Data Representation for Motor Imagery Classification

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Demonstration

OpenBCI Gui

Data stream and trial simulation

Hand detection

Key Takeaways

- Classifies images fairly well
  - Too well
  - Undesired feature from environment
- Offer great promise, but…
- Progress must be made before usable as real-time BCI
- Strength of signal images is in interpretability and cross-domain communication

Abstract

While much progress has been made towards the advancement of brain-controlled interfaces (BCI), there remains an information gap between the various domains involved in progressing this area of research. Thus, this research seeks to address this gap through creation of a method of representing brainwave signals in a manner that is intuitive and easy to interpret for both neuroscientists and computer scientists. This method of data representation was evaluated on the ability of the model to accurately classify motor imagery events in a timely manner.

The proposed data representation of electroencephalographic signals in the form of signal images was found to be able to perform adequately in the task of motor-imagery. However, the amount of time to record enough samples was on the scale of a fifth of a second following the onset of an input from the user. This time delay represents the minimum window size needed to classify the event, meaning that to reduce this delay would require a fundamental shift in the data that is acted upon to perform classification or to generate the signal images. Furthermore, the system performed better than expected, even in the face of random data, suggesting that the system may be relying on some external factor or undesired artifact present in the data in order to perform its task.

The strength of this approach came from its ability to be understood, visually examined, and altered in near-real-time in order to explore the data captured during a recording session. This was done after data had been recorded and involved altering sets of configuration parameters that affect the computations that go into generating a signal image. Namely, this included the window size, the function used to interpolate between two adjacent data points, and the amount of overlap of the windows. Effectively, this allows a researcher to playback the signal in an intuitive manner, watching for large shifts or edges in the images in order to detect large changes in the underlying data stream. Thus, while this approach may be unsuited for the task of classification, it would be an effective tool for conducting exploratory data analysis.

Motivation

- Unique means of user-control
  - requires no active muscle control
- Restore control for disabled
- Fully-immersive VR
- Allure of science-fiction

Key Considerations

- Hobbyists and low cost solution
- Cross-domain communication
- Control system
    - Reactivity
    - Accuracy

OpenBCI

Open-Source Software

- All tools and software is available on GitHub
- Active community supporting product development
- Blog highlights recent advances made in the field

https://github.com/OpenBCI/OpenBCI_GUI

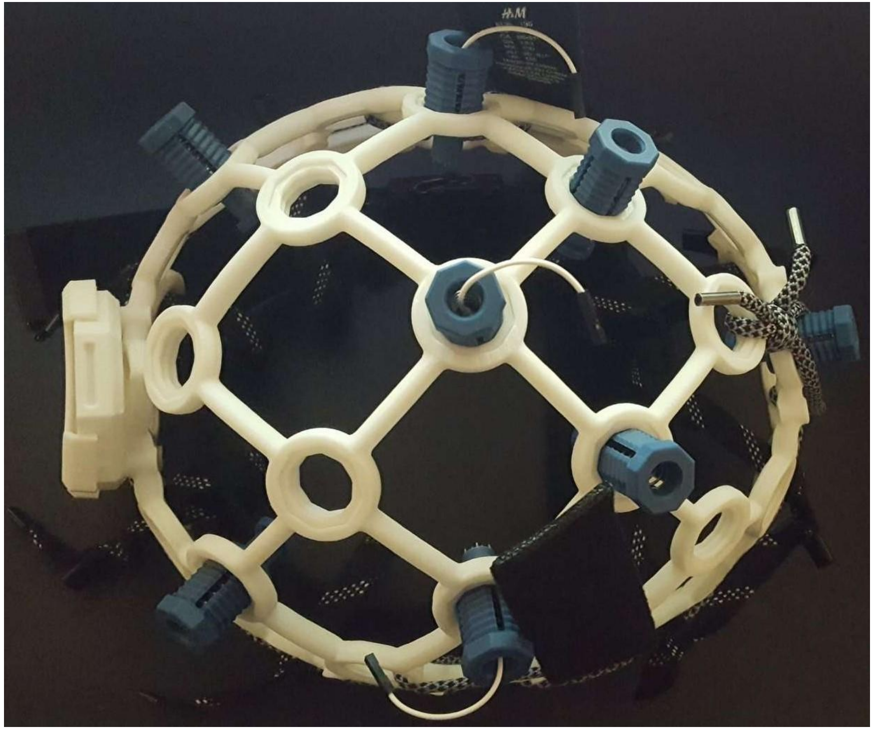
https://github.com/OpenBCI

Ganglion

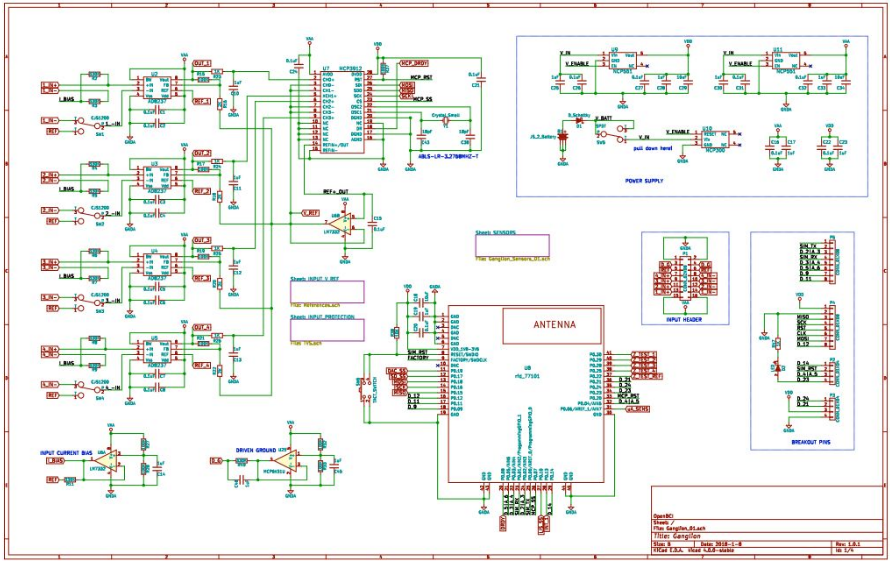
- 4 channels
- Bluetooth connection
- 200 Hz sampling rate
- Simblee on-board microcontroller
- 3 axis accelerometer

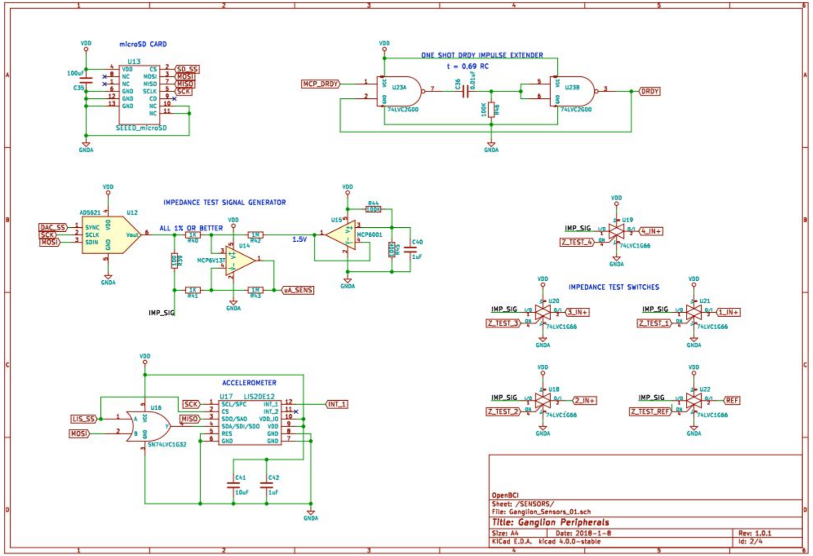
Modified Ultracortex Mark IV

- Supports up to 16 channels
  - C3
  - CZ
  - C4
- Dry, spiky electrodes
- Belt restraint on the inside of the base
- Neck strap



Open-Source Hardware





https://github.com/OpenBCI/V3_Hardware_Design_Files

https://github.com/OpenBCI

Background

Motor Imagery

- Evoked-potentials
  - user is presented with a stimulus
- Event-related potentials
  - user performs some task
- Mu-rhythm suppression

Convolutional Neural Network

- Convolution traditionally comes from signal processing
- Images can be interpreted as a discrete signal
- Operate on unstructured data

Data Acquisition

PhysioNet Dataset

- Build out and test system
- Verified and widely used
- Built using the BCI2000 system
  - 64 channels
  - 160 Hz sampling rate
- 6 trial types
  - Baseline trials - 2 minutes
  - All others - 3 minutes
- FIR band-pass filter 5 - 50 Hz
- Implicit trust in subject
- Subject knows next prompt
- About 3 seconds between events

Manual Dataset

- Similar protocol as PhysioNet
- No guarantee of rest event between left/right events
- Next event is always random
- About 5 seconds between events
- Slight jitter added to event delay

Signal Images

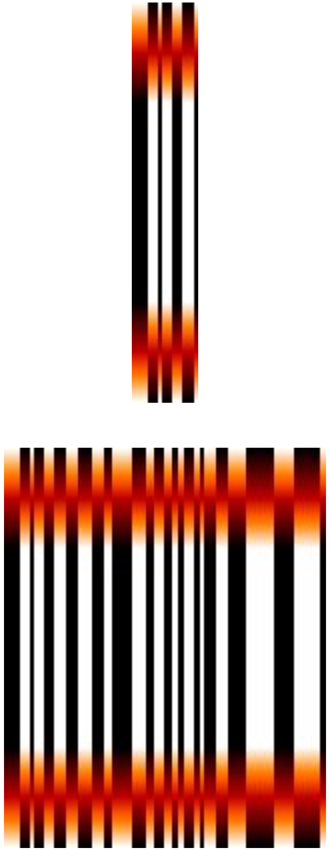
Signal Image

- Define row spacing
  - Provides height
- Width directly correlates to time
- Interpolation function
  - Linear
  - Quadratic
  - Cubic
- gist_heat colormap
  - More intuitively understandable
  - Frequency horizontal change from black to white

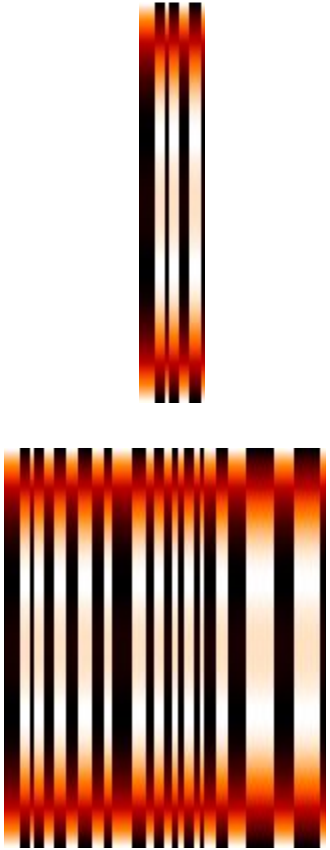
Classification Dataset Construction

- Window length
  - Amount of time of image
  - 0.2, 0.4, 0.6, 0.8, 1.0 seconds
- Window overlap
  - Number of steps shared between subsequent images
  - 20%
  - Larger effect on dataset size
- Interested in time per image

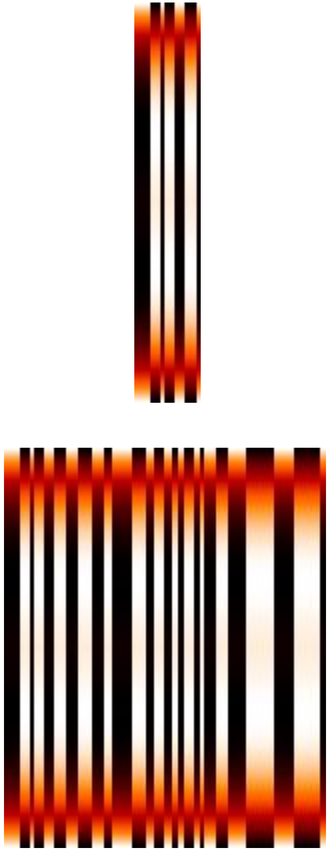
S001



Linear



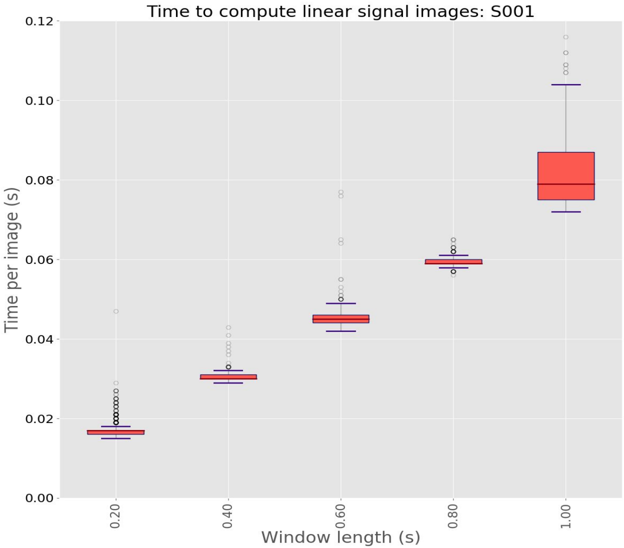
Quadratic

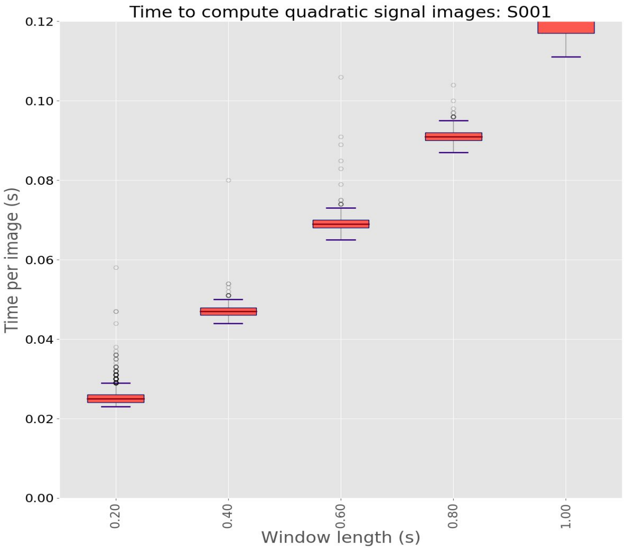


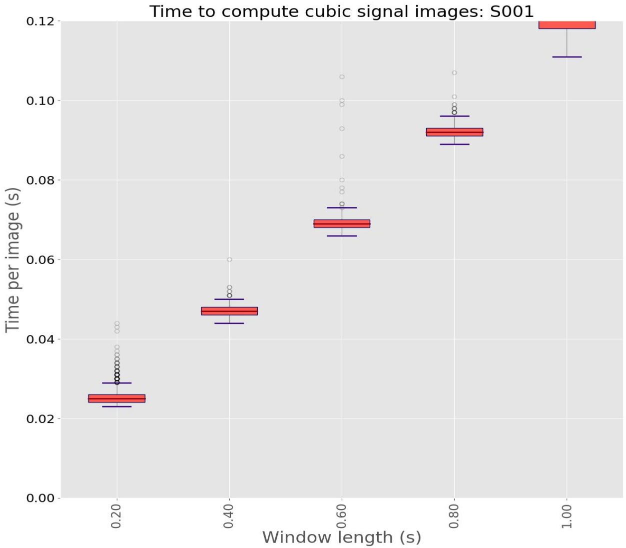
Cubic

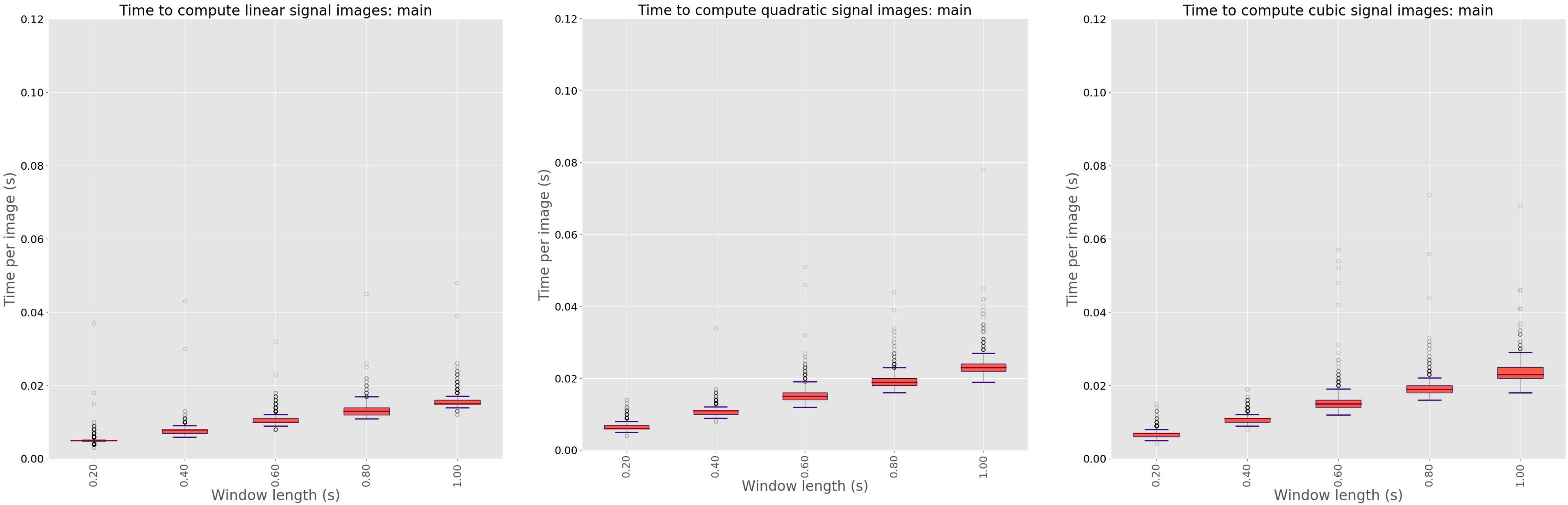
Main

Linear Quadratic Cubic


Time to compute linear signal images: S001
Time per image (s)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Window length (s)
0.20
0.40
0.60
0.80
1.00


Time to compute quadratic signal images: S001
Time per image (s)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Window length (s)
0.20
0.40
0.60
0.80
1.00


Time to compute cubic signal images: S001
Time per image (s)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Window length (s)
0.20
0.40
0.60
0.80
1.00


Time to compute linear signal images: main
Time to compute quadratic signal images: main
Time to compute cubic signal images: main
Time per image (s)
Window length (s)
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.20
0.40
0.60
0.80
1.00

Classification

Model Architecture

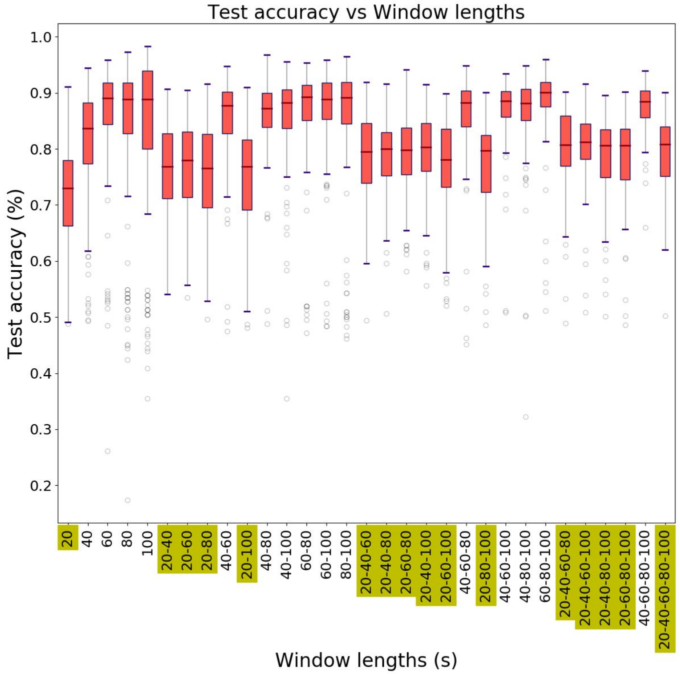
- Simple CNN
  - Focus on data representation rather than model tuning
- 3 channel 224x224 image
  - Secondary interpolation
  - Resizing an image scales the image in the frequency domain

Test Accuracy

- Using '0.20' during training generally lowered accuracy
- High standard deviations
  - Likely an effect of low snr
  - Large number of local minima and maxima
- Performed well where it shouldn't
  - 'Disconnected'
  - 'random'

Subject	0.20	0.40	0.60	0.80	1.00
disconnected_01	83.45	92.17	88.77	92.20	88.39
disconnected_03	78.59	82.44	85.56	86.73	91.37
disconnected_05	51.58	82.41	84.15	85.33	82.50
main	59.99	79.76	83.62	87.46	82.29
random	54.75	73.27	80.73	89.03	89.45

Table 7.4: Recorded Accuracy per Window Lengths



Questions?

Comments?

Future Work

- Custom EEG Board
- Active Electrodes
- Non-contact Electrodes

- Time-sequence Classification
- 3D Interpolation
- Transfer Learning
- User Authentication

Implementation Details
And
Design Patterns

Signal Generator

Trial Recorder

At the talk, the most valuable quantity is your audience's (i.e the committee's) response. In reality, it is the committee's questions and discussion that are the 'value added' for the defense. Your goal is to identify the most important contributions, techniques and results of your work to make the nature and value of the core of your work clear for the committee. Ideally, the talk is a tightly structured summary of your thesis/report that also provides a springboard for discussion.

Do not use an ‘overview’ slide. Rest assured - professors expect that you will provide an introduction, followed (in some order) by related work, methods, results, discussion, a conclusion and future work. Taking a couple of minutes of the talk to present a slide illustrating this does not engage the audience. It just reduces available time to talk about things that the committee does not already know about

In my experience, a better approach is to start with a simple example or illustration of the problem and main results, identify the main contribution/conclusions of interest, and then use these to structure the talk. I'll be hooked, whether I like it or not, because then I know what the talk is 'really' about, and then want to be taken through the details. In essence, this is similar to how trailers are used to motivate people to see a new movie

I suggest ’outlining’ the talk first - fill in the goals, contributions, and main findings, create slides for the main sections, etc. It’s easier to fill parts of a structure in, rather than create the talk from start to end, usually. There’s probably a bit of alternation here - outline a bit, fill in a few details, get stuck, try outlining a bit more, fill in more details, etc. The key idea here is to see the big picture - if you don’t know the form of your talk, you can’t pace the talk to emphasize the main points. Once you have a complete rough draft, then go ahead and do whatever feels natural to fill in the details. For myself, I tend to choose a section and ’polish it,’ and then move on to the next section. In the final stage, I make a number of passes over the complete talk to reorder topics, and remove or replace unimportant or awkward content.

Think carefully about where images, plots and graphs can communicate definitions, concepts, data, algorithms and results quickly. This is a very powerful way to include more content in a talk without taxing the audience. Well-chosen graphics can often help the committee immediately see a point faster and more clearly than you could present it in words alone (in particular, it allows you to show, rather than describe relationships and structure). One of my PhD advisors (Dorothea Blostein) once suggested drafting talks and papers by starting with the figures, which I’ve often found to be very useful.

As an example of using images to organize the presentation, I recently had a PhD student (Lei Hu) use section title slides that included images from the section about to be presented, which he would briefly summarize. This helped him engage the audience by foreshadowing the main ideas in a way that was easy for the audience to follow, and insured that they saw each of those images twice, making them easier to remember.