## Voxel-Based Representation Learning for Place Recognition Based on 3D Point Clouds

## Supplementary Material

Sriram Siva<sup>†</sup>, Zachary Nahman<sup>†</sup>, and Hao Zhang

## I. Proof of Theorem 1

In this section, we prove that Algorithm 1 (in the main paper) decreases the value of the objective function with each iteration and converges to the global optimal value. But first, we present a lemma:

**Lemma** 1: Given any two vectors  $\mathbf{u}$  and  $\tilde{\mathbf{u}}$ , the following inequality relation holds:  $\|\tilde{\mathbf{u}}\|_2 - \frac{\|\tilde{\mathbf{u}}\|_2^2}{2\|\mathbf{u}\|_2} \le \|\mathbf{u}\|_2 - \frac{\|\mathbf{u}\|_2^2}{2\|\mathbf{u}\|_2}$ .

Proof: We have:

$$(\|\widetilde{\mathbf{u}}\|_2 - \|\mathbf{u}\|_2)^2 \le 0 \tag{1}$$

$$-\|\widetilde{\mathbf{u}}\|_{2}^{2} - \|\mathbf{u}\|_{2}^{2} + 2\|\widetilde{\mathbf{u}}\|_{2}\|\mathbf{u}\|_{2} \le 0$$
 (2)

$$2\|\widetilde{\mathbf{u}}\|_2\|\mathbf{u}\|_2 - \|\widetilde{\mathbf{u}}\|_2^2 \le \|\mathbf{u}\|_2^2 \tag{3}$$

$$\|\widetilde{\mathbf{u}}\|_{2} - \frac{\|\widetilde{\mathbf{u}}\|_{2}^{2}}{2\|\mathbf{u}\|_{2}} \le \|\mathbf{u}\|_{2} - \frac{\|\mathbf{u}\|_{2}^{2}}{2\|\mathbf{u}\|_{2}}$$
 (4)

From Lemma 1, we can derive the following corollary:

**Corollary** 1: For any two given matrices  $\mathbf{U}$  and  $\tilde{\mathbf{U}}$ , the following inequality relation holds:  $\|\tilde{\mathbf{U}}\|_F - \frac{\|\tilde{\mathbf{U}}\|_F^2}{2\|\mathbf{U}\|_F} \leq \|\mathbf{U}\|_F - \frac{\|\mathbf{U}\|_F^2}{2\|\mathbf{U}\|_F}$ .

**Theorem** 1: Algorithm 1 converges to the optimal solution to the optimization problem in Eq. (4) of the main paper *Proof*: From Algorithm 1,

$$\mathbf{W}(t+1) = \min_{\mathbf{W}} \|\mathbf{X}^{\top}\mathbf{W} - \mathbf{Y}\|_{F}^{2}$$

$$+\lambda_{1} Tr \mathbf{W}^{\top} \mathbf{D}(t+1) \mathbf{W} + \lambda_{2} Tr \mathbf{W}^{\top} \tilde{\mathbf{D}}(t+1) \mathbf{W}.$$
(5)

Then, we can derive that

$$\mathcal{J}(t+1) + \lambda_1 Tr \mathbf{W}^{\top}(t+1) \mathbf{D}(t+1) \mathbf{W}(t+1)$$

$$+ \lambda_2 Tr \mathbf{W}^{\top}(t+1) \tilde{\mathbf{D}}(t+1) \mathbf{W}(t+1)$$

$$\leq \mathcal{J}(t) + \lambda_1 Tr \mathbf{W}^{\top}(t) \mathbf{D}(t+1) \mathbf{W}(t)$$

$$+ \lambda_2 Tr \mathbf{W}^{\top}(t) \tilde{\mathbf{D}}(t+1) \mathbf{W}(t),$$

where 
$$\mathcal{J}(t) = \|\mathbf{X}^{\top}\mathbf{W}(t) - \mathbf{Y}\|_F^2$$
.  
After substituting the definition of  $\mathbf{D}$  and  $\tilde{\mathbf{D}}$ , we obtain

$$\mathcal{J}(t+1) + \lambda_{1} \sum_{i=1}^{v} \frac{\|\mathbf{W}^{i}(t+1)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}}$$

$$+ \lambda_{2} \Big( \sum_{i=1}^{m} \frac{\|\mathbf{W}^{i}(t+1)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}} + \sum_{i=1}^{d} \frac{\|\mathbf{w}^{i}(t+1)\|_{2}^{2}}{2\|\mathbf{w}^{i}(t)\|_{2}} \Big)$$

$$\leq \mathcal{J}(t) + \lambda_{1} \sum_{i=1}^{v} \frac{\|\mathbf{W}^{i}(t)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}}$$

$$+ \lambda_{2} \Big( \sum_{i=1}^{m} \frac{\|\mathbf{W}^{i}(t)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}} + \sum_{i=1}^{d} \frac{\|\mathbf{w}^{i}(t)\|_{2}^{2}}{2\|\mathbf{w}^{i}(t)\|_{2}} \Big)$$

$$(6)$$

$$+ \lambda_{2} \Big( \sum_{i=1}^{m} \frac{\|\mathbf{W}^{i}(t)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}} + \sum_{i=1}^{d} \frac{\|\mathbf{w}^{i}(t)\|_{2}^{2}}{2\|\mathbf{w}^{i}(t)\|_{2}} \Big)$$

From Lemma 1 and Corollary 1, we can derive that

$$\sum_{i=1}^{v} \|\mathbf{W}^{i}(t+1)\|_{F} - \sum_{i=1}^{v} \frac{\|\mathbf{W}^{i}(t+1)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}} \leq \sum_{i=1}^{v} \|\mathbf{W}^{i}(t)\|_{F} - \sum_{i=1}^{v} \frac{\|\mathbf{W}^{i}(t)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}}.$$
(8)

$$\sum_{i=1}^{m} \|\mathbf{W}^{i}(t+1)\|_{F} - \sum_{i=1}^{m} \frac{\|\mathbf{W}^{i}(t+1)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}} \leq 
\sum_{i=1}^{m} \|\mathbf{W}^{i}(t)\|_{F} - \sum_{i=1}^{m} \frac{\|\mathbf{W}^{i}(t)\|_{F}^{2}}{2\|\mathbf{W}^{i}(t)\|_{F}},$$
(9)

and,

$$\sum_{i=1}^{d} \|\mathbf{w}^{i}(t+1)\|_{2} - \sum_{i=1}^{d} \frac{\|\mathbf{w}^{i}(t+1)\|_{2}^{2}}{2\|\mathbf{w}^{i}(t)\|_{2}} \leq \sum_{i=1}^{d} \|\mathbf{w}^{i}(t)\|_{2} - \sum_{i=1}^{d} \frac{\|\mathbf{w}^{i}(t)\|_{2}^{2}}{2\|\mathbf{w}^{i}(t)\|_{2}}, \tag{10}$$

Adding Eq. (6)-(10) on both sides, we have

$$\mathcal{J}(t+1) + \lambda_{1} \sum_{i=1}^{v} \|\mathbf{W}^{i}(t+1)\|_{F}$$

$$+ \lambda_{2} \left( \sum_{i=1}^{m} \|\mathbf{W}^{i}(t+1)\|_{F} + \sum_{i=1}^{d} \|\mathbf{w}^{i}(t+1)\|_{2} \right)$$

$$\leq \mathcal{J}(t) + \lambda_{1} \sum_{i=1}^{v} \|\mathbf{W}^{i}(t)\|_{F}$$

$$+ \lambda_{2} \left( \sum_{i=1}^{m} \|\mathbf{W}^{i}(t)\|_{F} + \sum_{i=1}^{d} \|\mathbf{w}^{i}(t)\|_{2} \right)$$
(12)

<sup>&</sup>lt;sup>†</sup>Authors contributed equally to this work.

S. Siva, Z. Nahman, and H. Zhang are with the Human-Centered Robotics Lab, Colorado School of Mines, Golden, CO 80401. Email: {sivasriram, znahman, hzhang}@mines.edu.

Eq. (11) decreases the value of the objective function with each iteration. As our objective function is convex, Algorithm 1 converges to the optimal value. Therefore, Algorithm 1 converges to the optimal solution to the optimization problem in Eq. (4) of the main paper.