## **Electrocardiographic Inverse Validation Study:**



# Model Development and Methodology

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### Introduction

The basic tool in the non-invasive assessment of cardiac electrical activity is the 12 lead ECG. This is a fast and efficient procedure for initial diagnosis, but has seen little in the way of development for several decades. The diagnostic capability of an ECG can be improved by increasing the number of leads used to sample the cardiac electric field bine this increases the amount of information available about the electrical activitive interpretation of this densely sampled data, in terms of the underlying cardiac electric activity, is an electrocardiographic inverse problem. Over the last few decades various mathematical algorithms have been developed in a attempt to solve this problem. Unfortunately, unless the approach is posed in a particular manner, the inverse problem is not uniquely determined. This means that in the presence of noise, which always exists, a solution to the inverse problem can produce a result which bears no resembalance to that of the true electrical generator. Methods for handling the ill-posed nature of the inverse problem have traditionally centered on mathematical constraints. These mathematical constraints fail to incorporate the underlying physiologal processes governing the generation of the body surface potentials, namely a progressing wave of cardiac activation. Another approach to the inverse problem has recently emerged (F Greensite and G Huiskamp, An improved method for estimating epicardial potential formulation, not least in that it deals directly with the underlying physiologal process responsible for generationg the body surface potentials. Recently, anew algorithm based on this activation imaging approach has recently emerged (F Greensite and G Huiskamp, An improved method for estimating epicardial potential formulation, not least in that it deals directly with the underlying physiologal process responsible for generationg the body surface. This mass flowed. EEE Trans. Biomed. Eng., **44**:433-446, 1997). **Aim of this study**: to quantitatively investigate and validate t

## Theory: Inverse Algorithms

Determining the electrical state of the heart from remote measurements of the electropotential field at the body surface is of considerable medical interest. The inverse problem of electrocardiography is a general name that encapsulates all methods that attempt to compute the time-varying (*t*) transmembrane potential field,  $\phi_n(x,t)$ , on the outer surface of the heart (denoted x) from extracellular potential measurements,  $\phi(y,t)$ , at remote locations on the body surface (denoted y).

#### Epicardial Potential Imaging

The electric field in the source-free region between heart and body surfaces is determined by Laplace's equation, with boundary conditions given by the vanishing of the normal component of current density on the body surface and the unknown epicardial potentials. The result is a linear relationship between the body surface and epicardial potentials. The full approach is given in Greensite *et al.*, *IEEE Trans Biomed Eng.* **45**:1-7, 1998.

This approach first produces a series of signals at every myocardial surface point in the mesh, which are used to identify epicardial breakthrough sites. The next

stage is a computationally intensive optimisation procedure to determine the full myocardial surface activation sequence. The full approach is given in Huiskamp

et al., IEEE Trans Biomed Eng. 44:433-446, 1997.

In a macroscopic sense, the relationship between the electropotential field and its intracardiac current sources is well understood, via the bidomain field equation: This approach first produces a series of sig

 $-\nabla \bullet [(\mathbf{G}_{i}(\mathbf{x}) + \mathbf{G}_{e}(\mathbf{x})) \nabla \phi(\mathbf{x}, t)] = \nabla \bullet [\mathbf{G}_{i}(\mathbf{x}) \nabla \phi_{m}(\mathbf{x}, t)]$ 

where  $G_i(x)$  and  $G_e(x)$  are the intra- and extracellular conductivity tensors, respectively. Two meaningful approaches for solving the inverse problem will be quantitatively investigated and validated



(a) Heart signals are recorded using an elasticated sock with 127 electrodes connected to a UnEmap cardiac mapping system. A single heart cycle is identified and the epicardial activation time for each electrode is identrinied using the most negative electropotential slope. An epicardial activation map is fitted to the electrode activation times and displayed using the 2D Hammer projection, where the left ventriele (LV) makes up the central portion of the projection, the right ventricle (RV) comprises the border regions and the apex is retained as a single point. Red and blue indicate regions of earliest and latest epicardial activation, respectively. LAD, PDA: left anterior and posterior descending coronary arteries, respectively.

(b) Torso signals are recorded using 256 electrodes sewn into an elasticated vest. A potential marker identifies the peak R wave of the ECG and torso electropotentials are displayed using a 2D representation of the body surface. The centre of the display reflects the left mid-auxillary line and the left and right edges of the display the right mid-auxillary line. Red and blue denote regions of positive and negative electropotential, respectively.

The geometric locations of the torso electrodes are obtained by direct measurement using a mechanical digitising arm. The geometric locations of some the epicardial electrodes are also obtained using the mechanical arm while the chest is open. In the future we plan to use digital sonomicrometry can be used to obtain the epicardial electrode locations *in-viva*.

### Method: Porcine Model Construction

To construct an anatomically accurate generic model of the pig a pig was placed in a CT scanner and a sequence of cross-sectional images obtained. These images were then digisted to provide 3D data sets for each anatomical surface (endocardium, epicardium, lungs, fat and torso). A non-linear optimisation procedure, which incorporated non-linear constraints and smoothing, was used to obtain a parametric representation of each surface in 3D space. C1 cubic Hermite elements were used to define the smoothly continuous anatomical geometry. Full details of the fitting procedure may be found in Bradley et al., Annals of Biomed Eng, 25:96-111, 1997. Approximately 2-10 hours of CPU time were required to fit each surface. For validation studies the generic model is customised to provide a computational model of each pig studied. The customisation of each pig is achieved by identifying a number of anatomical landmarks on the experimental animal using a mechanical digitising (FARO) arm. The same landmarks are located on the generic pig model and a non-linear fitting procedure which minimises the difference between the sets of anatomical landmarks is used to transform the generic model into a customised model. To obtain the size, orientation and location of the heart 3D ultrasound is used. The ultrasonic probe is mounted on a mechical digitising arm, and the position and orientation information generated by this arm is used to quantitatively register the ultrasound images with respect to the frame of reference used for the anatomical landmark positions. This hence alows the experimental heart geometry to be located inside the computational model







Ultrasound image of the porcine heart. The left frame shows a traditional ultrasound view with overlays of the reconstructed opicardial. left ventricular endocardial and aortic surfaces. The right hand frame shows a 3D reconstruction of the porcine heart. Also shown in this view are the multiple ultrasound image planes from the 3D ultrasound probe. The position and orientation of the ultrasound probe is recorded using a mechanical digitising arm in order for this reconstructed heart to be located within the computational mesh.

### **Results:** Sample Simulation

The figure to the right shows an example of the activation inverse solution using the porcine computational model. (a) Shows the model heart with a prescribed activation sequence. This sequence was then used to generate body surface maps viewed from the anteriror (d) and posterior (e). (b) shows the activation sequence obtained from the activation inverse algorithm using the calculated body surface potentials with 20  $\mu V$  RMS noise added. (c) shows the reconstructed activation sequence obtained when 100  $\mu V$  RMS noise is added. On the heart, blue represents activated myocardium and red represents resting tissue. For the body surface, blue represents negative potential and red represents postive potential.

For further information see the adjacent poster by Nash *et al.* "Electrocardiographic Inverse Validation Study: *Invivo* mapping and analysis"

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### Method: Cardiac and Body Surface Potential Mapping