Associative Memories

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Associative Memories

- Motivation
  - Human ability to retrieve information from applied associated stimuli
    - Ex. Recalling one’s relationship with another after not seeing them for several years despite the other’s physical changes (aging, facial hair, etc.)
    - Enhances human awareness and deduction skills and efficiently organizes vast amounts of information
  - Why not replicate this ability with computers?
    - Ability would be a crucial addition to the Artificial Intelligence Community in developing rational, goal oriented, problem solving agents

Capacity Vs. Robustness Challenges

- In early memory models, capacity was limited to the length of the memory and allowed for negligible input distortion
  - Ex. Linear Associative Memory
- Recent years have increased the memory's robustness, but sacrificed capacity
  - J. J. Hopfield's proposed Hopfield Network
  - Capacity: $\frac{n}{2\log n}$, where n is the memory length
- Current research offers a solution which maximizes memory capacity while still allowing for input distortion
  - Morphological Neural Model
    - Capacity: essentially limitless (2^n in the binary case)
    - Allows for Input Distortion
    - One Step Convergence

Morphological Memories

- Formulated using Mathematical Morphology Techniques
  - Image Dilation
  - Image Erosion
- Training Constructs Two Memories: M and W
  - M used for recalling dilated patterns
  - W used for recalling eroded patterns
- M and W are not sufficient…Why?
  - General distorted patterns are both dilated and eroded
    - solution: hybrid approach
- Incorporate a kernel matrix, Z, into M and W
  - General distorted pattern recall is now possible!
    - Input $\rightarrow M_Z \rightarrow W_Z \rightarrow$ Output

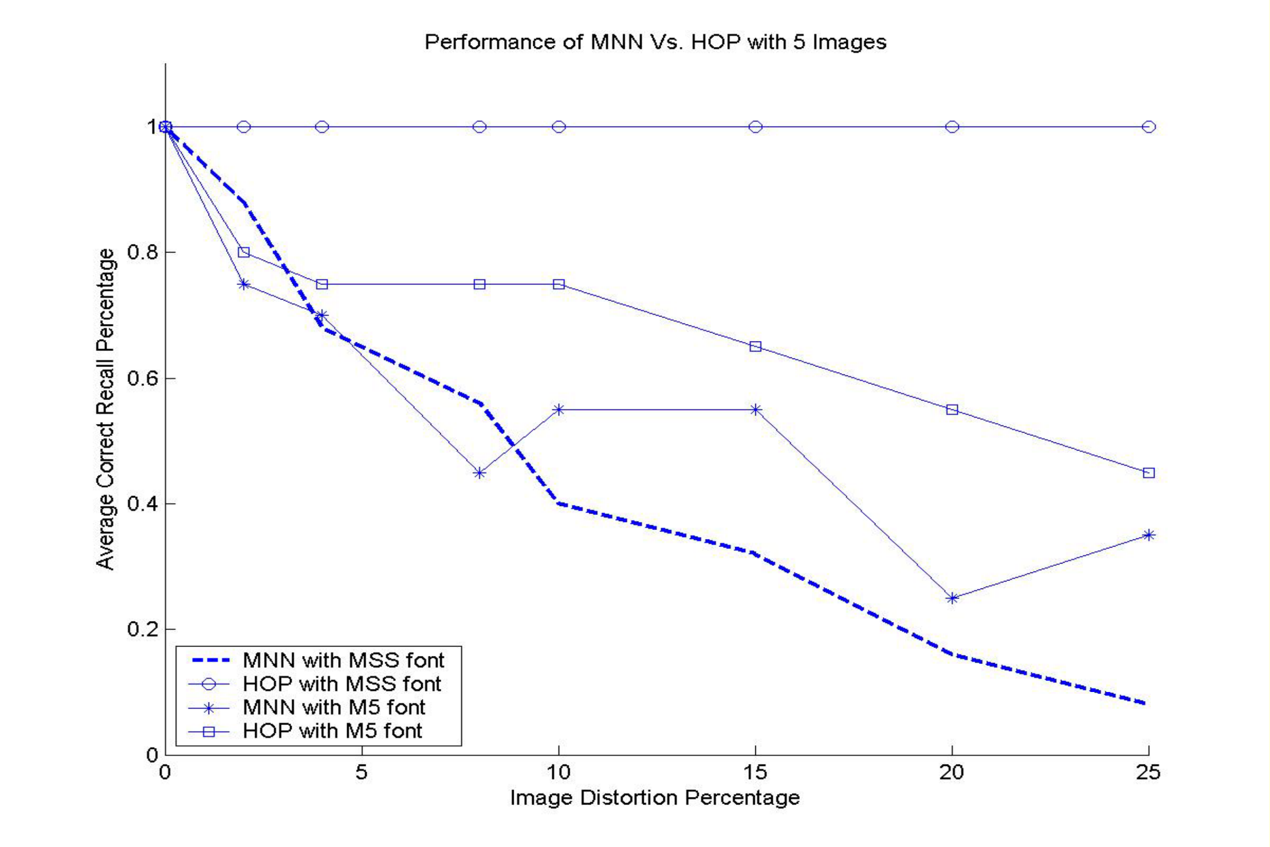
Improving Limitations

- Experiment
  - Construct a binary morphological auto-associative memory to recall bitmap images of capital alphabetic letters
    - Use Hopfield Model for baseline
    - Construct letters using Microsoft San Serif font (block letters) and Math5 font (cursive letters)
    - Attempt recall 5 times for each pattern for each image distortion at 0%, 2%, 4%, 8%, 10%, 15%, 20%, and 25%
    - Use different memory sizes: 5 images, 10, 26, and 52
    - Use Average Recall Rate per memory size as a performance measure, where recall is correct if and only if it is perfect

Results

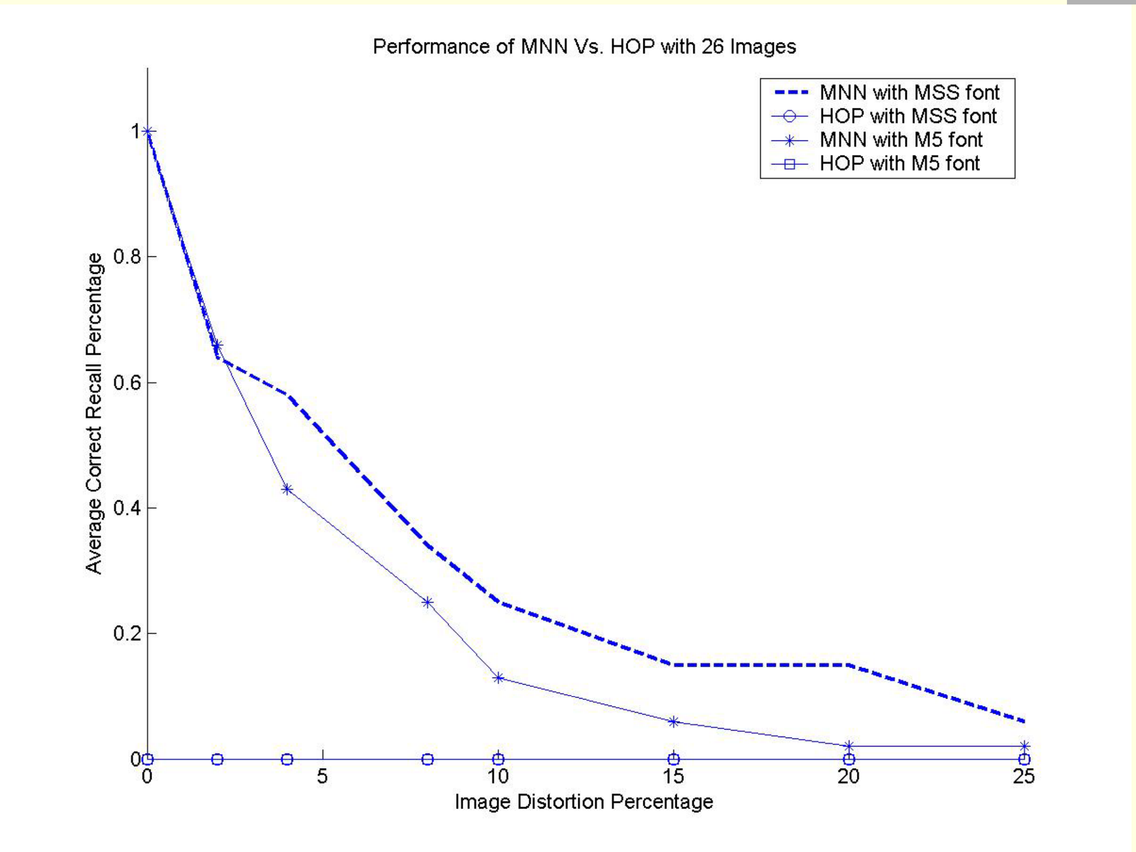
- Morphological Model and Hopfield Model:
  - Both degraded in performance as memory size increased
  - Both recalled letters in Microsoft San Serif font better than Math5 font
- Morphological Model:
  - Always perfect recall with 0% image distortion
  - Performance smoothly degraded as memory size and distortion increased
- Hopfield Model:
  - Never correctly recalled images when memory contained more than 5 images

Results using 5 Images



MNN = Morphological Neural Network
HOP = Hopfield Neural Network
MSS = Microsoft San Serif font
M5 = Math5 font

Results using 26 Images



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Summary

- The ability for humans to retrieve information from associated stimuli continues to elicit great interest among researchers
- Progress Continues with the development of enhanced neural models
  - Linear Associative Memory → Hopfield Model → Morphological Model
- Using Morphological Model
  - Essentially Limitless Capacity
  - Guaranteed Perfect Recall with Undistorted Input
  - One Step Convergence