TreeNet: Deep Point Cloud Embedding for Routing Tree Construction

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Biography

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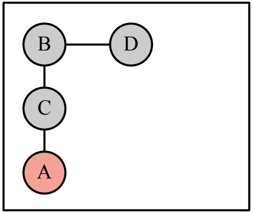
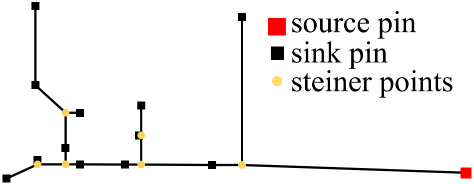
Wei Li is a year-2 MPhil student supervised by Prof. Bei Yu at the Department of Computer Science and Engineering, The Chinese University of Hong Kong (CUHK). He received his bachelor degree in ELITE stream, CSE department from Chung Chi College, CUHK.

Routing Tree Construction

Routing Tree Construction: Given a input net $V = \{v_0, V_s\}$, v_0 is the source (red node) and V_s is the set of sinks (black node), construct a tree optimizing both wire length and path length.



(a)



(b)

Examples of routing tree construction. Left: spanning tree; right: Steiner tree.

Wire length (WL) and path length (PL)

Wire length (WL) metric: lightness

- WL ratio with that of minimum spanning tree (MST).
- $lightness = \dfrac{w(T)}{w(MST(G))}$, $w(\cdot)$ is the total weight.

Path length (PL) metric: shallowness by SALT∗ or normalized path length by PD-II†

- Shallowness $= \max\{\dfrac{d_T(v_0, v)}{d_G(v_0, v)} | v \in V_s\}$, G is the connected weighted routing graph.
- Normalized path length $= \dfrac{\sum_{v \in V} d_T(v_0, v)}{\sum_{v \in V} d_G(v_0, v)}$.

∗Gengjie Chen and Evangeline FY Young (2019). "SALT: provably good routing topology by a novel steiner shallow-light tree algorithm". In: *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.

†Charles J Alpert et al. (2018). "Prim-Dijkstra Revisited: Achieving Superior Timing-driven Routing Trees". In: *Proc. ISPD*. pp. 10–17

Some questions

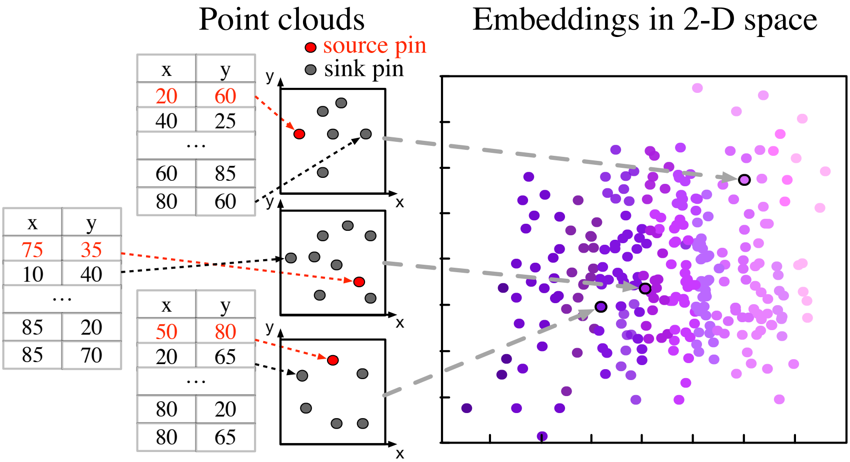
Best algorithm?

- Neither PD-II nor SALT, two most prominent ones, always dominates the other one in terms of both WL and PL for all nets.

Best parameter?

- Both PD-II and SALT use a parameter to help balance WL and PL.
- Given one WL constraint, what is the best parameter to obtain the best PL?

Point cloud and its embedding



Cloud embeddings for tree construction, where point clouds are transformed into unified 2-D Euclidean space.

Problem formulation

Given a set of 2-D pins and two routing tree construction algorithms, SALT‡ and PD-II, our objective is to **obtain the embedding** of the given point cloud by TreeNet such that

1. the embedding can be used to **select the best algorithm** for the given point cloud;
2. the embedding can be used to **estimate the best parameter ϵ of SALT** for the given point cloud;
3. the embedding can be used to **estimate the best parameter α of PD-II** for the given point cloud.

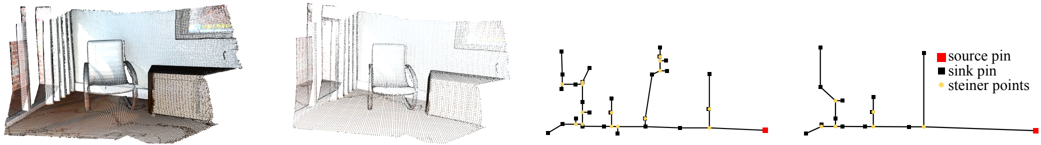
‡Gengjie Chen and Evangeline FY Young (2019). "SALT: provably good routing topology by a novel steiner shallow-light tree algorithm". In: *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.

Charles J Alpert et al. (2018). "Prim-Dijkstra Revisited: Achieving Superior Timing-driven Routing Trees". In: *Proc. ISPD*, pp. 10–17.

Property 1: Down-sampling

Property

Let $d : \boldsymbol{V} \rightarrow \boldsymbol{V}'$ be a function for down-sampling, where $\boldsymbol{V}'$ is a proper subset of $\boldsymbol{V}$. $f(\boldsymbol{V}) \neq f(d(\boldsymbol{V}))$ holds if there exists $v \in \boldsymbol{V} - d(\boldsymbol{V})$ so that v is not the steiner point in $f(d(\boldsymbol{V}))$.



(a) (b) (c) (d)

Examples of the down-sampling: (a) The general point cloud without the down-sampling; (b) The general point cloud with the down-sampling; (c) The constructed tree without the down-sampling; (d) The constructed tree with the down-sampling.

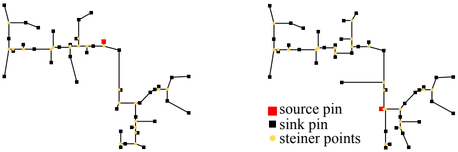
Property 2 & 3: Permutation

Property

Let $\boldsymbol{V}_s^p$ be the permutation of the sink set $\boldsymbol{V}_s$. $f(\{v_0, \boldsymbol{V}_s^p\}) = f(\{v_0, \boldsymbol{V}_s\})$ holds for any $\boldsymbol{V} = \{v_0, \boldsymbol{V}_s\}$.

Property

Let $\boldsymbol{V}^p$ be the permutation of the input net $\boldsymbol{V}$. $f(\boldsymbol{V}^p) \neq f(\boldsymbol{V})$ holds if the source in $\boldsymbol{V}^p$ is different from the source in $\boldsymbol{V}$.



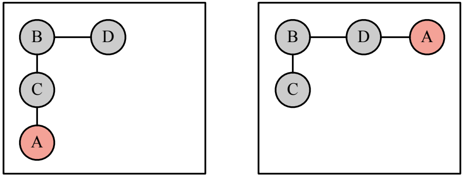
(a) (b)

Examples of the routing trees with the same node coordinates but different source (highlighted by red).

Property 4: Inequality of the same V_s

Property

For any sink set V_s with $|V_s| > 1$, there exists two different pins, v_0 and v_0' in the 2-D plane so that $f(\{v_0, V_s\}) \neq f(\{v_0', V_s\})$. Moreover, the inequality holds when we only consider the topology.



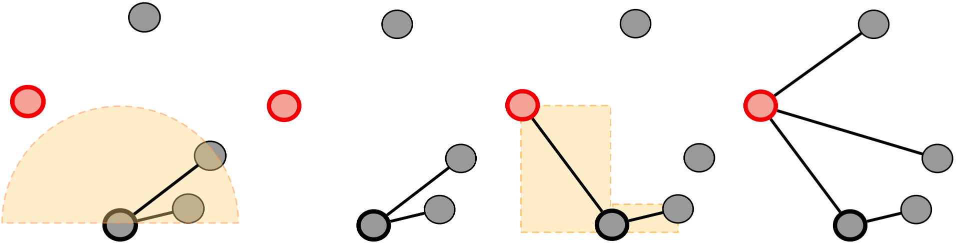
(a) (b)

Examples of the node with the same coordinates and local neighbors but different parent-child relationships. Here root is highlighted in red.

Property 5: Graph construction methods

Property

Let G_{ball}, G_{knn} and G_{bbox} be the graph constructed from V by ball query, k nearest neighbor and bounding box respectively. The minimum spanning tree, T may not be the subgraph of G_{ball} or G_{nn}, but always the subgraph of G_{bbox}.



(a) ball (b) k-nn (c) k-bbox (d) routing tree

Comparison among ball query (a) k-nn (b) and k-bbox (c) grouping methods ($k = 2$ in this example). The orange regions represent the query ball in (a) and bounding boxes in (c). The centroid is highlighted by black and the root is by red.

TreeConv

- `Sampling` selects a set of centroids from the original point cloud
  - Omited considering Property 1.
  - Each node is selected as the centroid.
- `Grouping` selects a set of neighbors for each centroid.
  - Selecting k nearest *bbox-neighbors* of u_i as the neighbors.
  - `Grouping` returns a list of neighbors $\boldsymbol{E}_i \in \mathbb{R}^k$ for each centroid u_i.
- `Encoding` is to encode the new centroid feature using the original one and the local feature aggregated from the neighbors of the centroid.
  - $v'_{ic} = \max_{j \in E_i} \sigma(\boldsymbol{\theta}_c \cdot \mathtt{CONCAT}(\boldsymbol{v}_i, \boldsymbol{v}_i - \boldsymbol{v}_j, \boldsymbol{v}_i - \boldsymbol{v}_r))$
  - followed by a Squeeze-and-Excitation (SE) block¶

¶Jie Hu, Li Shen, and Gang Sun (2018). "Squeeze-and-excitation networks". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141.

TreeConv

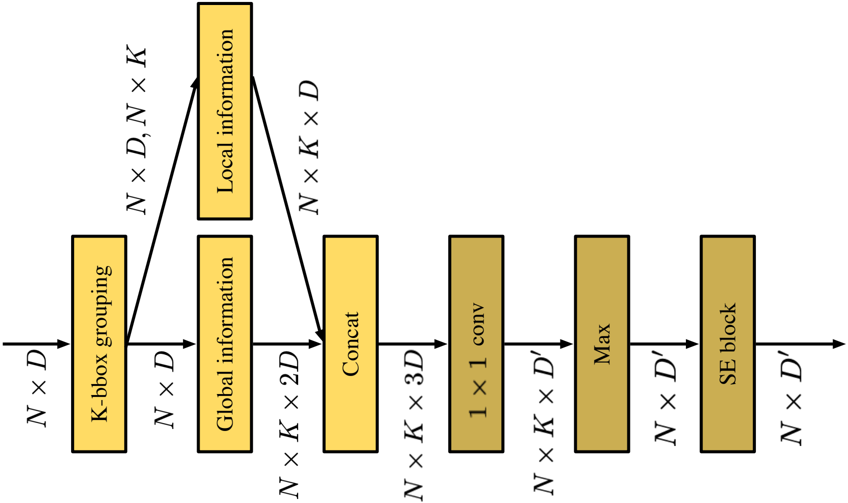


Illustration of TreeConv. Brighter blocks indicate `Grouping` and darker blocks indicate `Encoding`.

TreeConv vs. existing methods.

	Sampling	Grouping	Encoding
PointNet‖	-	-	$v'_{ic} = \sigma(\boldsymbol{\theta}_c \boldsymbol{v}_i)$
PointNet++∗∗	Fathest Point Sampling (FPS)	ball query's local neighborhood	$v'_{ic} = \max_{j \in E_i} \sigma(\boldsymbol{\theta}_c \boldsymbol{v}_j)$
PointCNN††	Random/FPS	k nearest neighbor	$\boldsymbol{v}'_i = \texttt{Conv}(X \times \boldsymbol{\theta}(\boldsymbol{v}_i - \boldsymbol{v}_j))$
DGCNN‡‡	-	k nearest neighbor	$v'_{ic} = \max_{j \in E_i} \sigma(\boldsymbol{\theta}_c \cdot \texttt{CONCAT}(\boldsymbol{v}_i, \boldsymbol{v}_i - \boldsymbol{v}_j))$
Our work	-	k bounding box neighbor	$v'_{ic} = \max_{j \in E_i} \sigma(\boldsymbol{\theta}_c \cdot \texttt{CONCAT}(\boldsymbol{v}_i, \boldsymbol{v}_i - \boldsymbol{v}_j, \boldsymbol{v}_i - \boldsymbol{v}_r))$

‖Charles R Qi et al. (2017). "Pointnet: Deep learning on point sets for 3d classification and segmentation". In: *Proc. CVPR*, pp. 652–660.

∗∗Charles Ruizhongtai Qi et al. (2017). "PointNet++: Deep hierarchical feature learning on point sets in a metric space". In: *Advances in Neural Information Processing Systems*, pp. 5099–5108.

††Yangyan Li et al. (2018). "PointCNN: Convolution on x-transformed points". In: *Advances in Neural Information Processing Systems*, pp. 820–830.

‡‡Yue Wang et al. (2019). "Dynamic graph CNN for learning on point clouds". In: *ACM Transactions on Graphics* 38.5, pp. 1–12.

TreeNet

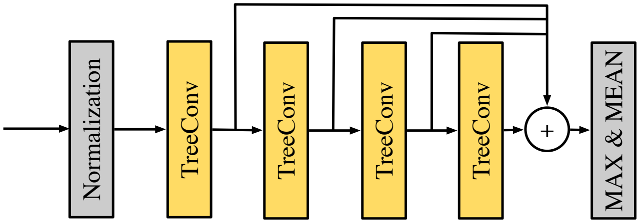


Illustration of TreeNet Architecture for the cloud embedding.

- Normalization: $\tilde{\boldsymbol{v}}_i = \dfrac{\boldsymbol{v}_i - \boldsymbol{v}_r}{d_{max}}$.

Algorithm selction & parameter predition

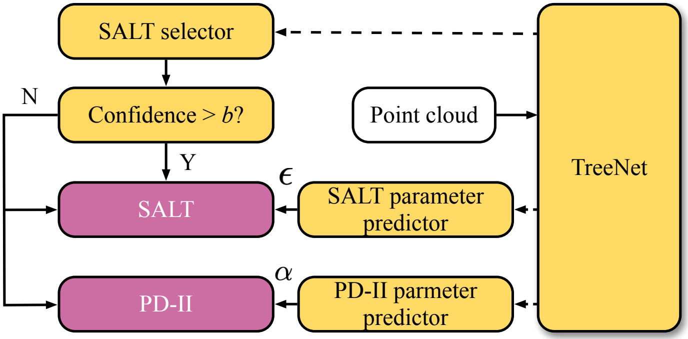
Algorithm selction

$$\boldsymbol{y} = \mathtt{softmax}(\boldsymbol{W}_3\sigma(\boldsymbol{W}_2\sigma(\boldsymbol{W}_1\boldsymbol{H}_c + \boldsymbol{b}_1) + \boldsymbol{b}_2)),$$

Parameter predition

- 20 valid parameter $\epsilon_i, i \in \{1, ..., 20\}$ candidates for SALT
- Following similar structure with algorithm selection to obtain the output $\boldsymbol{y} \in \mathbb{R}^{20}$.
- Given the output $\boldsymbol{y}$, the predicted parameter ϵ is calculated by an element-wise summation and can be formulated as $\epsilon = \sum_{i=1}^{20} \epsilon_i \cdot y_i$.
- The predicted parameter guides the routing tree construction by a simple heuristic rule

Framework



The workflow of our framework. Dotted arrows represent that TreeNet generates cloud embeddings and use them to select the algorithm or to predict parameters. The yellow blocks are executed in our framework while the purple blocks are executed by the selected algorithms.

Comparison to existing methods

Method	Accuracy	Precision	Recall*
PointNet	54.13	53.95	1.91
PointNet++	81.31	82.50	2.65
PointCNN	62.18	64.24	1.16
DGCNN	92.24	94.62	11.84
TreeNet w.o. Nor	87.22	88.62	15.69
TreeNet w.o. global	92.40	94.63	25.53
TreeNet w. knn	92.58	94.79	26.76
TreeNet	**94.09**	**95.38**	**50.74**

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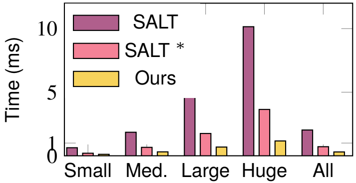
Comparison to SALT & PD-II (shallowness & normalized PL)

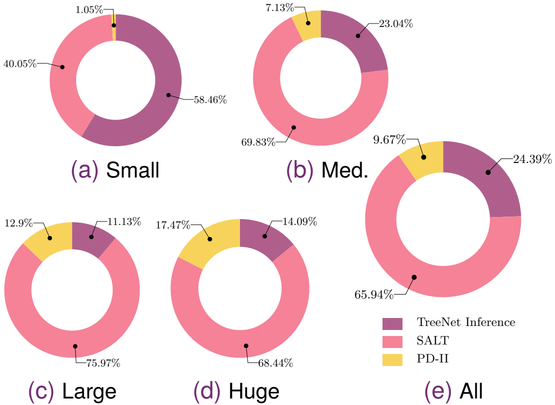
|V|	Method	WL deg. 0%	5%	10%	15%	20%
Small	PD-II	1.0606	1.0369	1.0240	1.0161	1.0114
	SALT	1.0462	1.0216	1.0078	1.0022	1.0006
	SALT*	1.0462	1.0216	1.0079	1.0023	1.0006
	Ours	1.0461	1.0210	1.0074	1.0021	1.0005
	Imp. (%)	**0.28**	**2.62**	**4.40**	**5.42**	**8.25**
	Imp.* (%)	**0.32**	**3.04**	**5.14**	**6.75**	**9.94**
Med.	PD-II	1.3849	1.2518	1.1688	1.1176	1.0851
	SALT	1.3456	1.1775	1.0838	1.0391	1.0181
	SALT*	1.3463	1.1815	1.0868	1.0410	1.0192
	Ours	1.3435	1.1689	1.0790	1.0370	1.0172
	Imp. (%)	**0.62**	**4.85**	**5.72**	**5.57**	**5.41**
	Imp.* (%)	**0.80**	**6.95**	**8.98**	**9.92**	**10.41**
Large	PD-II	1.9093	1.5584	1.3595	1.2473	1.1805
	SALT	1.7976	1.3549	1.1568	1.0727	1.0358
	SALT*	1.8083	1.3689	1.1648	1.0771	1.0382
	Ours	1.7755	1.3339	1.1481	1.0690	1.0341
	Imp. (%)	**2.77**	**5.91**	**5.53**	**5.11**	**4.78**
	Imp.* (%)	**4.06**	**9.50**	**10.12**	**10.52**	**10.77**
Huge	PD-II	2.1660	1.7169	1.4771	1.3438	1.2603
	SALT	2.0111	1.4398	1.2083	1.0987	1.0466
	SALT*	2.0291	1.4567	1.2183	1.1039	1.0489
	Ours	1.9793	1.4152	1.1975	1.0941	1.0444
	Imp. (%)	**3.15**	**5.61**	**5.17**	**4.69**	**4.64**
	Imp.* (%)	**4.85**	**9.09**	**9.50**	**9.47**	**9.20**
All	PD-II	1.2921	1.1822	1.1193	1.0827	1.0604
	SALT	1.2531	1.1175	1.0524	1.0236	1.0110
	SALT*	1.2555	1.1210	1.0546	1.0248	1.0117
	Ours	1.2481	1.1114	1.0495	1.0223	1.0104
	Imp. (%)	**1.97**	**5.18**	**5.43**	**5.21**	**5.08**
	Imp.* (%)	**2.89**	**7.98**	**9.23**	**9.95**	**10.38**

|V|	Method	WL deg. 0%	5%	10%	15%	20%
Small	PD-II	1.0156	1.0099	1.0065	1.0044	1.0031
	SALT	1.0113	1.0055	1.0020	1.0006	1.0002
	SALT*	1.0113	1.0055	1.0020	1.0006	1.0002
	Ours	1.0112	1.0053	1.0019	1.0005	1.0001
	Imp. (%)	**0.25**	**2.86**	**4.88**	**6.57**	**10.55**
	Imp.* (%)	**0.29**	**3.38**	**5.83**	**8.29**	**12.75**
Med.	PD-II	1.0897	1.0579	1.0373	1.0248	1.0170
	SALT	1.0778	1.0428	1.0204	1.0096	1.0044
	SALT*	1.0780	1.0440	1.0214	1.0102	1.0048
	Ours	1.0773	1.0396	1.0185	1.0086	1.0040
	Imp. (%)	**0.63**	**7.35**	**9.45**	**10.01**	**10.00**
	Imp.* (%)	**0.82**	**9.90**	**13.70**	**15.74**	**16.65**
Large	PD-II	1.1968	1.1146	1.0671	1.0413	1.0267
	SALT	1.1665	1.0815	1.0365	1.0172	1.0086
	SALT*	1.1690	1.0854	1.0390	1.0187	1.0095
	Ours	1.1616	1.0726	1.0318	1.0150	1.0076
	Imp. (%)	**2.95**	**10.92**	**12.81**	**12.91**	**12.49**
	Imp.* (%)	**4.35**	**15.02**	**18.29**	**19.70**	**20.35**
Huge	PD-II	1.2472	1.1415	1.0830	1.0513	1.0328
	SALT	1.2120	1.1054	1.0489	1.0224	1.0105
	SALT*	1.2160	1.1106	1.0522	1.0242	1.0112
	Ours	1.2045	1.0917	1.0413	1.0190	1.0088
	Imp. (%)	**3.54**	**13.03**	**15.54**	**15.54**	**16.25**
	Imp.* (%)	**5.31**	**17.12**	**20.97**	**21.52**	**21.87**
All	PD-II	1.0658	1.0398	1.0244	1.0157	1.0105
	SALT	1.0550	1.0278	1.0125	1.0056	1.0026
	SALT*	1.0555	1.0289	1.0132	1.0061	1.0029
	Ours	1.0538	1.0253	1.0111	1.0050	1.0023
	Imp. (%)	**2.05**	**9.17**	**11.35**	**11.94**	**12.16**
	Imp.* (%)	**3.01**	**12.43**	**16.04**	**17.98**	**19.11**

Runtime



Runtime comparison with SALT and SALT*.



Runtime breakdown of our framework.

Conclusion

- We formalize **special properties** of the point cloud for the routing tree construction;
- We design **TreeNet**, a novel deep net architecture to obtain the cloud embedding for the tree construction;
- We propose an **adaptive flow** for the routing tree construction, which uses the cloud embedding to **select the best approach** and **predict the best parameter**;
- Experiments on widely used benchmarks demonstrate the effectiveness of our embedding representation, compared with all other deep learning models;
- Experiments also show that our methods outperform other state-of-the-art routing tree construction methods in terms of both quality and runtime.