A Hybrid Compact Neural Architecture for Visual Place Recognition

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Agenda

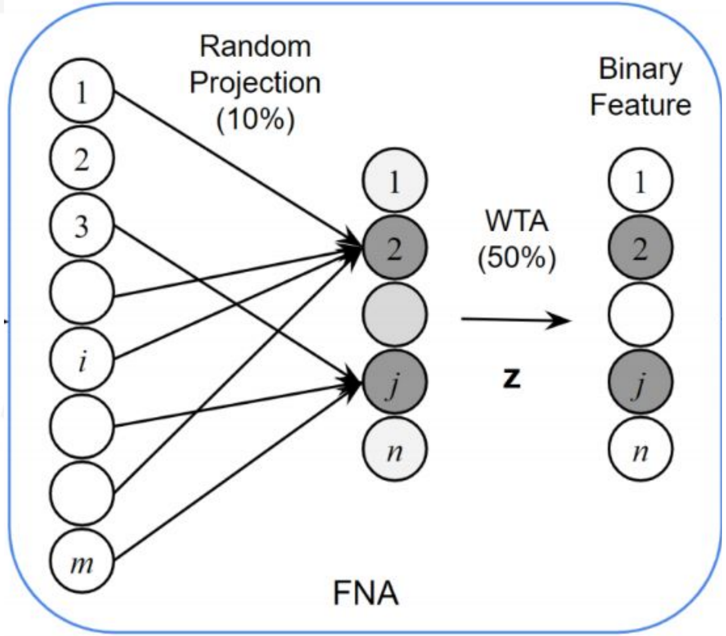
- Introduction
- Network Architecture
- Dataset
- Implementation details
- Tests performed
- Results
- Network Improvements
- Conclusion

Introduction

- Visual Place Recognition (VPR) is the process of matching one view of a specific location with another.
  - Differences in weather, lighting, perspective, etc.
- Modern solutions require large, complex neural networks/algorithms.
  - Too slow and computationally intensive to be practical
- Biologically inspired systems can be leveraged to improve performance.
- This project aims to perform VPR using FlyNet, a compact neural network based on the brain of a fly.

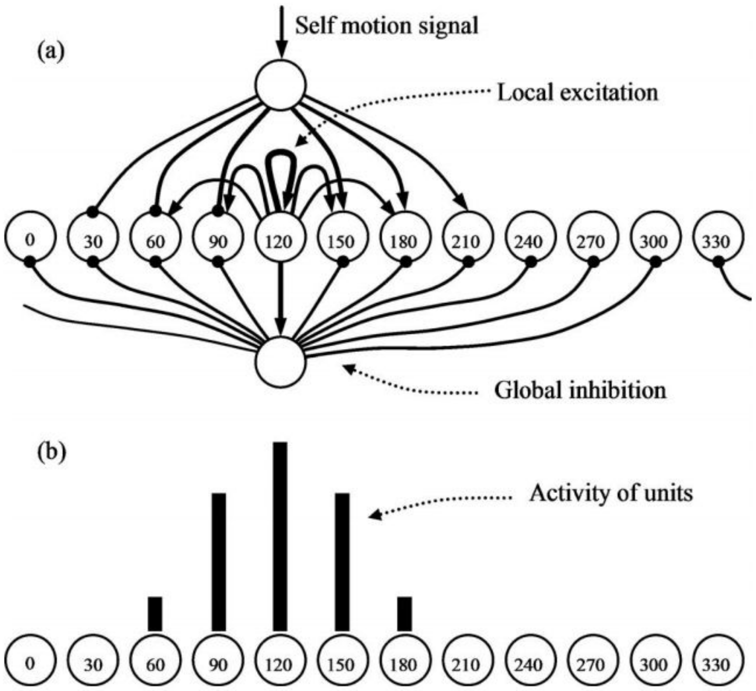
FlyNet

- Based on behavior from the olfactory system of a fruit fly.
- The FlyNet architecture consists of 3 layers.
- A random projection matrix connects the input layer randomly with the hidden layer.
- Finally, We obtain a binary feature vector using a winner takes all approach.



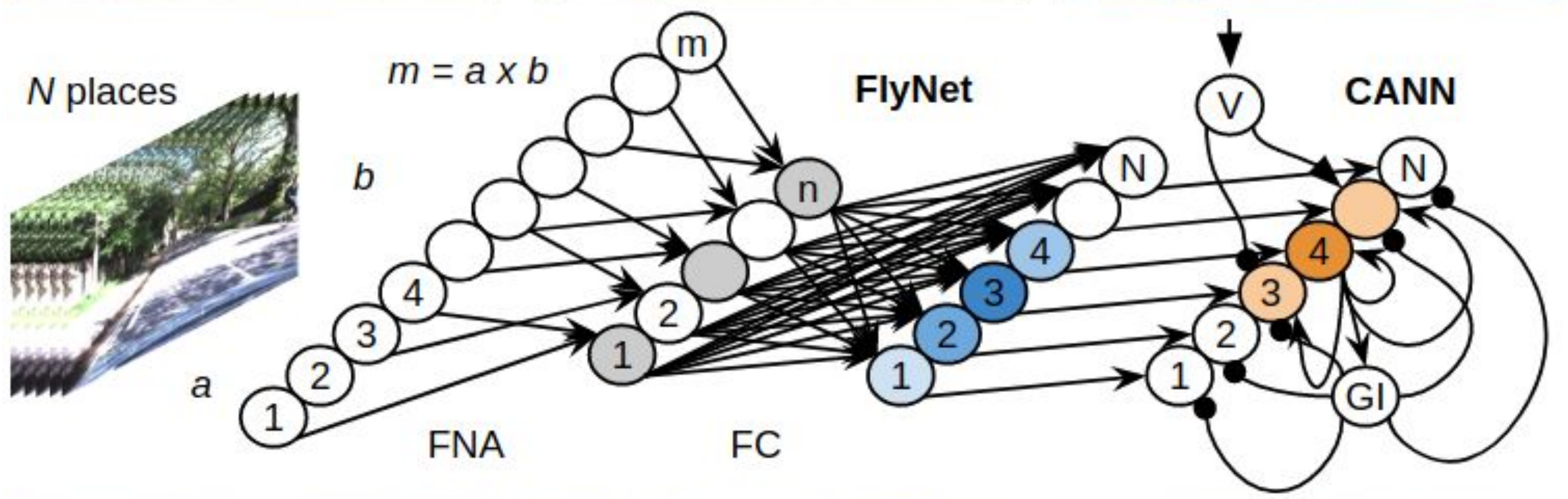
Continuous Attractor Neural Networks (CANNs)

- CANNs model continuous physical spaces by using recurrent connections between the neurons which reflect the distance between the neurons in the state space
- Each unit excites itself and units near itself while inhibiting all other cells
- The figure explains CANN using head direction space of an animal (RatSlam paper)
- In the figure, arrows are used to show excitation and rounds represent inhibition
- The figure is for a head direction of 120 degrees



FlyNet + CANN

- Creating a hybrid network greatly improves VPR performance
- The output of *FlyNet* is directly fed into the CANN



Dataset

- Nordland Railcar: Consists of images from traversal of a train in Norway
- 4 different traversals were taken for 4 different seasons: Spring, summer, fall, winter.
- The original dataset consists of over 14000 images but we use 1000 images for each season in our experiments.
- Images for Summer were used for training and images for fall and winter for testing.

Summer

Fall

Winter

Implementation details (FlyNet)

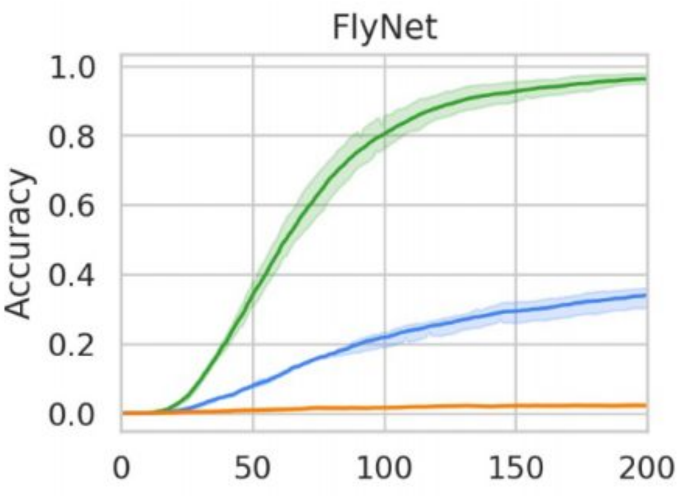
- Data preprocessing
  - Convert images to grayscale
  - Pixel values normalized between 0 and 1
  - Image size is reduced to 32 x 64
- FlyNet receives the input image which then passes through random projection layer with a hidden size of 64. Random projection is set at 10%
- The output of the random projection layer is converted into the binary feature vector by the winner-takes-all mechanism. We use a WTA value of 50%.
- So, the neurons with scores in the the top 50% are set to 0 and rest to 0.
- These outputs go through a fully connected layer of 1000 hidden units which acts as the classifier for the FlyNet.
- The output is filtered using CANN during inference.
- The coding is done in PyTorch (Python)

Tests Performed

- *FlyNet* Hyperparameter tuning
  - Testing the performance of *FlyNet* when trained at various epochs
- Creating a *FlyNet* + CANN Hybrid Network
  - Testing the performance versus *FlyNet* by itself and other competing network types
- Random Projection Ratio Manipulation
  - Testing the behavior of different random projection ratios for the input connection of *FlyNet*
- Comparing the performance of single-frame Flynet with other neural networks
  - Multi-layer perceptron (with and without dropout), CNNs, etc.

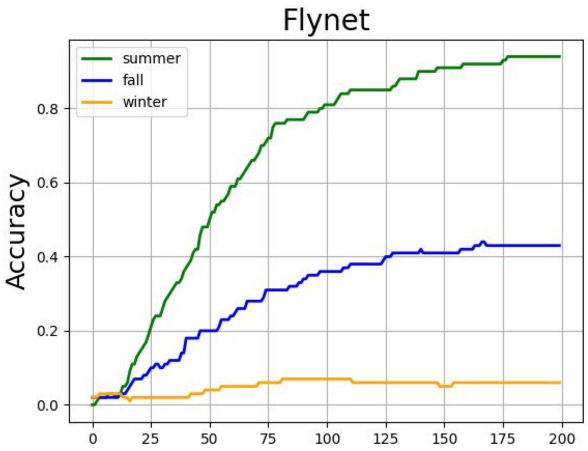
FlyNet Hyperparameter Tuning Results

Original Results:



# of Epochs

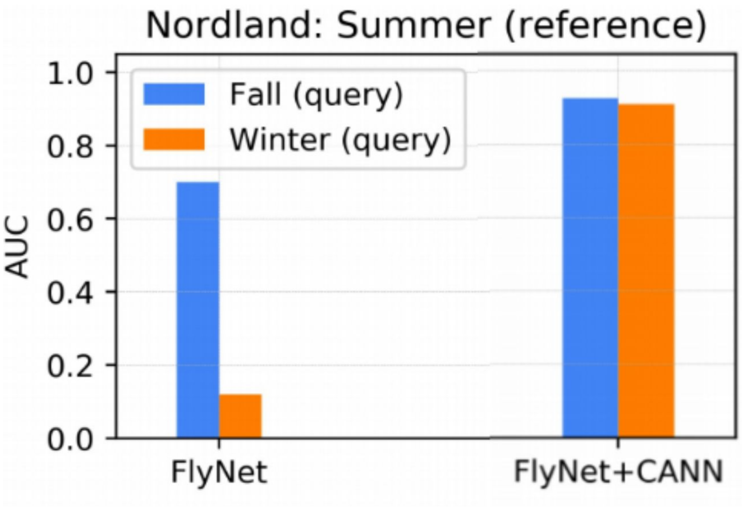
Our Results



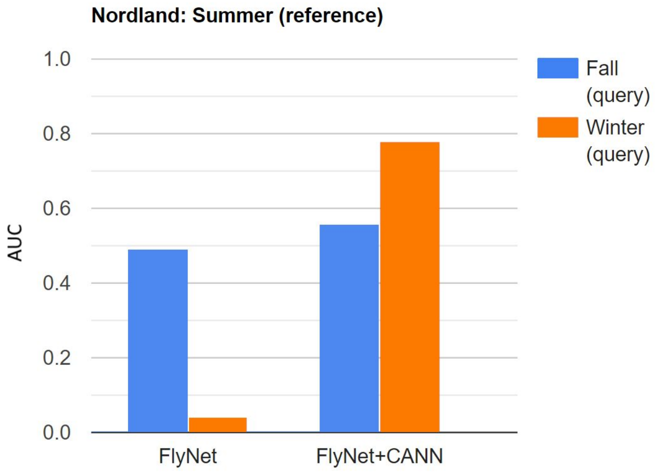
# of Epochs

CANN Hybrid Network Results

Original Results:

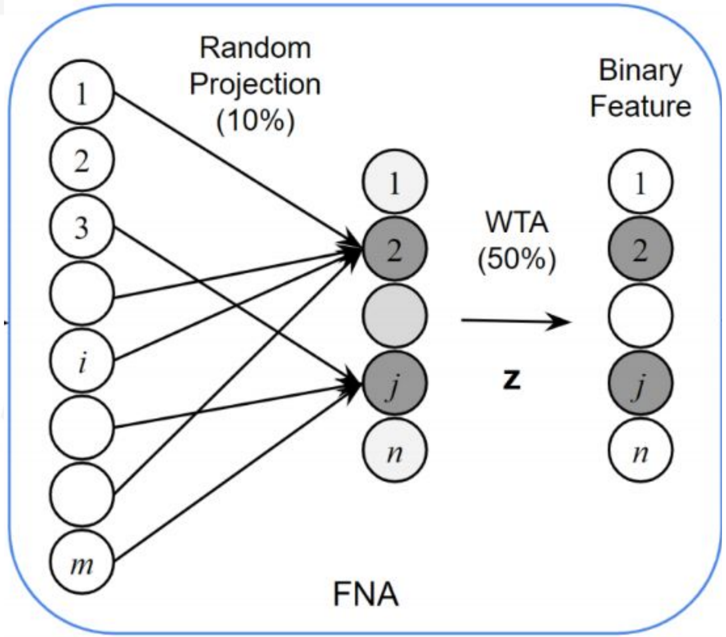


Our Results:

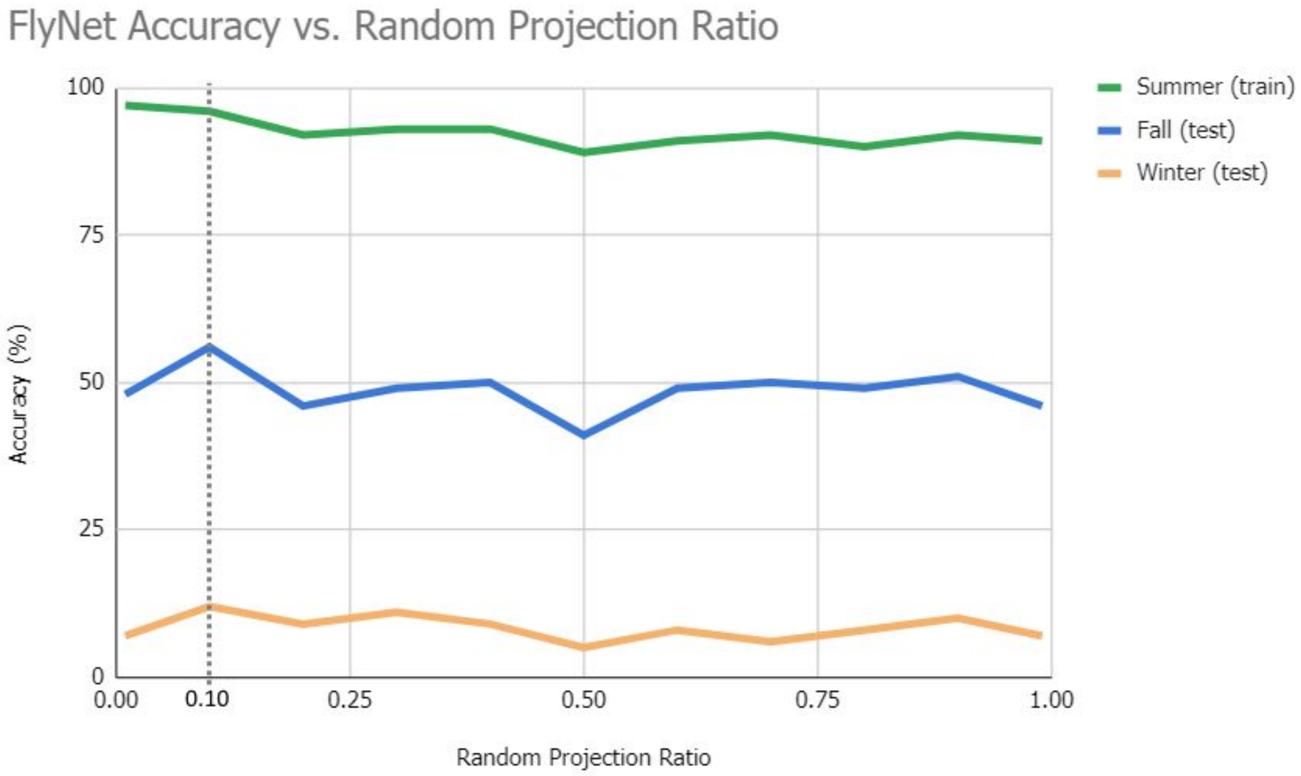


Random Projection Ratio Manipulation

- The input layer of *FlyNet* is randomly projected onto the WTA circuit
- Random Projection Ratio is 10% in paper
- Test 1-100% projection ratio
- Achieved best results with a random projection ratio of 10%

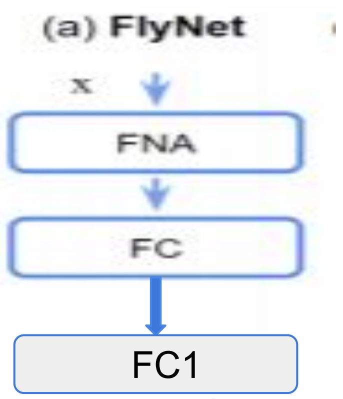


Random Projection Ratio Manipulation Results



Improved Flynet Architecture

- We introduced a new FC layer in between the fna and fc layer of the Flynet network.
- Tested on various different hyperparameters for better results and achieved best results on :
  Lr : 0.005, Random Projection: 10%, WTA : 50%, hidden_size = (64, 1000)
- New Training Accuracy - 98%
- Original (Paper) Training Accuracy - 96%



Conclusion

- FlyNet performs VPR quickly and efficiently underscoring the efficacy of biologically inspired computing with VPR
- FlyNet+CANN was implemented somewhat successfully and resulted in a drastic decrease of false positives for the winter test dataset.
- FlyNet, when compared with other neural networks, perform on par while having a lot less parameters.
- Changing the random projection matrix or the WTA parameter from the values in the paper did not report any improvement in performance.
- We propose a improved version of the FlyNet with better performance on the testing sets.

Future Work

- Further work on CANN to achieve matching performance with the original paper
- Exploration of other insect brains for VPR
- Test the viability of other hybrid networks based on FlyNet

References

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Thank you!

Questions?