

# Supplementary Materials of Deep Hashing with Minimal-Distance-Separated Hash Centers

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We analyze the convergence of the the following optimization problem (Eq.(5) in the main paper).

$$\begin{aligned} \min_{h_i, v_1, v_2, v_3} \quad & \sum_{j:j \neq i} h_i^T h_j \\ \text{s.t.} \quad & h_i^T H_{\sim i} + v_3 = (q - 2d)1_{c-1}, v_3 \in R_+^{c-1}, \\ & h_i = v_1, h_i = v_2, v_1 \in \mathcal{V}_{box}, v_2 \in \mathcal{V}_{sph}. \end{aligned} \quad (1)$$

The augmented Lagrange function w.r.t. Eq.(1) is:

$$\begin{aligned} L(h_i, v_1, v_2, v_3, k_1, k_2, k_3) = & \sum_{j \neq i} h_i^T h_j + k_1^T (h_i - v_1) + \\ & \frac{\mu}{2} \|h_i - v_1\|_2^2 + k_2^T (h_i - v_2) + \frac{\mu}{2} \|h_i - v_2\|_2^2 \\ & + k_3^T (h_i^T H_{\sim i} + v_3 - e) + \frac{\mu}{2} \|h_i^T H_{\sim i} + v_3 - e\|_2^2 \\ \text{s.t.} \quad & v_1 \in V_{box}, v_2 \in V_{sph}, v_3 \in R_+^{c-1}, \end{aligned} \quad (2)$$

where  $e = (q - 2d)1_{c-1}$ , and  $k_1, k_2, k_3$  are Lagrange multipliers.

We adopt the  $\ell_p$ -box ADMM method to solve Eq.(1), which is shown in the red lines in Algorithm 1. Next we will show that, under mild assumptions, by using this  $\ell_p$ -box ADMM scheme, the optimization problem Eq.(1) will converge.

We first present two assumptions that are adapted from [1], by using our notations.

**Assumption 1** Let  $\mu^t$  be the value of the parameter  $\mu$  at  $t$ -th iteration. Then the parameter  $\mu$  is a finite value, i.e.,  $\lim_{t \rightarrow \infty} \mu^t \in (0, \infty)$ .

**Assumption 2** Let  $k^t = (k_1^t, k_2^t, k_3^t)$  be the values of the Lagrange multipliers  $k_1, k_2$  and  $k_3$  at  $t$ -th iteration. Then the parameter sequence  $\{k^t\}$  satisfies a)  $\sum_{t=0}^{\infty} \|k^{t+1} - k^t\|_2^2 < \infty$ , which also hints that  $k^{t+1} - k^t \rightarrow 0$  and b)  $k^t$  is bounded for all  $t$ .

Note that, if we replace the range constraint  $S_b(z) = \{0 \leq z \leq 1\}$  by a similar range constraint  $\{-1 \leq z \leq 1\}$ , we can verify that the optimization problem Eq.(1) is a

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## Algorithm 1 Optimization Procedure to Generate Hash Centers

**Initialize:** initialize  $h_1, \dots, h_c$  by Hadamard matrix and Bernoulli sampling.  $\rho = 1.02, \max_{\mu} = 10^{10}, \epsilon = 10^{-6}, T = 50$ .

**For**  $t = 1, 2, \dots, T$

**For**  $i = 1, 2, \dots, c$

    Set  $v_1, v_2, v_3, k_1, k_2, k_3$  to be zero vectors. Set  $\mu = 10^{-6}$ .

**Repeat**

      Update  $h_i$  via Eq.(7) in the main paper.

      Update  $v_1, v_2, v_3$  via Eq.(10) in the main paper.

      Update  $k_1, k_2, k_3$  via Eq.(11) in the main paper.

      Update  $\mu$  by  $\mu \leftarrow \min(\rho\mu, \max_{\mu})$ .

**Until**  $\max(\|h_i - v_1\|_{\infty}, \|h_i - v_2\|_{\infty}, \|h_i^T H_{\sim i} + v_3 - e\|_{\infty}) \leq \epsilon$ .

**End For**

$T \leftarrow T + 1$ .

**End For**

**Output:**  $h_i$  ( $i = 1, 2, \dots, c$ )

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special case of the problem (8) in [1]. By the Proposition 2 in [1], the problem (8) in [1] will converge under some assumptions. Similarly, we have the following theorem.

**Theorem 1** (adapted from Proposition 2 in [1]) Given Assumptions 1 and 2, then any cluster point of the whole variable sequence  $\{(h_i^t, v_1^t, v_2^t, v_3^t, k_1^t, k_2^t, k_3^t)\}_0^{\infty}$  generated by the ADMM method will satisfy the KKT conditions of the problem Eq.(1). Moreover,  $\{(h_i^t, v_1^t, v_2^t)\}_0^{\infty}$  will converge to the binary solutions.

The proof of Theorem 1 is nearly identical to the proof of Proposition 2 in [1] because the optimization problem Eq.(1) can be regarded as a special case of the problem (8) in [1]. The difference in range constraints  $S_b(z)$  has no impact on the proof.

Then, we illustrate that, by using the ADMM method in Algorithm 1, Assumption 1 and 2 hold and the optimization problem Eq.(1) will converge.

With the update rules  $\mu \leftarrow \min(\rho\mu, \max_{\mu})$  for the parameter  $\mu$ , we can see that  $\mu$  is always bounded by a constant  $\max_{\mu} = 10^{10}$ . Hence Assumption 1 holds.

With the update rules for  $k_1, k_2$  and  $k_3$  (Eq.(11) in the main paper) and the stopping criteria  $\max(\|h_i - v_1\|_{\infty}, \|h_i - v_2\|_{\infty}, \|h_i^T H_{\sim i} + v_3 - e\|_{\infty}) \leq \epsilon$ , we can verify that Assumption 2 holds.

Hence, by applying Theorem 1, the optimization prob-

lem Eq.(1) will converge.

## References

- [1] Baoyuan Wu and Bernard Ghanem.  $\ell_p$ -Box ADMM: A Versatile Framework for Integer Programming. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(7):1695–1708, 2019. [1](#)