) Orientation of the skull determines a rotation to bring the mid-sagittal profile into a common pose.
d) Feature Asymmtery (FA) identifies edges in rotated image and enables selection of largest connected region with FA > 0.
e) Local Orientation (LO) of edges in (d) codes regions as LO>0 (green) and LO<0 (red).
f) Regions with FA > 0 (indicating an edge) and LO > 0 (upward facing edge) are preserved (green).
g) The profile is segmented (red).



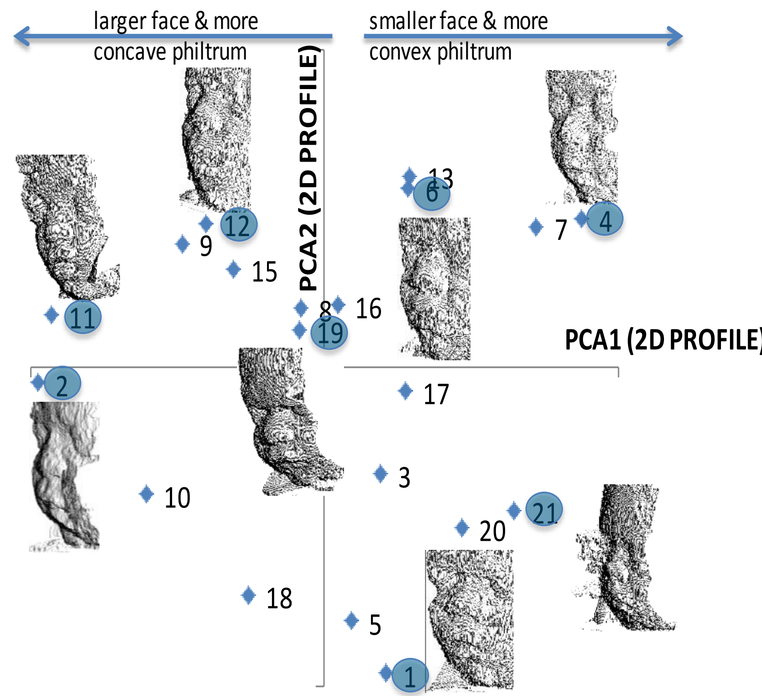
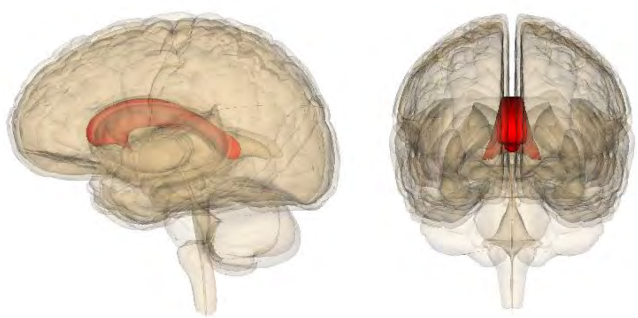
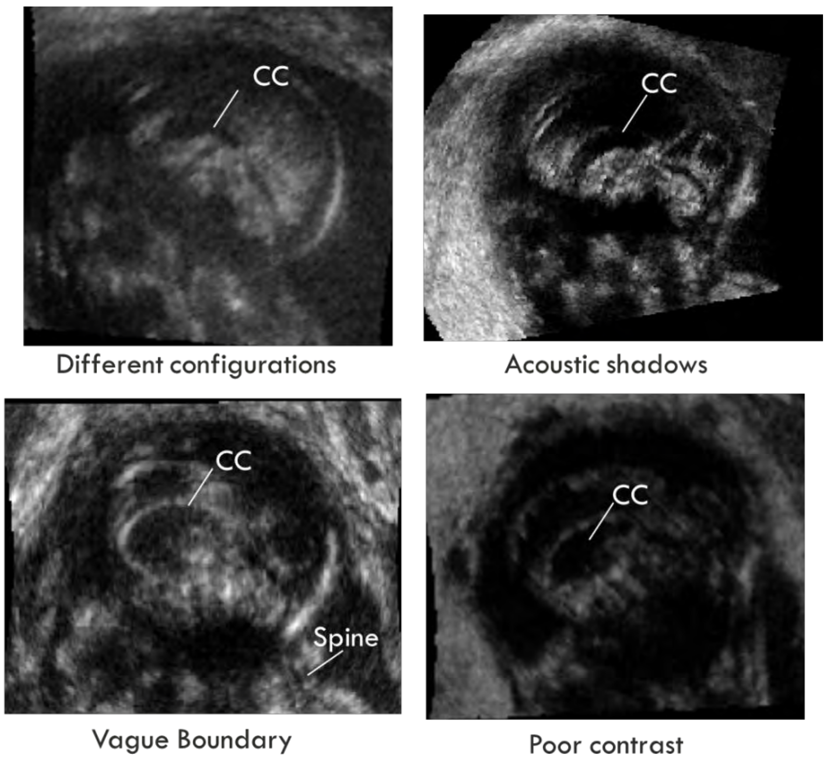


Figure 5 Scatter plot of PCA1 and PCA2 for 2D mid-line facial profile annotated with 3D point clouds



Detecting and Characterizing the Corpus Callosum in Ultrasound Images



The Corpus Callosum (CC) is a blob-like structure but difficult to model due to imaging artefacts and acquistion-related variations in appearance.

We weakly model the structure as a maximal stable extremal region (MSER) augmented with intensity and geometric descriptors.

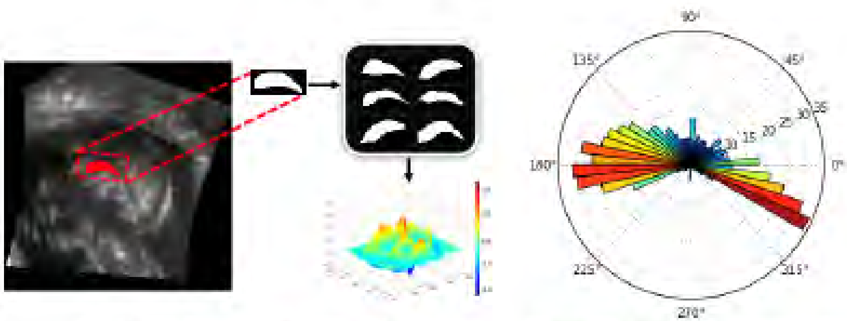
The resulting regional descriptor is used in a RUSboost (machine learning) object detection framework to detect the structure of interest.

Huang, Namburete and Noble, in preparation 2016

Work in progress

Detecting and Characterizing the Corpus Callosum in Ultrasound Images

(a) Mid-sagittal plane (b) Manual Segmentation (c) MSERs



(a) Shape features using templates

(b) Shape features using area distribution

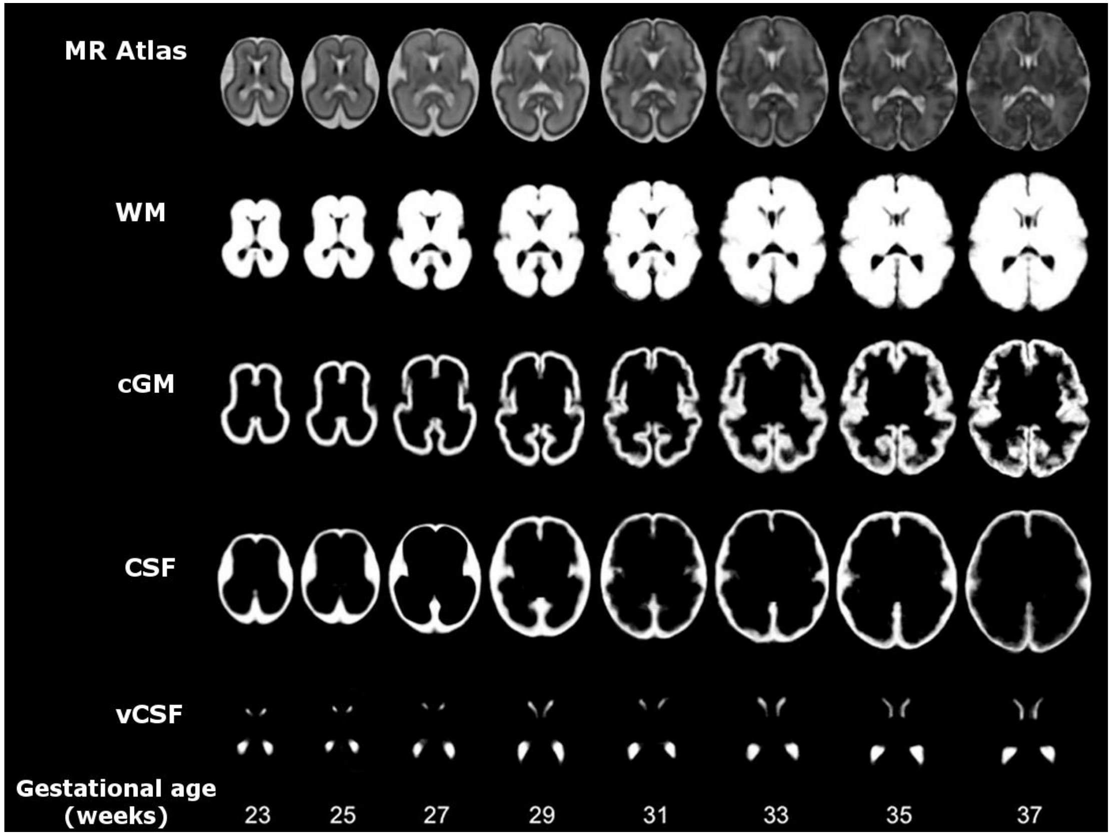
Fig. 2: Shape features. Candidate region is firstly binarized, rescaled and rotate to remove information unrelated to shape. (a) Features generated by calculating the maximum value of normalized cross correlation between the candidate region and a set of templates. (b) Features derived from the area distribution of the candidate region on a polar coordinate system. Colours represents the number of pixels lies within each fan section, while red represents the maximum and blue represents the minimum.

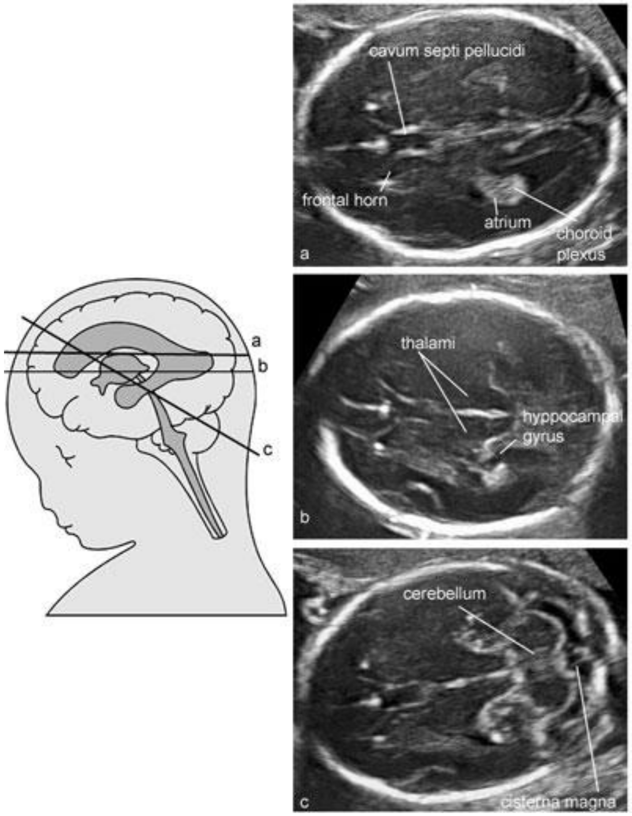
Table 1: Results of automatic brain structures segmentation

Brain Structure	Region classification		Quantitative Validation	
	Accuracy	Precision	$d_H\,(mm)$	DC
CP	97.4%	96.1%	7.7 ± 3.4	0.78 ± 0.06
CC	98.1%	96.4%	2.8 ± 0.9	0.76 ± 0.08

Huang, Namburete and Noble, in preparation 2016

How can we characterise the developing brain using imaging?

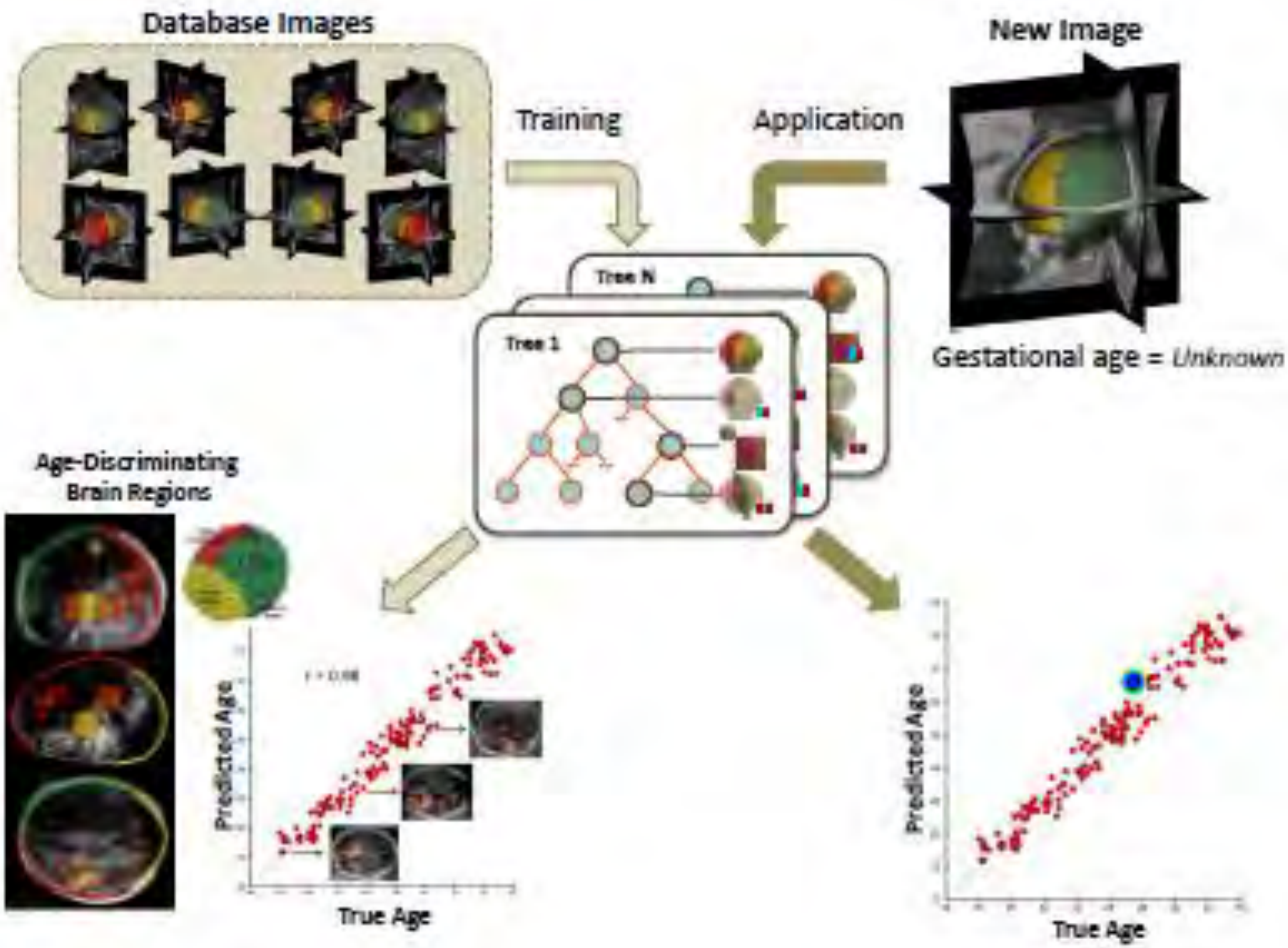




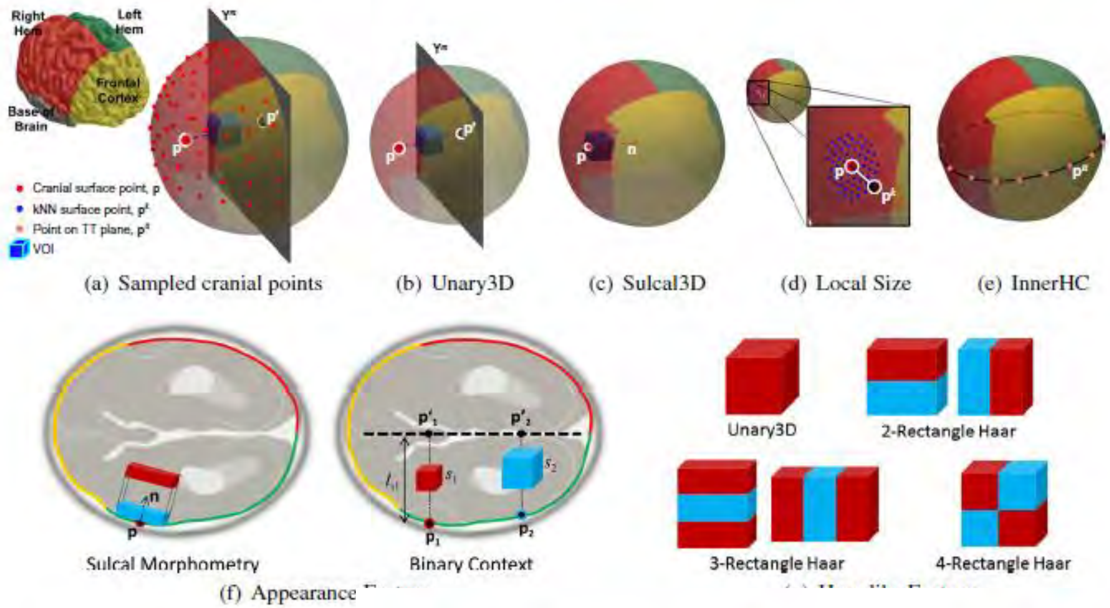
Are there unique sonographic signatures/patterns which tell us how well a given brain is developing?

“Can you estimate the Gestational Age of a fetus for a mother presenting at the clinic for the first time late in pregnancy?”

(Doctoral research of Ana Namburete (IBME) and Bryn Kemp (NDOG))



Namburete et al, Medical Image Analysis 2015



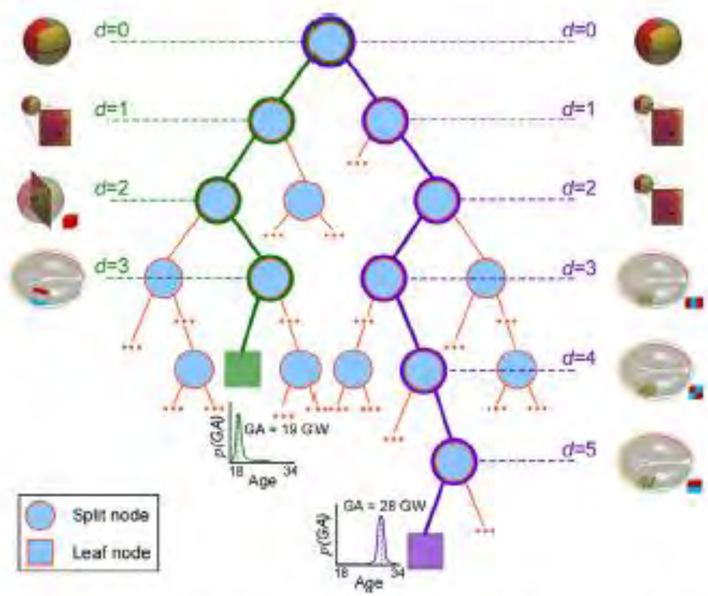
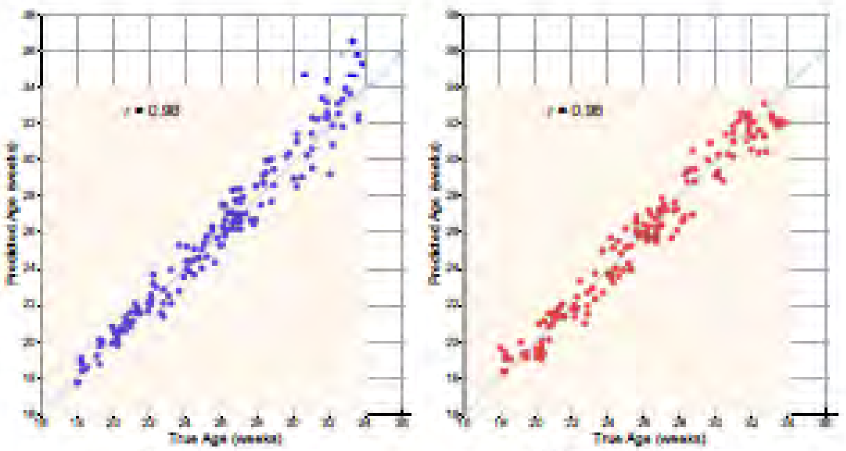


Fig. 6. Example feature selection. Illustration of feature selection paths for two different fetuses at 19 and 28 GW, demonstrating typical tree traversal.

The model features were chosen based on knowledge of longitudinal anatomical change, and needed to be computable from volumetric data of varied clinical quality (quality decreases with increased GA).

Namburete et al, Medical Image Analysis 2015



(a) Clinical HC GA Estimation (b) Model-Based GA Estimation

The machine learning solution is more accurate than the current “golden standard” manual clinical measurement for late pregnancy.

The analysis uses a standard clinical scan.

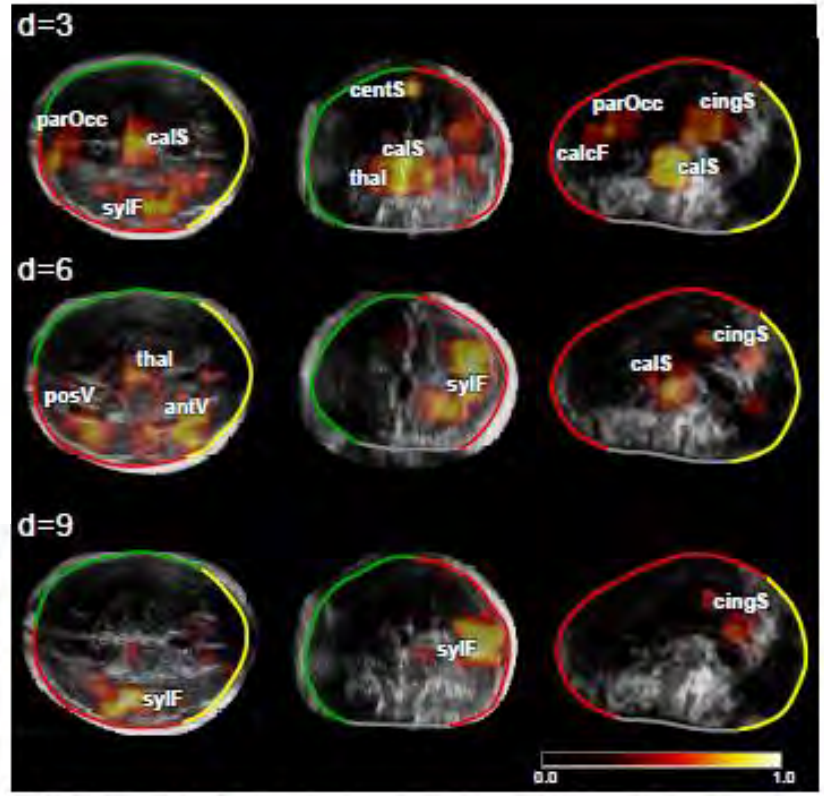
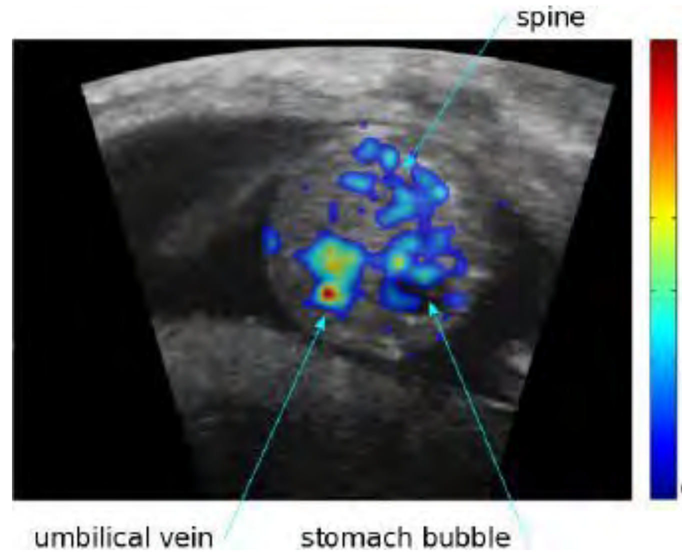


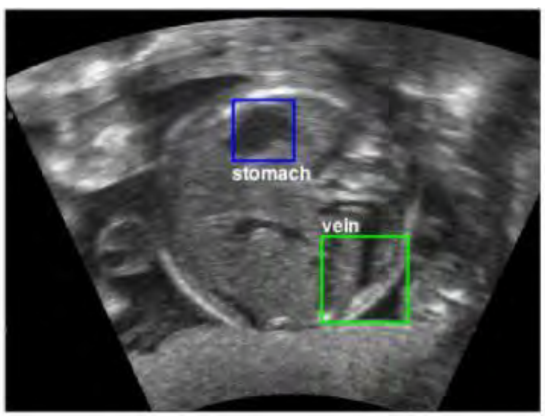
Figure 8: **GA-discriminating brain regions.** Visual example of the feature locations selected at three different levels of the forest ($d = 3,6,9$) superimposed on axial (left column), coronal (centre column), and sagittal slices (right column). The heat map corresponds to the relative feature importance, such that bright regions correspond to frequently selected brain regions. *sylF*: Sylvian Fissure, *calS*: Callosal Sulcus, *centS*: Central Sulcus, *parOcc*: Parieto-occipital Fissure, *cingS*: Cingulate Sulcus, *calcF*: Calcarine Fissure, *posV*: Posterior Ventricle, *antV*: Anterior Ventricle, *thal*: Thalami

Key sonographic patterns driving machine-learning correspond to known anatomical structures that change in early brain development and go beyond the radiologists eye…

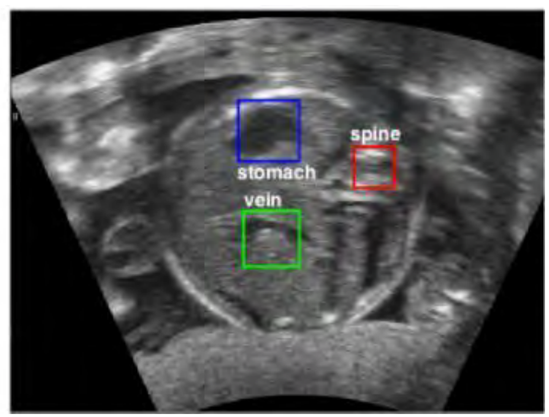
Namburete et al, Medical Image Analysis 2015

Tracking Eye Movements to Boost Recognition of Anatomical Features in Fetal Ultrasound





Detection without using spine as a reference

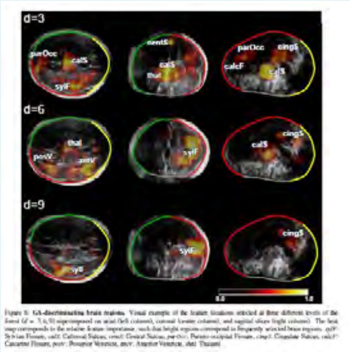


Detection with using spine as a reference

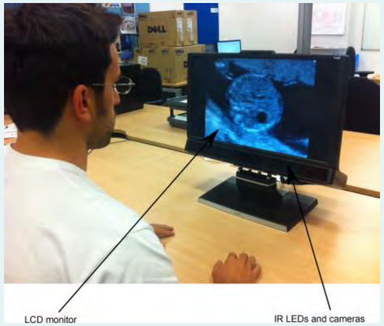
Detection increases to 87.2% (+4.5%) for stomach bubble and 83.2% (+9.6%) for umbilical vein.

(Ahmed and Noble MIUA 2015)

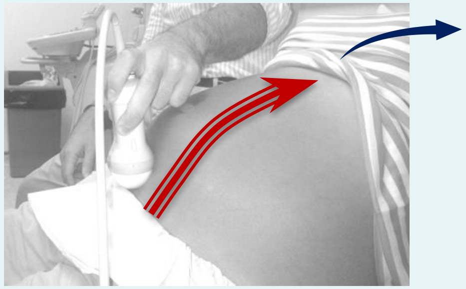
Summary



Biomarkers based on sonographic patterns that are not readily seen by eye



Eye-tracking during sonography to inform solution design



Simplify scanning. Intelligent interpretation.

The inter-play of (ultra) sound and vision (computer and human) to advance use of ultrasound in clinical practice is entering an exciting new era. One particular area of exciting possibilities is to support improved diagnosis of fetal conditions