Connectome Mapping: Shape-Memory Network via Interpretation of Contextual Semantic Information

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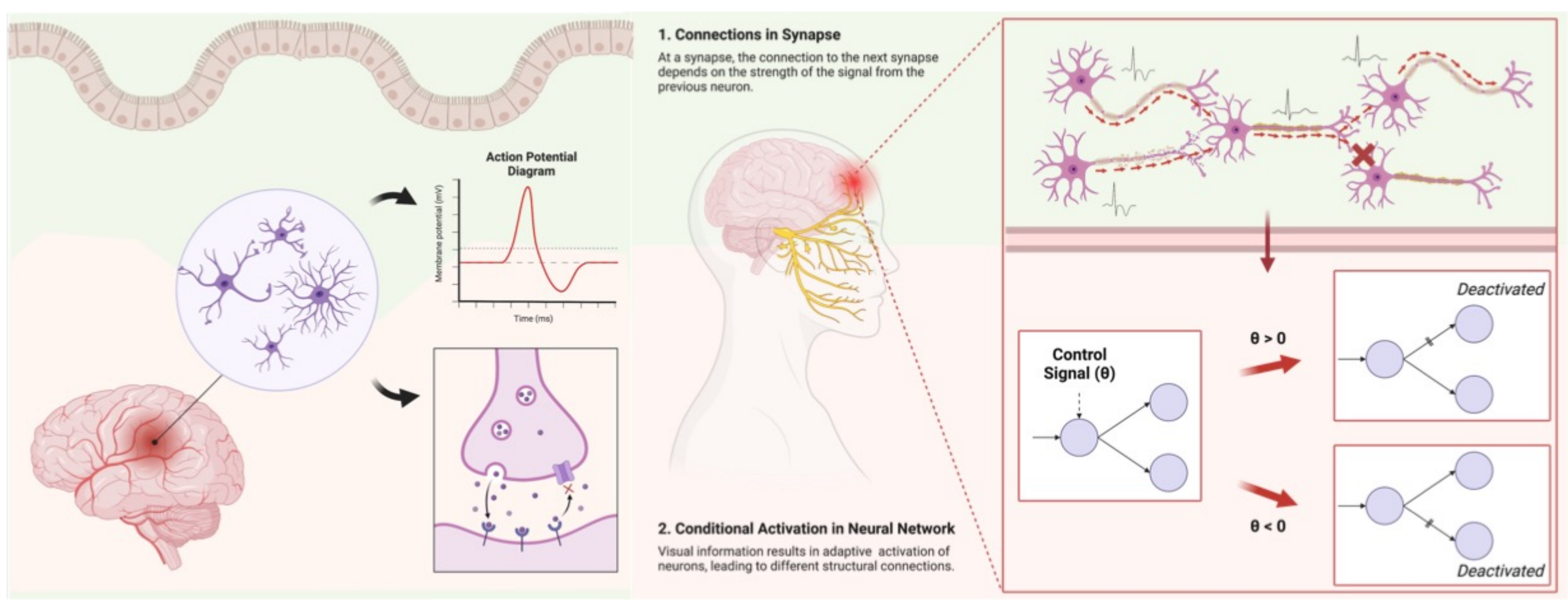
I. Abstract

Contextual semantic information plays a pivotal role in the brain's visual interpretation of the surrounding environment. When processing visual information, electrical signals within synapses facilitate the dynamic activation and deactivation of synaptic connections, guided by the contextual semantic information associated with different objects. In the realm of Artificial Intelligence (AI), neural networks have emerged as powerful tools to emulate complex signaling systems, enabling tasks such as classification and segmentation by understanding visual information. However, conventional neural networks have limitations in simulating the conditional activation and deactivation of synapses, collectively known as the connectome, a comprehensive map of neural connections in the brain. Additionally, the pixel-wise inference mechanism of conventional neural networks failed to account for the explicit utilization of contextual semantic information in the prediction process. To overcome these limitations, we developed a novel neural network, dubbed the Shape Memory Network (SMN), which excels in two key areas: (1) faithfully emulating the intricate mechanism of the brain's connectome, and (2) explicitly incorporating contextual semantic information during the inference process. The SMN memorizes structure suitable for contextual semantic information and leverages this structure at the inference. The structural transformation emulates the conditional activation and deactivation of synaptic connections within the connectome

II. Introduction



- **Contextual semantic information** is essential features for the brain's interpretation of visual stimuli.
- In the human brain, synaptic connections are dynamically activated & deactivated based on context, forming the connectome.

- **Challenge in Existing Neural Networks**
  ① Conventional AI neural networks struggle to emulate this conditional connectivity and often neglect contextual features during inference.
  ② Lack of dynamic synaptic modeling (i.e., no connectome-level control).
  ③ Inference is typically pixel-wise, with limited context integration.

- **Novelty & Contributions**
  ① Emulates **brain-like connectome** activation patterns.
  ② Explicitly incorporates contextual semantic information during inference with **control neurons**.
  ③ Learns and stores structure optimal for context → **reuses at inference.**
  ④ Structural transformation = synaptic on/off switching.

- **SMN bridges neuroscience and AI** by faithfully mimicking the **brain's dynamic synaptic behavior**, achieving **context-aware high-performance vision tasks**.

III. Methods

Algorithm 1: Fine-tuning and Inference of the Shape-Memory Network

Input : sample x_i in test-set ($\mathcal{X} \subset \mathbb{R}^{H\times W\times 3}$), such that $x_i \in \mathcal{X}$, where H and W are height and width, respectively, and the pre-trained SMN (M).

Output : Predicted segmentation map ($y_i \in \mathcal{Y} \subset \mathbb{R}^{H\times W\times C}$) corresponding to input (x_i), where C is the number of category.

Assumption : $\mathcal{X} = \bigcup_i^N \mathcal{X}_i$ where N is the number of subset. $\bigcap_i^N \mathcal{X}_i = \emptyset$, indicating that the $\mathcal{X}_i$ represents distinct domain.

$\bar{y}^i \leftarrow \mathbb{D}\Big(\mathbb{E}(I_i); [\sum_k^C W_k^c \sum_{x,y} \mathbb{E}(I_i)] \cdot \mathcal{M}\Big)$; /* Predict pseudo-label */

$\bar{\mathcal{C}}_1 \leftarrow -\bar{y}^i \log \bar{y}^i$; /* Entropy-map by segmentation pipeline */

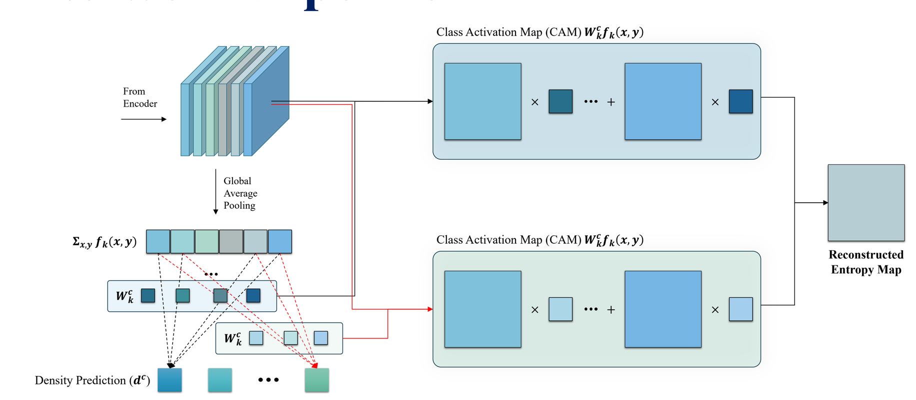
$\bar{\mathcal{C}}_2 \leftarrow -\sum_c^C \bar{d}^c(I^i)\|_{h,w} \log \bar{d}^c(I^i)\|_{h,w}$; /* Entropy-map by EM algorithm */

$\mathcal{M}' \leftarrow \underset{\mathcal{M}}{\mathrm{argmin}}\mathcal{L}_{\mathrm{ssim}}(\mathcal{E}(I^i), \mathrm{EM}(I^i))$; /* Fine-tune $\mathcal{M}$ */

$y^i \leftarrow \mathbb{D}\Big(\mathbb{E}(I_i); [\sum_k^C W_k^c \sum_{x,y} \mathbb{E}(I_i)] \cdot \mathcal{M}'\Big)$;

[Network Architecture of SMN]

Network Pipeline



Segmentation Map: $Y_i = \mathbb{D}\Big(\mathbb{E}(I_i); [\sum_k^C W_k^c \sum_{x,y} \mathbb{E}(I_i)] \cdot \mathcal{M}\Big)$

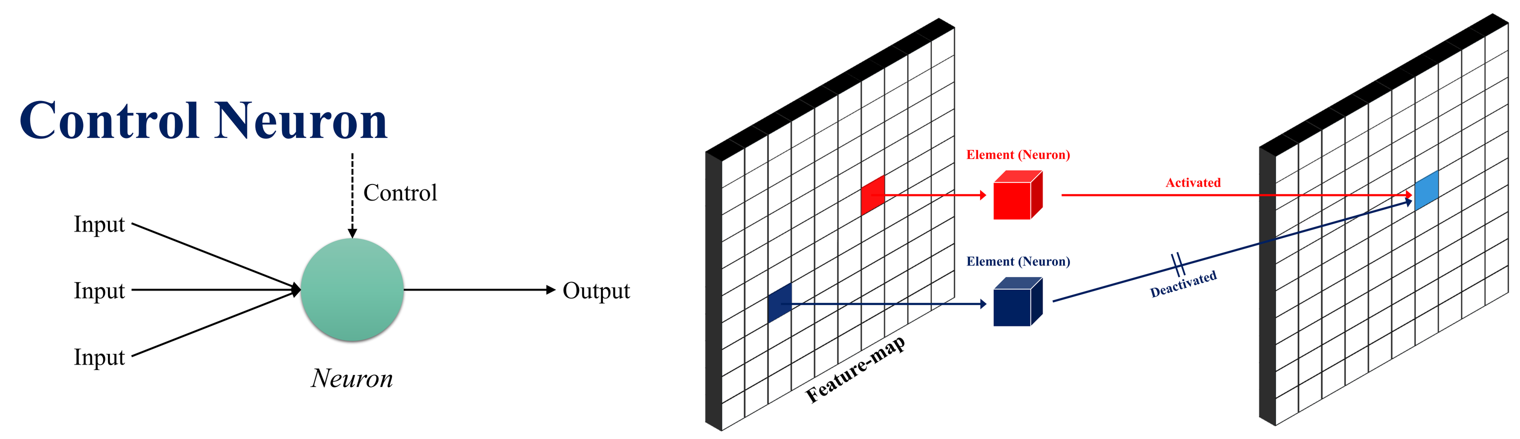
Density-regression: $d^c(I^i) = \sum_k W_k^c \sum_{x,y} \mathbb{E}(I_i)$

Class Activation Map: $\mathbf{C}^c(I^i) = \sum_k W_k^c f_k = \sum_k W_k^c \mathbb{E}(I^i)$

Entropy-map: $\mathcal{E}(I^i) = -Y_i \log Y_i$

$\mathrm{EM}(I^i)\|_{h,w} = -\sum_c^C \bar{d}^c(I^i)\|_{h,w} \log \bar{d}^c(I^i)\|_{h,w}$ where $\bar{d}^c(I^i)\|_{h,w}$

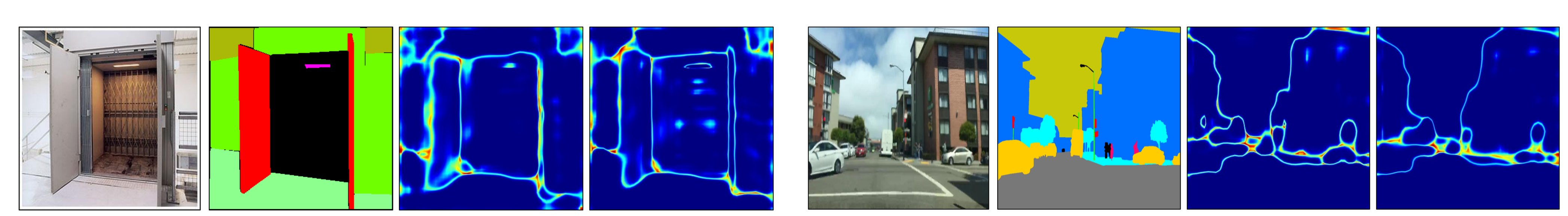
Control Neuron

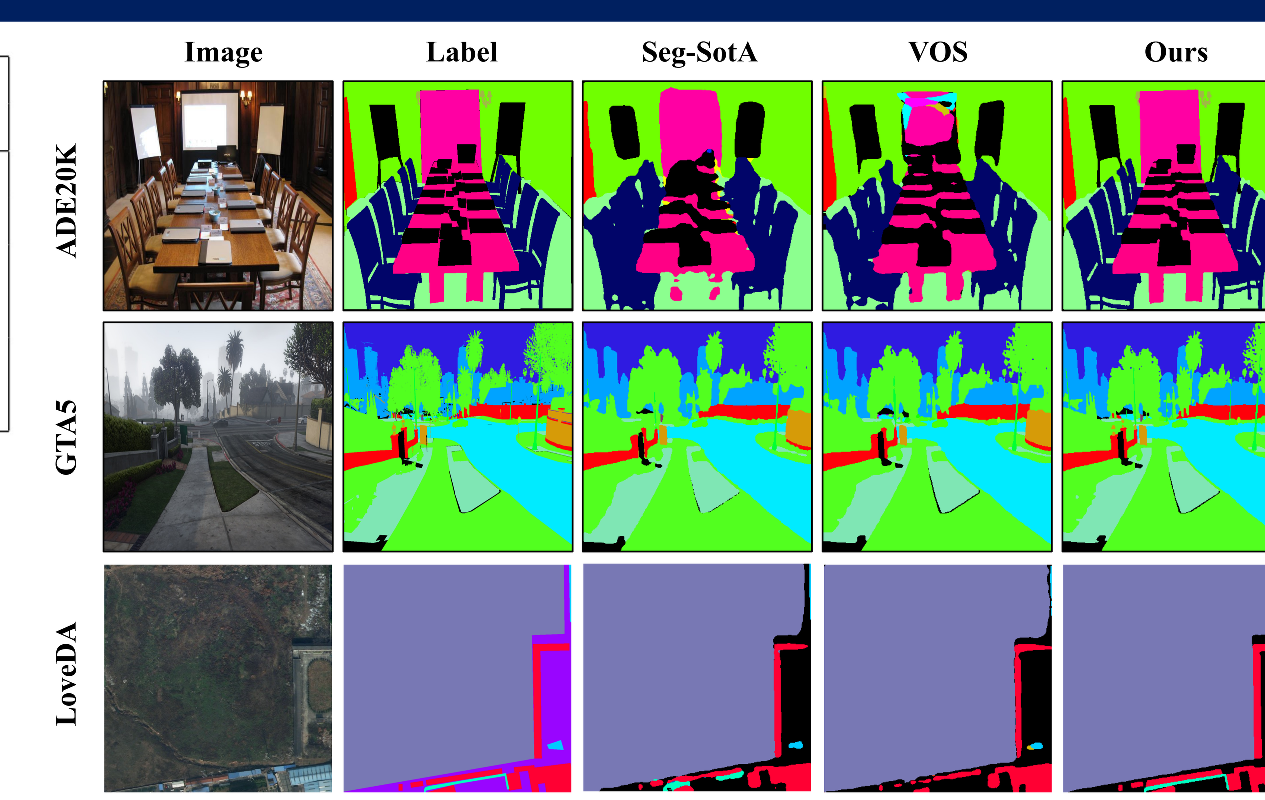


$$s_n^{\mathrm{out}} = s^{\mathrm{in}} * \Big(\sigma\big(-2\alpha_1(g(s_n^{\mathrm{out}}; \mathcal{F}) - m_{\mathcal{F}} + z_k * \mathrm{v}_{\mathcal{F}})\big) + \sigma\big(-2\alpha_2(s^{\mathrm{ct}} - \lambda_n)\big)\Big)$$

IV. Experiments & Conclusion

	Baseline Model		Multi-Path		Seg SotA		VOS		Ours	
	U-Net	SegFormer	LADDERNet	MPDNet	InternImage	BEiT-3	Xmem	AOST	Ours - SA	Ours
Inria	62.96%	67.97%	64.77%	64.51%	68.60%	66.69%	64.85%	69.30%	68.60%	**72.72%**
LoveDA	47.71%	51.33%	49.66%	48.25%	49.81%	49.63%	51.29%	50.57%	50.40%	**54.28%**
ADE20K	42.61%	46.72%	52.66%	44.30%	51.04%	51.67%	44.88%	52.06%	48.84%	**55.76%**
Youtube-VOS	77.12%	81.07%	86.04%	83.57%	85.13%	86.67%	83.36%	87.09%	85.66%	**88.66%**
BDD100K	36.69%	42.59%	41.13%	40.03%	47.25%	39.85%	42.69%	43.09%	43.81%	**48.83%**
GTA5	65.84%	65.99%	68.64%	70.69%	70.94%	70.90%	68.00%	71.06%	69.07%	**76.58%**





V. Acknowledgement

This work was partially supported by the 2024 innovation base artificial intelligence data convergence project project with the funding of the 2024 government (Ministry of Science and ICT) (S2201-24-1002), and by the Korea Research Institute for Defense Technology Planning and Advancement (KRIT) through the Korea Government (MND) under Grant (R230206). This work was partially supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government Ministry of Science and ICT (MSIT) (No. RS-2024-00358888).