An Intrinsic Coordinate System of the Developing Human Brain

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INTRODUCTION:

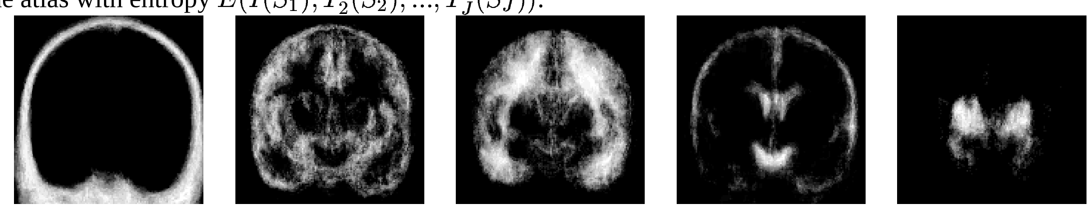
Magnetic resonance imaging of newborn infants with gestational age ranging from 24 to 40 weeks indicates major developmental changes in the human brain over this time period [1]. Assessment of normal and abnormal anatomical variability requires a coordinate system enabling inter-subject comparison [2,3,4]. We present a method for identifying an intrinsic coordinate system of the developing brain by applying a minimum entropy criterion to determine affine transformations to bring a group of subject scans into alignment.

METHOD:

Acquisition and Tissue Classification: Spoiled Gradient Recalled (coronal T1w) and Conventional Spin Echo (axial T2w/PDw) MR acquisitions of newborn infants are acquired at our institution under a protocol with IRB approval. 22 acquisitions of subjects with GA $<$ 34 weeks were analysed. T1w and T2w volumes were aligned. Supervised statistical classification was used to identify tissue classes [5].

Minimum Entropy Alignment: We define the joint pixelwise entropy of a collection of J binary images, $S_j, j \in 1...J$, each brought into alignment by a transform T_j, as $E(T_1(S_1), T_2(S_2), ...T_J(S_J)) = \sum_{i=1}^{N} H(v_i)$ where N is the number of voxels of the data set, v_i is the binary random variable defined by the values of pixel i across the images and $H(\cdot)$ is the discrete entropy function. We treat each tissue class as a separate binary volume and sum the entropy for each to obtain the total entropy of a given alignment of a collection of classified images. A minimum entropy alignment seeks to identify the set of transforms T_j which minimizes the entropy of the collection i.e. $\arg\min_{T_1,...,T_J} E(T_1(S_1), T_2(S_2), ..., T_J(S_J))$. Differing from [6], here we propose to approximate this by fixing one data set and computing the minimum entropy transform between this and the other tissue classifications [7], giving the optimization problem of $\arg\min_{T'_k} E(I(S_1), T'_k(S_k)) \forall k \in 2...J$, where $I(\cdot)$ is the identity transform, and hence we construct the atlas with entropy $E(I(S_1), T'_2(S_2), ..., T'_J(S_J))$.

RESULTS:



The above figure shows the minimum entropy tissue class atlases obtained with affine registration for (left to right) skin, gray matter, unmyelinated white matter, cerebrospinal fluid and basal ganglia.

DISCUSSION:

A minimum entropy criterion provides a means to obtain a coordinate system intrinsic to the data being studied. Anatomical variability is encoded in the transform bringing subject scans into alignment. Applying this approach to scans of many subjects grouped by age should allow the construction of a spatiotemporal atlas of the developing brain.

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