Biology Inspired Automatic Segmentation of Brain Images with Chaos Synchronization

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Outline

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- Brain and Chaos.
- Chaos Synchronization.
- Mackey-Glass Equation.
- Otsu Adaptive Threshold.
- Algorithm.
- Simulation Results.
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- Continuing Research.
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Objective:
- Chaotic synchronization used for automatic image segmentation in brain MRI images.

Motivation:
- Neural dynamics are heavily dependent on chaotic activity.
- The fundamental unit of the brain is termed a neuron. A neuron communicates to other neurons via electrical impulses, also called potentials, and chemical secretions called neurotransmitters, whose effect is not perfectly understood. Electrical input to one neuron comes from many others, each having a specific amount of influence, or weight, on the neuron.
Brain and Chaos

- Dendrite
  - Receiving input signals
- Axon
  - Sending output signals
- Synapse
  - Connection between Dendrite and Axon
Brain and Chaos

- Nonlinear dynamics/chaos
  - Chaos: looks random but it’s not, includes patterns
  - Self-organization in complex systems (physics, biology, etc)
- In order to classify the behavior of a system as chaotic, the system must be: sensitive on the initial conditions.

### Behavior of two adjacent points:

Adjacent points, no matter how close, will diverge to any arbitrary distance and all points will trace out orbits that eventually visit every region of the space.

- **Convergence**: \( \lambda < 0 \)
- **Stable**: \( \lambda = 0 \)
- **Divergence**: \( \lambda > 0 \)
Brain and Chaos

- Chaotic behavior has been observed in the brain (microscopic, macroscopic).
- Two or more chaotic systems can be synchronized by using a common driving signal or coupled together.
- A central issue of cognitive neuroscience is to understand how a large collection of coupled neurons combines external signals with internal memories into new coherent patterns of meaning.
- The synchronization of spike trains of many individual neurons is the basis of a coherent perception.
Chaos Synchronization

- Evaluate characteristic existing in status space of system by time series.
- **Correlation Integral** method to find the synchronization of a chaotic time series. The N points of such a long-time series can be defined by,

\[
\{\tilde{X}_i\}_{i=1}^N \equiv \{\tilde{X}_i(t + i\tau)\}_{i=1}^N
\]

where \(\tau\) is an arbitrary but fixed time increment. The definition of correlation integral is

\[
C(r) \equiv \lim_{N \to \infty} \frac{1}{N^2} \sum_{i,j=1}^{N} \theta(r - |\tilde{X}_i - \tilde{X}_j|)
\]

\[
\equiv \int_0^r d^d r' c(r'),
\]

where \(\theta(x)\) is the Heaviside function and \(c(r')\) is the standard correlation function.
Mackey-Glass Equation

- It is a non-linear, delay-differential equation whose dynamics exhibit chaotic behavior for some parameter values.

\[ \frac{dx}{dt} = \frac{ax(t-\tau)}{1 + x^c(t-\tau)} - bx(t) \]

- The parameters chosen are \( a=0.2 \), \( b=0.1 \), \( c=10 \). These are general choice. \( \tau \) controls the complexity of the series dynamics. \( \tau = 30 \) is used.

- Characteristic of chaotic dynamics is that the resulting attractors often have a much more intricate geometrical structure in the phase space than do the typical attractors.
Otsu Adaptive Threshold

- Otsu method: let the weighted sum of group variances is denoted by $\sigma^2_w$, the variance of class $C_0$ with intensity value from 1 to $t$ is $\sigma^2_1(t)$ and variance of class $C_1$ with intensity value from $t+1$ to $l$ is $\sigma^2_2(t)$. According to Otsu method the best threshold value $t^*$ is value of $t$ that minimizes $\sigma^2_w$ where

$$\sigma^2_w = q_1(t)\sigma^2_1(t) + q_2(t)\sigma^2_2(t)$$

with

$$q_1(t) = \sum_{i=1}^{t} P(i) \quad q_2(t) = \sum_{i=t+1}^{l} P(i)$$

and

$$\mu_1(t) = \frac{\sum_{i=1}^{t} iP(i)}{q_1(t)} \quad \mu_2(t) = \frac{\sum_{i=t+1}^{l} iP(i)}{q_2(t)}$$

$$\sigma^2_1(t) = \frac{\sum_{i=1}^{t} [i - \mu_1(t)]^2 P(i)}{q_1(t)}$$

$$\sigma^2_2(t) = \frac{\sum_{i=t+1}^{l} [i - \mu_2(t)]^2 P(i)}{q_2(t)}$$

in which $P(i)$ is histogram probabilities of the observed gray value $i = 1,..,l$

$$P(i) = \frac{\text{number}\{(r, c) | \text{image}(r, c) = i\}}{(R \times C)}$$

and $r, c$ is index for row and column of the image, respectively. $R$ and $C$ is the number of rows and columns of the image, respectively.

- Threshold value is calculated by minimizing the within-group variance.
Algorithm

- Basic Idea:
  - image pixel :: individual neuron.
  - add activation properties to each neuron using non-linear dynamics.
  - synchronize homogeneous group of elements.
Algorithm

Feature Extraction (Spatial)

Normalized Feature Vector (n x m)

Mackey Glass Equation Non-Linear Dynamics (Temporal)

Co-Relation Integral 1D Vector (CRV)

Median and Mean (Scalar Signature of the CRV)

Median Vector (Mg_Md), Mean Vector (Mg_Mn)

Largest Cluster (Histogram) in Mg_Md and MG_Mn. Homogeneous Segment.

Map-back to Spatial Space

Algorithm Illustration.
Algorithm

Steps

1. Manual segmentation of the object (tumor in this case). We use a square window size of $n \times n$ (i.e., 130 x 130). These we call are our area of interest.

2. Normalize the image intensity pixels to create Feature Vector.

3. Each element of the Feature Vector is plug-ed in as seed to the Mackey Glass equation. So for each image segment we have $n^2$ (i.e., 130 x 130 = 16900) seed values. This process will generate $n^2$ time series maps.

4. Find the Correlation Integral Matrix of each of the time series. This will generate 1D vector. Take the median and mean of this vector as two scalar signature of each time series. The Median and the Mean matrix are each same size ($n^2$) 1D vector.

5. Generate a similarity matrix to find out the closely synchronized points. Identify the largest cluster from the Mean and Median matrix.

6. Define a small interval window. It is calculated from a linear equation. We do this for both the Median and Mean matrix vectors.
   
   $\frac{[\text{maximum(matrix)} - \text{minimum(matrix)}]}{(2*p)}$ 

   where $p$ is an integer.

7. Map-back largest cluster elements (interval window from the center of the cluster). Reshape back the original $n \times n$ dimension with identified cluster points.
Simulation Results

- We have not yet included any perceptual quantitative measure. Will include manual segmented reference image by domain experts to compare with the result images.

- Using human visual perception, our algorithm provides satisfactory performance for the segmentation of the brain MRI.
## Simulation Results

<table>
<thead>
<tr>
<th>Original Image Segment 130 x 130</th>
<th>Our result with automatic segmentation (Median)</th>
<th>Our result with automatic segmentation (Mean)</th>
<th>Otsu Adaptive threshold segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td><img src="image2.png" alt="Image 2" /></td>
<td><img src="image3.png" alt="Image 3" /></td>
<td><img src="image4.png" alt="Image 4" /></td>
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<td><img src="image5.png" alt="Image 5" /></td>
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<td><img src="image7.png" alt="Image 7" /></td>
<td><img src="image8.png" alt="Image 8" /></td>
</tr>
</tbody>
</table>
Simulation Results

Original Image Segment 150 x 150

Original Image Segment 130 x 130
Application Specifics

- The biological model of primate brain is an inspiration for our application.

- Currently resource intensive. For a segment of 130 x 130 MRI image our application takes around 32.8006 hours.

- We used n=500 for Mackey Glass, plan to increase time series elements.

- The application may use any type and number of feature extraction module.

- Resultant matrix is a smaller feature vector, which actually contributes to a smaller object descriptor, good for large-scale image database maintenance.
Continuing Research

- Brain MRI the basic tissue classification is as follows: volumes of White Matter, Gray Matter, Cerebrospinal Fluid (CSF), Bone, Muscle (Skin), and Abnormal Tissues. With different size clusters and window intervals, it is possible to segment different tissues. The results will be included in the next phase.

- Add more feature extraction modules (color, texture, shape).

- Use neighborhood interaction using Coupled Map Lattice.
  - 1D lattice for $1 \leq i \leq n$, $x_i(k + 1) = f(x_i(k)) + c(f(x_{i-1}(k)) + f(x_{i+1}(k)) - 2f(x_i(k)))$ with periodic boundary conditions $f(x_0(k)) = f(x_n(k))$ and $f(x_{n+1}(k)) = f(x_1(k))$, and
  - 2D lattice for $i = (i_1, i_2)$ with $1 \leq i_1, i_2 \leq n$, $x_i(k + 1) = f(x_i(k)) + c(f(x_{i_1+1,i_2}(k)) + f(x_{i_1-1,i_2}(k)) + f(x_{i_1,i_2+1}(k)) + f(x_{i_1,i_2-1}(k)) - 4f(x_i(k)))$ with $f(x_{0,i_2}(k)) = f(x_{n,i_2}(k))$, $f(x_{i_1,0}(k)) = f(x_{i_1,n}(k))$ and $f(x_{i_1,n+1}(k)) = f(x_{i_1,1}(k))$, where $f$ is a one-dimensional logistic map $x(k + 1) = f(x(k)) = \gamma x(k)(1 - x(k))$ with $f : (0, 1) \rightarrow (0, 1)$ and $\gamma \approx 3.57, 4$.
  - The map $f$ becomes chaotic whenever $\gamma$ increases from 3.57 to 4.
References


[10] Rong Zhao and W.I. Grosky, “From Features to Semantics: Some Preliminary Results”, Department of Computer Science, Wayne State University, Detroit, MI 48202, USA, 2000 IEEE.


Questions?