

MeshRunner: Improving MeshWalker

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Background



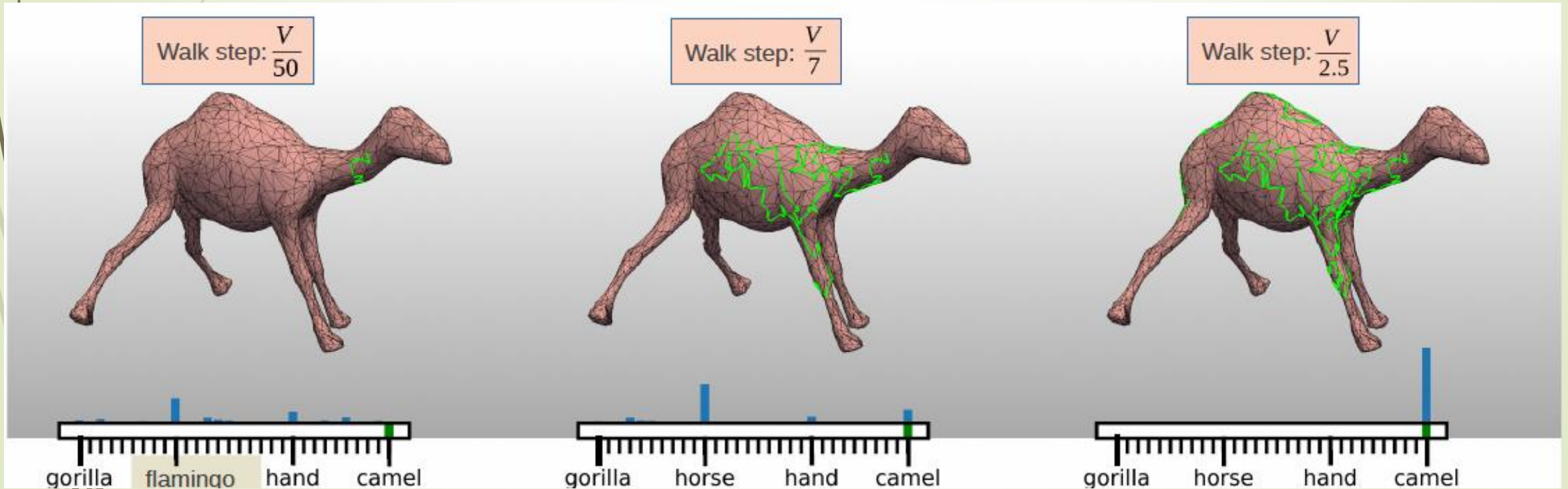
Reminder – what is MeshWalker?

- Apply Deep Learning directly on meshes
- Perform random walks on the mesh's surface and feed it to an RNN
- Use the RNN's hidden state to represent the mesh
- Perform classification (or segmentation) over the representation



Visualization

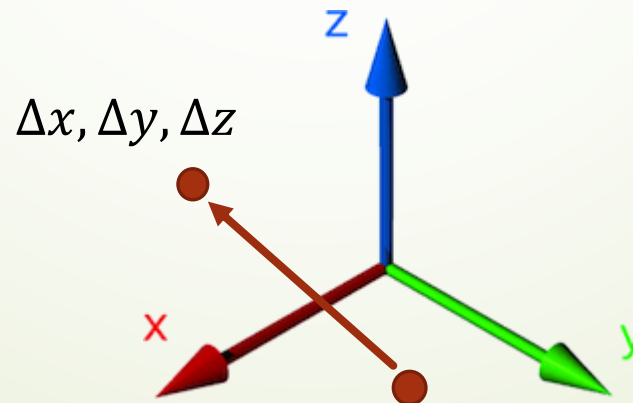
V – total number of vertices



What is a walk?

Walk Generation

- Start with a random vertex in the mesh
- Iteratively adding vertices
 - next vertex \leftarrow randomly chosen from the **unvisited** adjacent vertices
 - If none exist, go back (Backtracking)
 - If stuck, **jump** to a new random vertex



SHREC11 dataset

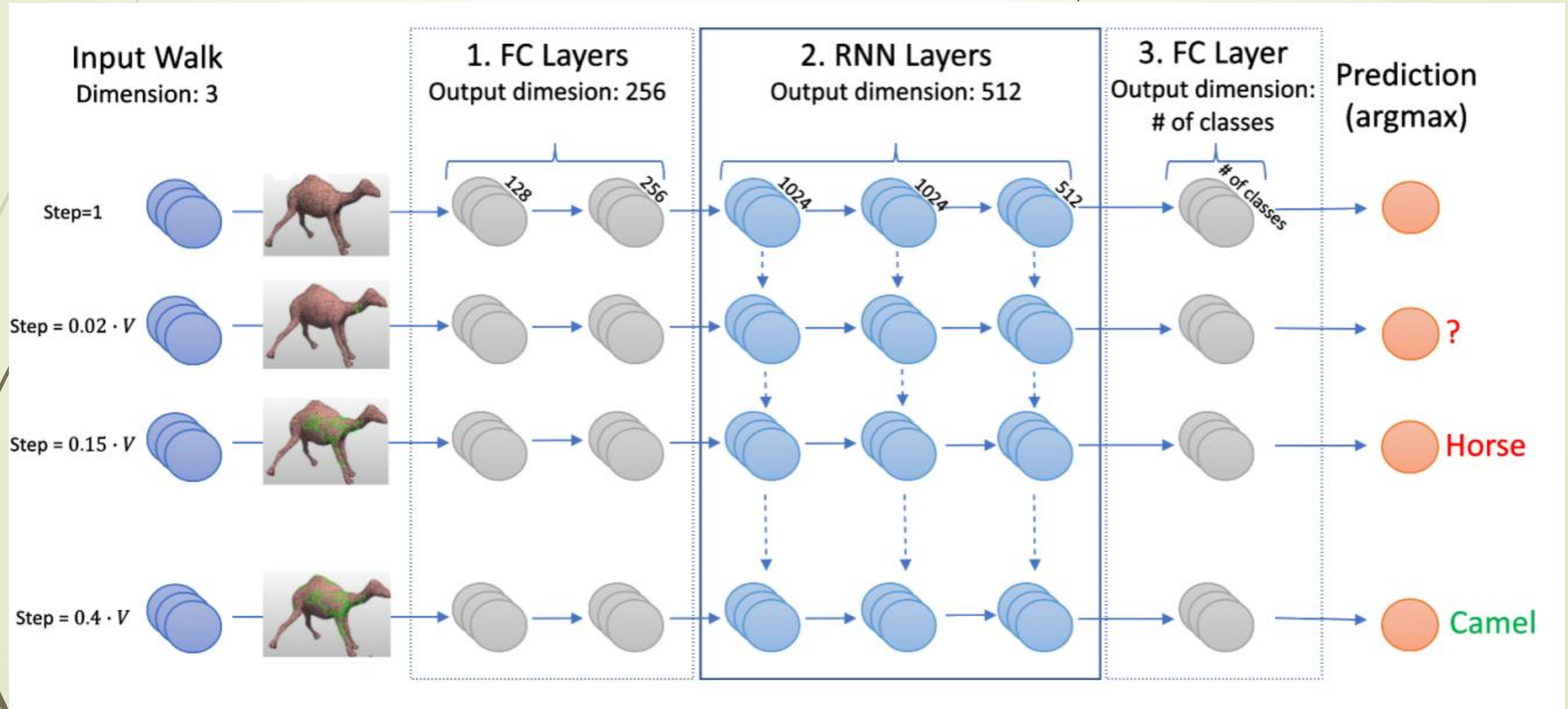
- Relatively simple mesh dataset
- Consists of 30 classes, 20 examples per class
- After simplification, the meshes contain 250 vertices



Architecture

Network depth

Steps in the walk

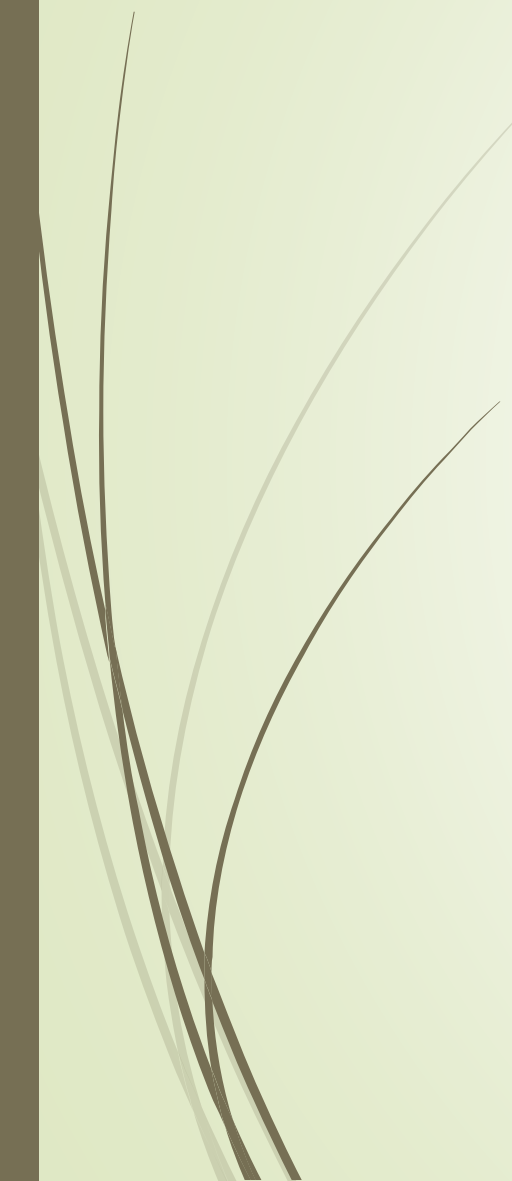


Our Approach



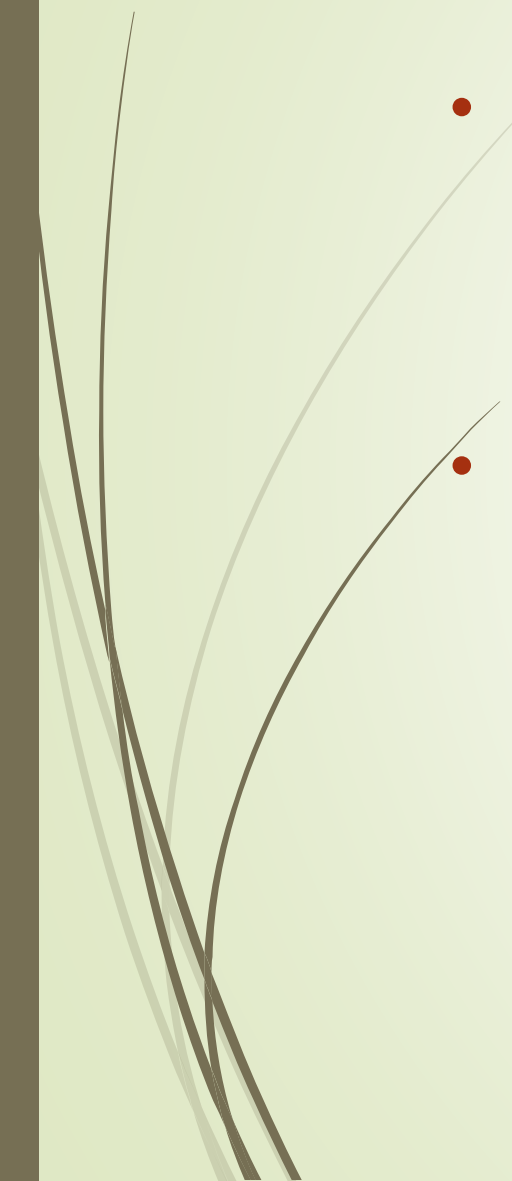


Our approach

- Improved walk generation
 - Choose starting point by analyzing saliency
 - Apply skips, jumps and ordering
 - Improved walk representation
 - Attention based information exchange between walks
- 



Exploring the Walk Generation

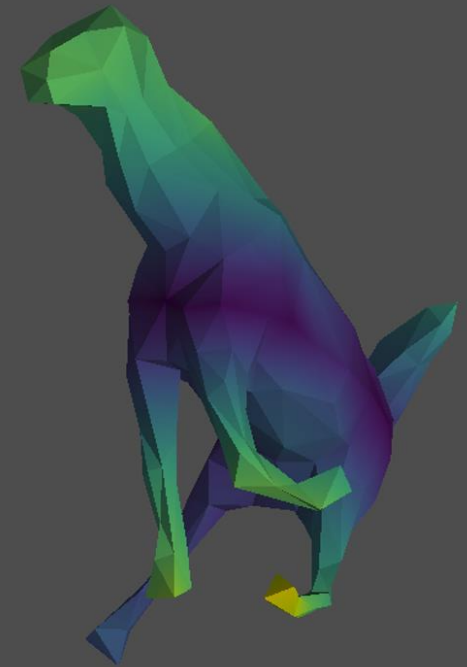
- What is a good walk?
 - Focus on important areas
 - High mesh coverage
 - Limited Resources:
 - Running Time
 - Walk Length (RNN)
- 

Walk Generation - Saliency

- A heatmap of the mesh vertices
- Highlights the informative parts of the topology
- Used to improve the random vertex choice
- Our implementation is based on [the Mesh Saliency paper](#)

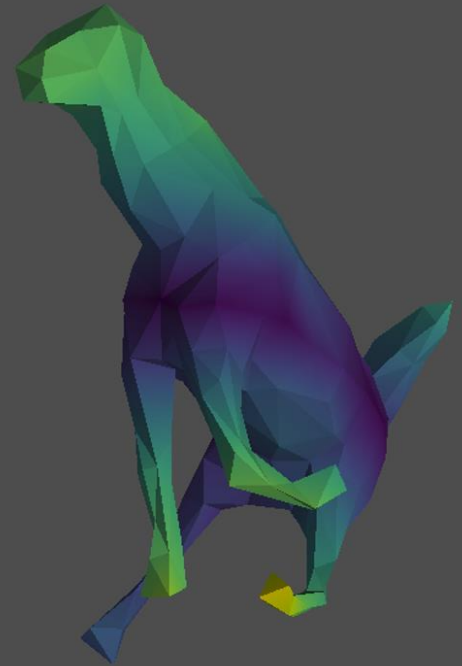
$$G(\mathcal{C}(v), \sigma) = \frac{\sum_{x \in N(v, 2\sigma)} \mathcal{C}(x) \exp[-\|x - v\|^2 / (2\sigma^2)]}{\sum_{x \in N(v, 2\sigma)} \exp[-\|x - v\|^2 / (2\sigma^2)]}$$

$$\mathcal{S}(v) = |G(\mathcal{C}(v), \sigma) - G(\mathcal{C}(v), 2\sigma)|$$



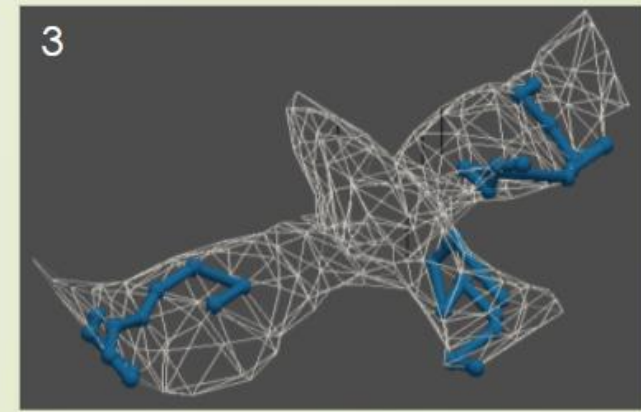
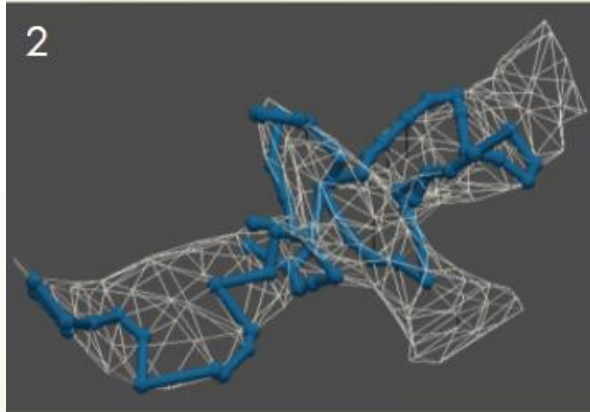
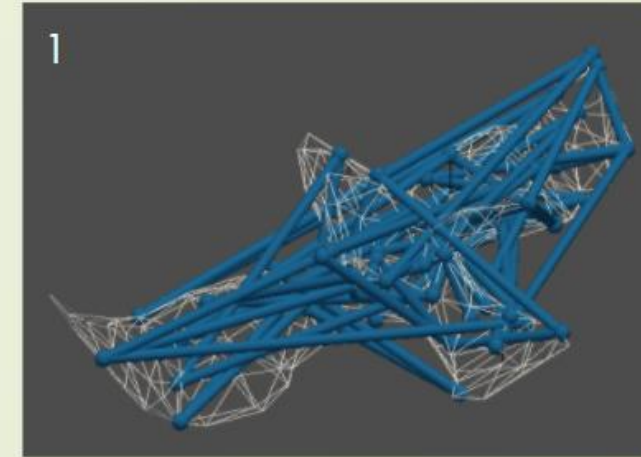
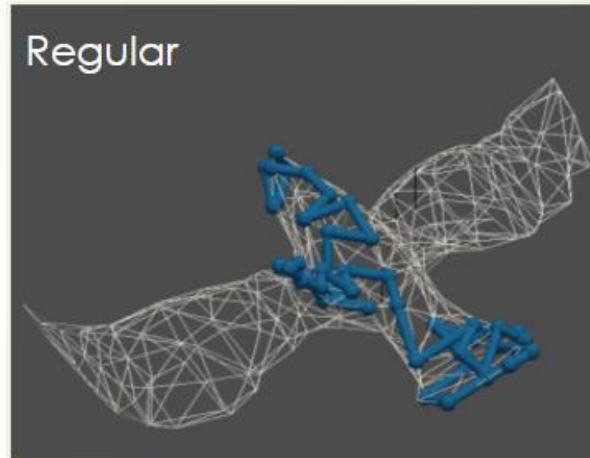
Saliency - Implementation Issues

- Radius
- Temperature
- Performance



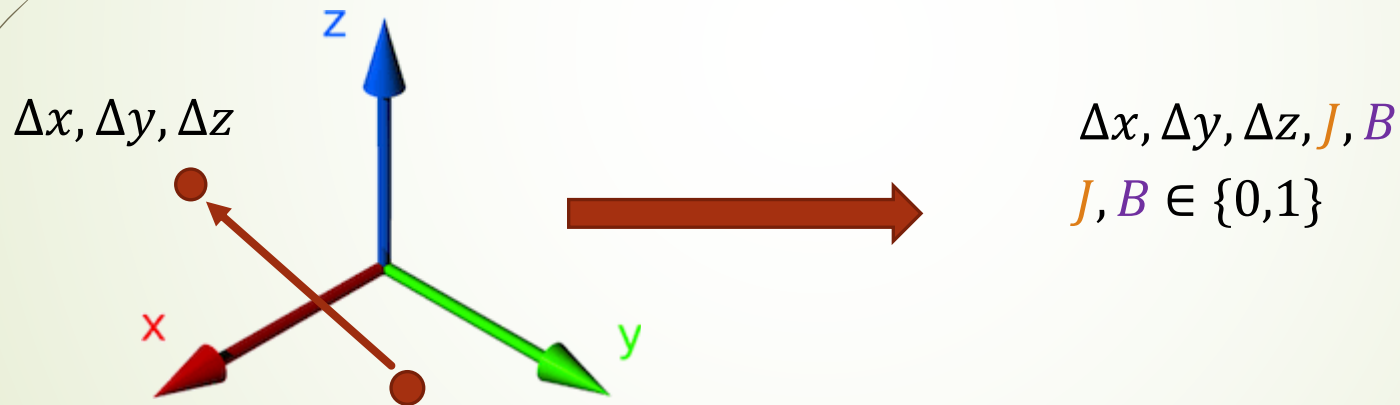
Exploring the Walk Generation

- Random Vertices(1)
- Skips(2)
- Jumps(3)
- Fixed sorting order
 - Inspired by [Polygen \(DeepMind, 2021\)](#)
 - Completely ignore edges



Improved Walk Representation

- Inform the network about jumps or backtracking



Information exchange between walks



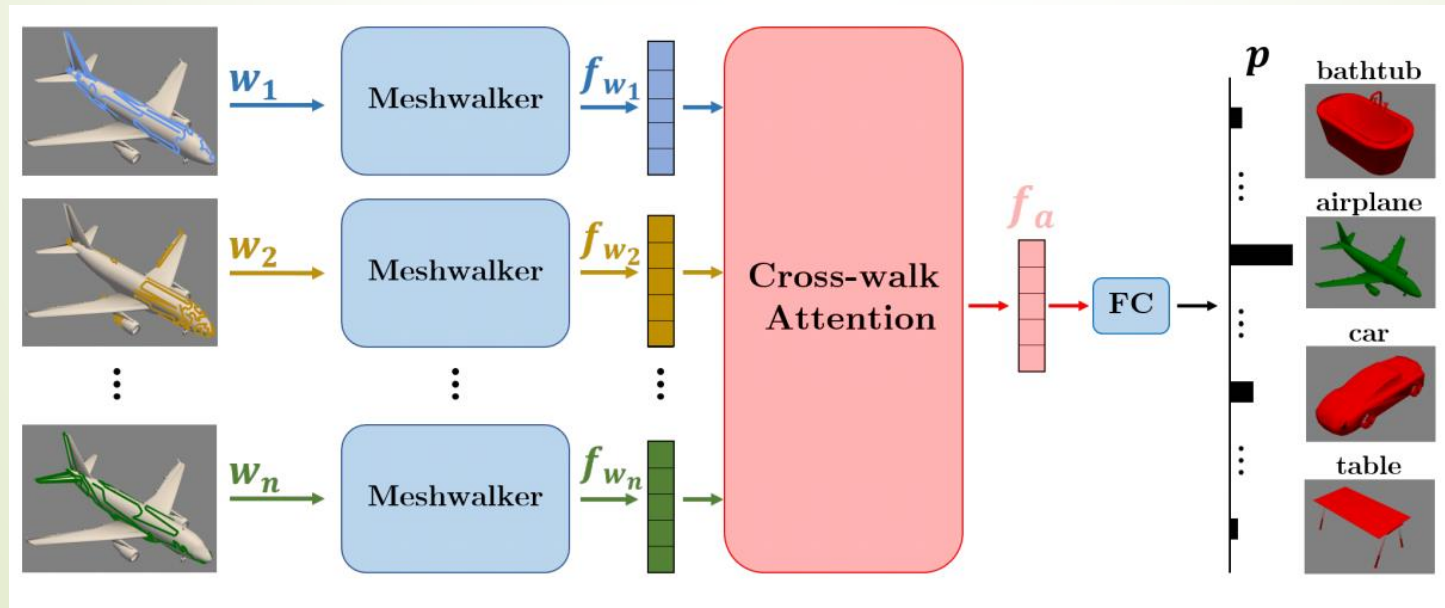


Previous approaches - MeshWalker

- Training - No information exchange
- Inference
 - Each walk produces a vector of probabilities to belong to the different classes (**dim=30**)
 - These vectors are **averaged** to produce the final result

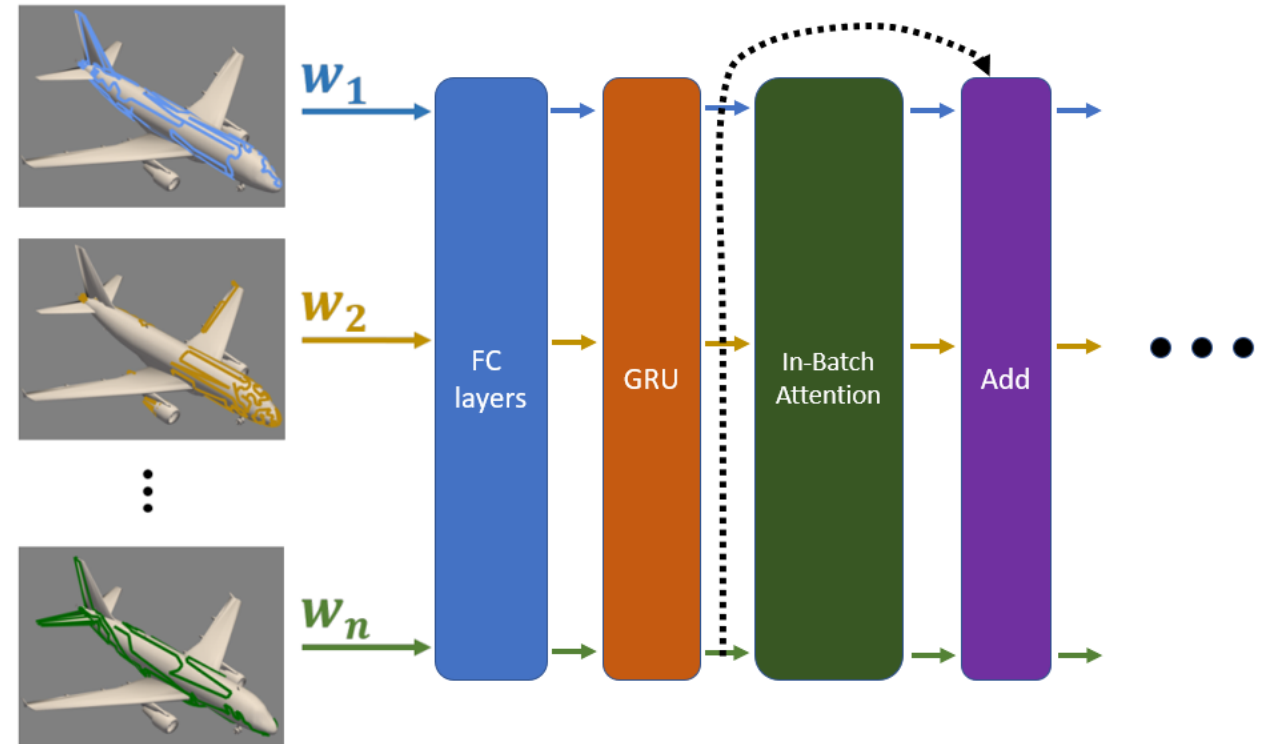
Previous approaches - AttWalk

- Each walk produces a feature vector (**dim=512**)
- Uses Many-to-One **attention** to generate a single feature vector (no code yet)



Our Approach – In-Batch Attention

- Integrating information exchange into the model
- Different walks are aware of each other
 - As **they progress**, not just at the end
 - Both in training and inference





Challenges

- Dataset (SHREC11):
 - Mesh size
 - 100% classification acc
- Tailored design choices
- Randomness
- Hyper-Parameter strategy

Results



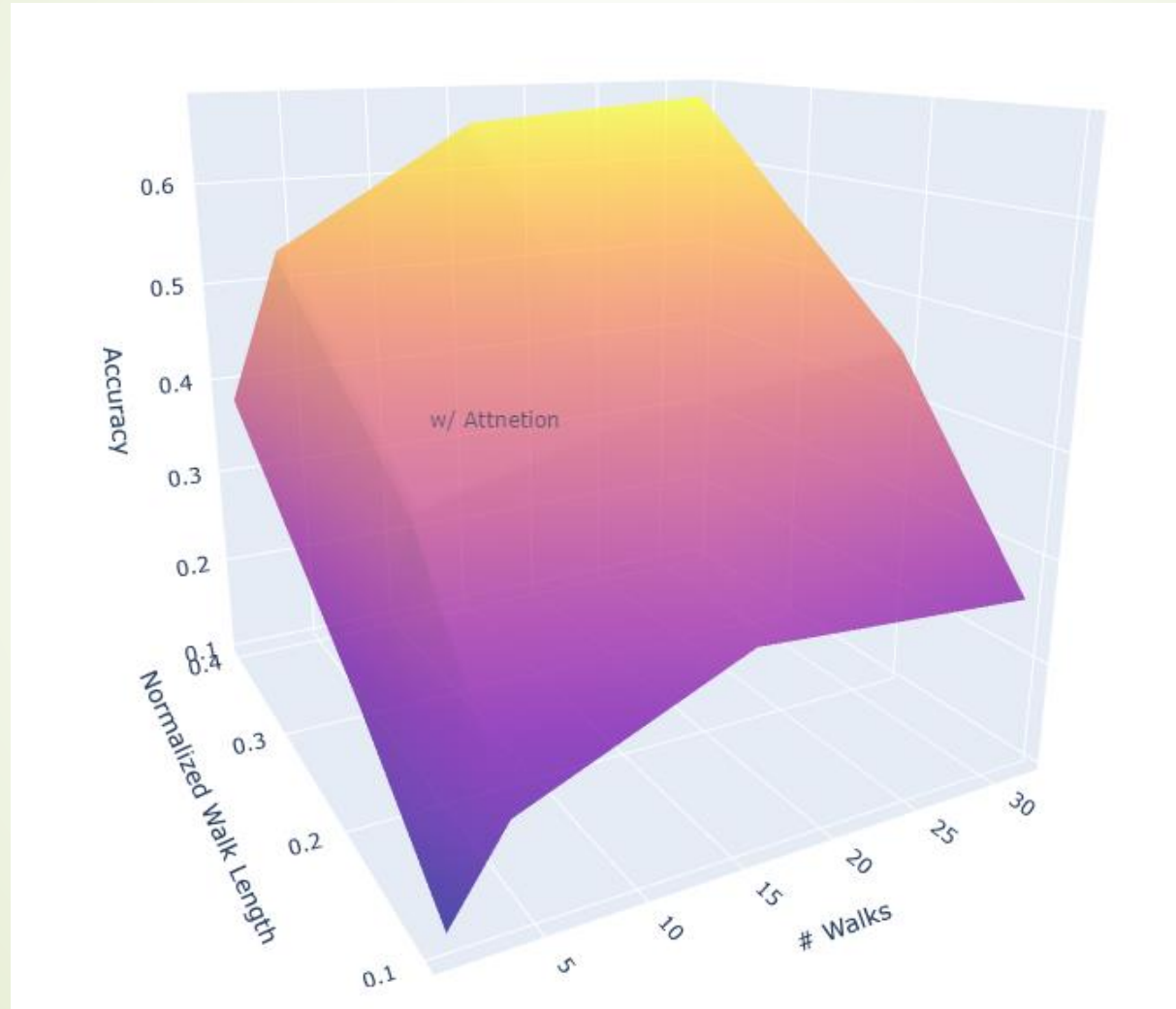
Different Approaches

	Number of walks					
	1		4		16	
	acc	rank	acc	rank	acc	rank
Baseline	0.4	4	0.59	5	0.71	4
+ Attention	0.37	5	0.67	2	0.79	1
+ Representation	0.44	3	0.63	4	0.74	3
+ Saliency	0.46	2	0.65	3	0.70	5
All	0.49	1	0.68	1	0.77	2

Changing the walk generation method

	Number of walks					
	1		4		16	
	acc	rank	acc	rank	acc	rank
Baseline	0.42	4	0.56	3	0.73	2
Representation	0.49	1	0.67	1	0.8	1
Skips(2)	0.46	3	0.59	2	0.68	3
Skips(4)	0.42	5	0.53	5	0.64	4
Jumps(0.1) w representation	0.32	7	0.47	6	0.54	6
Jumps(0.03) w representation	0.47	2	0.58	4	0.63	5
Random jumps (dx,dy,dz)	0.09	9	0.11	9	0.13	9
Random jumps (x,y,z)	0.38	6	0.46	7	0.51	7
Order	0.12	8	0.19	8	0.25	8

Effect of # walks & walk length



Conclusion

