

1 Appendix

2 Organization of the Appendix

3 In Appendix A we review classical results on the Taylor expansions for functions on Riemannian
 4 manifold. In Appendix B we provide the proof of Lemma 2 which requires to expand the iterates on
 5 the tangent space in the the saddle point. Finally, in Appendix C, we provide the proofs of Lemma 7
 6 and Lemma 8 which enable to prove the main theorem of the paper.

7 Throughout the paper we assume that the objective function and the manifold are smooth. Here we
 8 list the assumptions that are used in the following lemmas.

9 **Assumption 1** (Lipschitz gradient). *There is a finite constant β such that*

$$\|\text{grad}f(y) - \Gamma_x^y \text{grad}f(x)\| \leq \beta d(x, y) \quad \text{for all } x, y \in \mathcal{M}.$$

10 **Assumption 2** (Lipschitz Hessian). *There is a finite constant ρ such that*

$$\|H(y) - \Gamma_x^y H(x) \Gamma_y^x\|_2 \leq \rho d(x, y) \quad \text{for all } x, y \in \mathcal{M}.$$

11 **Assumption 3** (Bounded sectional curvature). *There is a finite constant K such that*

$$|K(x)[u, v]| \leq K \quad \text{for all } x \in \mathcal{M} \text{ and } u, v \in \mathcal{T}_x \mathcal{M}$$

12 A Taylor expansions on Riemannian manifold

13 We provide here the Taylor expansion for functions and gradients of functions defined on a Riemannian
 14 manifold.

15 A.1 Taylor expansion for the gradient

16 For any point $x \in \mathcal{M}$ and $z \in \mathcal{M}$ be a point in the neighborhood of x where the geodesic $\gamma_{x \rightarrow z}$ is
 17 defined.

$$\begin{aligned} \Gamma_z^x(\text{grad}f(z)) &= \text{grad}f(x) + \nabla_{\gamma'_{x \rightarrow z}(0)} \text{grad}f + \int_0^1 (\Gamma_{\gamma_{x \rightarrow z}(\tau)}^x \nabla_{\gamma'_{x \rightarrow z}(\tau)} \text{grad}f - \nabla_{\gamma'_{x \rightarrow z}(0)} \text{grad}f) dx_\tau \\ &= \text{grad}f(x) + \nabla_{\gamma'_{x \rightarrow z}(0)} \text{grad}f + \Delta(z), \end{aligned} \quad (1)$$

18 where $\Delta(z) := \int_0^1 (\Gamma_{\gamma_{x \rightarrow z}(\tau)}^x \nabla_{\gamma'_{x \rightarrow z}(\tau)} \text{grad}f - \nabla_{\gamma'_{x \rightarrow z}(0)} \text{grad}f) d\tau$. The Taylor approximation in
 19 Eq. (1) is proven by Absil et al. (2009, Lemma 7.4.7).

20 A.2 Taylor expansion for the function

21 Taylor expansion of the gradient enables us to approximate the iterations of the main algorithm, but
 22 obtaining the convergence rate of the algorithm requires proving that the function value decreases
 23 following the iterations. We need to give the Taylor expansion of f with the parallel translated
 24 gradient on LHS of Eq. (1). To simplify the notation, let γ denote the $\gamma_{x \rightarrow z}$.

$$f(z) - f(x) = \int_0^1 \frac{d}{d\tau} f(\gamma(\tau)) d\tau \quad (2a)$$

$$= \int_0^1 \langle \gamma'(\tau), \text{grad}f(\gamma(\tau)) \rangle d\tau \quad (2b)$$

$$= \int_0^1 \langle \Gamma_{\gamma(\tau)}^x \gamma'(\tau), \Gamma_{\gamma(\tau)}^x \text{grad}f(\gamma(\tau)) \rangle d\tau \quad (2c)$$

$$= \int_0^1 \langle \gamma'(0), \Gamma_{\gamma(\tau)}^0 \text{grad}f(\gamma(\tau)) \rangle d\tau \quad (2d)$$

$$= \int_0^1 \langle \gamma'(0), \text{grad}f(x) + \nabla_{\tau \gamma'(0)} \text{grad}f + \Delta(\gamma(\tau)) \rangle d\tau \quad (2e)$$

$$= \langle \gamma'(0), \text{grad}f(x) + \frac{1}{2} \nabla_{\gamma'(0)} \text{grad}f + \bar{\Delta}(z) \rangle. \quad (2f)$$

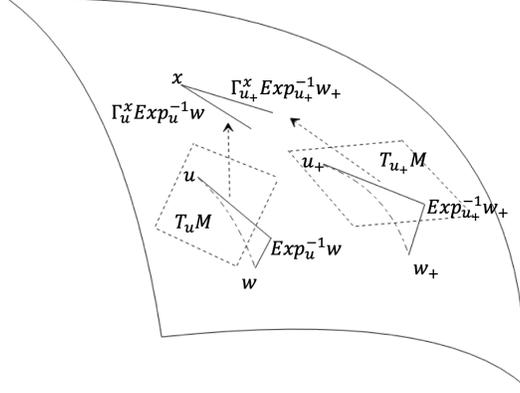


Figure 1: Lemma 1. First map w and w_+ to $\mathcal{T}_u \mathcal{M}$ and $\mathcal{T}_{u_+} \mathcal{M}$, and transport the two vectors to $\mathcal{T}_x \mathcal{M}$, and get their relation.

25 $\Delta(z)$ is defined in Eq. (1). $\bar{\Delta}(z) = \int_0^1 \Delta(\gamma(\tau)) d\tau$. The second line is just rewriting by definition.
 26 Eq. (2c) means the parallel translation preserves the inner product (Tu, 2017, Prop. 14.16). Eq. (2d)
 27 uses $\Gamma_{\gamma(t)}^x \gamma'(t) = \gamma'(0)$, meaning that the velocity stays constant along a geodesic (Absil et al., 2009,
 28 (5.23)). Eq. (2e) uses Eq. (1). In Euclidean space, the Taylor expansion is

$$f(z) - f(x) = \langle z, \nabla f(x) + \nabla^2 f(x)z + \int_0^1 (\nabla^2 f(\tau z) - \nabla^2 f(x))z d\tau \rangle. \quad (3)$$

29 Compare Eq. (2) and Eq. (3), z is replaced by $\gamma'(0) := \gamma'_{x \rightarrow z}(0)$ and τz is replaced by $\tau \gamma'_{x \rightarrow z}(0)$ or
 30 $\gamma_{x \rightarrow z}(\tau)$.

31 Now we have

$$f(u_t) = f(x) + \langle \gamma'(0), \text{grad} f(x) \rangle + \frac{1}{2} H(x)[\gamma'(0), \gamma'(0)] + \langle \gamma'(0), \bar{\Delta}(u_t) \rangle.$$

32 B Linearization of the iterates in a fixed tangent space

33 In this section we linearize the progress of the iterates of our algorithm in a fixed tangent space $\mathcal{T}_x \mathcal{M}$.
 34 We always assume here that all points are within a region of diameter $R := 12\mathcal{S} \leq \mathcal{J}$. In the course
 35 of the proof we need several auxilliary lemmas which are stated in the last two subsections of this
 36 section.

37 B.1 Evolution of $\text{Exp}_u^{-1}(w)$

38 We first consider the evolution of $\text{Exp}_u^{-1}(w)$ in a fixed tangent space $\mathcal{T}_x \mathcal{M}$. We show in the following
 39 lemma that it approximately follows a linear recursion.

40 **Lemma 1.** Define $\gamma = \sqrt{\hat{\rho}\epsilon}$, $\kappa = \frac{\beta}{\gamma}$, and $\mathcal{S} = \sqrt{\eta\beta\frac{\gamma}{\hat{\rho}} \log^{-1}(\frac{d\kappa}{\delta})}$. Let us consider x be a $(\epsilon, -\sqrt{\hat{\rho}\epsilon})$
 41 saddle point, and define $u^+ = \text{Exp}_u(-\eta \text{grad} f(u))$ and $w^+ = \text{Exp}_w(-\eta \text{grad} f(w))$. Under
 42 Assumptions 1, 2, 3, if all pairwise distances between u, w, u^+, w^+, x are less than $12\mathcal{S}$, then for
 43 some explicit constant $C_1(K, \rho, \beta)$ depending only on K, ρ, β , there is

$$\begin{aligned} & \|\Gamma_{u^+}^x \text{Exp}_{u^+}^{-1}(w^+) - (I - \eta H(x)) \Gamma_u^x \text{Exp}_u^{-1}(w)\| \\ & \leq C_1(K, \rho, \beta) d(u, w) (d(u, w) + d(u, x) + d(w, x)). \end{aligned}$$

44 for some explicit function C_1 .

45 This lemma is illustrated in Fig. 1.

46 *Proof.* Denote $-\eta \text{grad} f(u) = v_u$, $-\eta \text{grad} f(w) = v_w$. v is a smooth map. We first prove the
 47 following claim.

Claim 1.

$$d(u_+, w_+) \leq c_6(K)d(u, w),$$

48 where $c_6(K) = c_4(K) + 1 + c_2(K)R^2$.

49 To show this, note that

$$d(u_+, w_+) \leq d(u_+, \tilde{w}_+) + d(\tilde{w}_+, w_+),$$

50 and using Lemma 5 with $\tilde{w}_+ = \text{Exp}_w(\Gamma_u^w v_u)$,

$$\begin{aligned} d(\tilde{w}_+, w_+) &= d(\text{Exp}_w(v_w), \text{Exp}_w(\Gamma_u^w v_u)) \\ &\leq (1 + c_2(K)R^2)\|v_w - \Gamma_u^w v_u\| \\ &\leq \beta(1 + c_2(K)R^2)d(u, w). \end{aligned}$$

51 Using Lemma 5,

$$d(\tilde{w}_+, u_+) \leq c_4(K)d(u, w). \quad (4)$$

52 Adding the two inequalities proves the claim.

53 We use now Lemma 3 between (u, w, u_+, w_+) in two different ways. First let us use it for $a =$
54 $\text{Exp}_u^{-1}(w)$ and $y = \Gamma_w^u v_w$. We obtain:

$$d(w_+, \text{Exp}_u(\text{Exp}_u^{-1}(w) + \Gamma_w^u v_w)) \leq c_1(K)d(u, w)(d(u, w)^2 + \|v_w\|^2). \quad (5)$$

55 Then we use it for $a = \text{Exp}_u^{-1}(v_u)$ and $y = \Gamma_{u_+}^u \text{Exp}_{u_+}^{-1}(w_+)$ which yields

$$\begin{aligned} &d(w_+, \text{Exp}_u(v_u + \Gamma_{u_+}^u \text{Exp}_{u_+}^{-1}(w_+))) \\ &\leq c_1(K)d(u_+, w_+)(d(u_+, w_+)^2 + \|v_u\|^2) \\ &\leq c_1(K)c_5(K, \|v_u\|, \|v_w\|)d(u, w) \cdot [c_5(K, \|v_u\|, \|v_w\|)^2 d(u, w)^2 + \|v_u\|^2]. \end{aligned}$$

56 Using the triangular inequality we have

$$\begin{aligned} &d(\text{Exp}_u(\text{Exp}_u^{-1}(w) + \Gamma_w^u v_w), \text{Exp}_u(v_u + \Gamma_{u_+}^u \text{Exp}_{u_+}^{-1}(w_+))) \\ &\leq d(w_+, \text{Exp}_u(\text{Exp}_u^{-1}(w) + \Gamma_w^u v_w)) + d(w_+, \text{Exp}_u(v_u + \Gamma_{u_+}^u \text{Exp}_{u_+}^{-1}(w_+))) \\ &\leq c_7 d(u, w) \end{aligned}$$

57 with c_7 defined as

$$c_7 = c_1(K)c_6(K) \cdot [c_5(K, \|v_u\|, \|v_w\|)^2 d(u, w)^2 + \|v_u\|^2 + \|v_w\|^2].$$

58 We use again Lemma 4,

$$\|\Gamma_{u_+}^u \text{Exp}_{u_+}^{-1}(w_+) - \text{Exp}_u^{-1}(w) - [v_u - \Gamma_w^u v_w]\| \leq (1 + c_3(K)R^2) \cdot c_7 d(u, w).$$

59 Therefore we have linearized the iterate in $T_u \mathcal{M}$. We should see how to transport it back to $T_x \mathcal{M}$.

60 With Lemma 6 we have

$$\|[\Gamma_u^x \Gamma_{u_+}^u - \Gamma_{u_+}^x] \text{Exp}_{u_+}^{-1}(w_+)\| = c_5(K)d(u, x)d(u_+, w_+)\|v_u\|.$$

61 Note v_u and v_w are $-\eta \text{grad}f(u)$ and $-\eta \text{grad}f(w)$, we define $\nabla v(x)$ the gradient of v , i.e., $-\eta H$.

62 Using Hessian Lipschitz,

$$\begin{aligned} &\|v_u - \Gamma_w^u v_w + \eta H(u) \text{Exp}_u^{-1}(w)\| \\ &= \|v_u - \Gamma_w^u v_w - \nabla v(u) \text{Exp}_u^{-1}(w)\| \\ &\leq \rho d(u, w)^2, \end{aligned}$$

63 and

$$\|\nabla v(u) \text{Exp}_u^{-1}(w) - \Gamma_x^u \nabla v(x) \Gamma_u^x \text{Exp}_u^{-1}(w)\| \leq \rho d(u, w)d(u, x).$$

64 So we have

$$\begin{aligned} &\|\Gamma_{u_+}^x \text{Exp}_{u_+}^{-1}(w_+) - (I + \nabla v(x)) \Gamma_u^x \text{Exp}_u^{-1}(w)\| \\ &\leq c_7 d(u, w) + \rho d(u, w)(d(u, w) + d(u, x)) + c_5(K)d(u, x)d(u_+, w_+)\|v_u\| := D_1 \end{aligned} \quad (6)$$

65 \square

66 **B.2 Evolution of $\text{Exp}_x^{-1}(w) - \text{Exp}_x^{-1}(u)$**

67 We consider now the evolution of $\text{Exp}_x^{-1}(w) - \text{Exp}_x^{-1}(u)$ in the fixed tangent space $\mathcal{T}_x\mathcal{M}$. We show
68 in the following lemma that it also approximately follows a linear iteration.

69 **Lemma 2.** Define $\gamma = \sqrt{\rho\epsilon}$, $\kappa = \frac{\beta}{\gamma}$, and $\mathcal{S} = \sqrt{\eta\beta}\frac{\gamma}{\rho} \log^{-1}(\frac{d\kappa}{\delta})$. Let us consider x be a $(\epsilon, -\sqrt{\rho\epsilon})$
70 saddle point, and define $u^+ = \text{Exp}_u(-\eta\text{grad}f(u))$ and $w^+ = \text{Exp}_w(-\eta\text{grad}f(w))$. Under
71 Assumptions 1, 2, 3, if all pairwise distances between u, w, u^+, w^+, x are less than $12\mathcal{S}$, then for
72 some explicit constant $C(K, \rho, \beta)$ depending only on K, ρ, β , there is

$$\begin{aligned} & \|\text{Exp}_x^{-1}(w^+) - \text{Exp}_x^{-1}(u^+) - (I - \eta H(x))(\text{Exp}_x^{-1}(w) - \text{Exp}_x^{-1}(u))\| \\ & \leq C(K, \rho, \beta)d(u, w) (d(u, w) + d(u, x) + d(w, x)). \end{aligned} \quad (7)$$

73 This lemma controls the error of the linear approximation of the iterates hen mapped in $\mathcal{T}_x\mathcal{M}$ and
74 largely follows from Lemma 1.

75 *Proof.* We have that

$$w = \text{Exp}_x(\text{Exp}_x^{-1}(w)) \quad (8)$$

$$= \text{Exp}_u(\text{Exp}_u^{-1}(w)). \quad (9)$$

76 Use Eq. (9), let $a = \text{Exp}_x^{-1}(u)$ and $v = \Gamma_u^x \text{Exp}_u^{-1}(w)$, Lemma 3 suggests that

$$\begin{aligned} & d(\text{Exp}_u(\text{Exp}_u^{-1}(w)), \text{Exp}_x(\text{Exp}_x^{-1}(u) + \Gamma_u^x \text{Exp}_u^{-1}(w))) \\ & \leq c_1(K)\|\text{Exp}_u^{-1}(w)\|(\|\text{Exp}_u^{-1}(w)\| + \|\text{Exp}_x^{-1}(u)\|)^2. \end{aligned}$$

77 Compare with Eq. (8), we have

$$\begin{aligned} & d(\text{Exp}_x(\text{Exp}_x^{-1}(w)), \text{Exp}_x(\text{Exp}_x^{-1}(u) + \Gamma_u^x \text{Exp}_u^{-1}(w))) \\ & \leq c_1(K)\|\text{Exp}_u^{-1}(w)\|(\|\text{Exp}_u^{-1}(w)\| + \|\text{Exp}_x^{-1}(u)\|)^2 \\ & := D. \end{aligned} \quad (10)$$

78 Denote the quantity above by D . Now use Lemma 4

$$\|\text{Exp}_x^{-1}(w) - (\text{Exp}_x^{-1}(u) + \Gamma_u^x \text{Exp}_u^{-1}(w))\| \leq (1 + c_3(K)R^2)D.$$

79 Analogously

$$\|\text{Exp}_x^{-1}(w_+) - (\text{Exp}_x^{-1}(u_+) + \Gamma_{u_+}^x \text{Exp}_{u_+}^{-1}(w_+))\| \leq (1 + c_3(K)R^2)D_+$$

80 where

$$D_+ = c_1(K)\|\text{Exp}_{u_+}^{-1}(w_+)\|(\|\text{Exp}_{u_+}^{-1}(w_+)\| + \|\text{Exp}_x^{-1}(u_+)\|)^2 \quad (11)$$

81 And we can compare $\Gamma_u^x \text{Exp}_u^{-1}(w)$ and $\Gamma_{u_+}^x \text{Exp}_{u_+}^{-1}(w_+)$ using Eq. (6). In the end we have

$$\begin{aligned} & \|\text{Exp}_x^{-1}(w^+) - \text{Exp}_x^{-1}(u^+) - (I - \eta H(x))(\text{Exp}_x^{-1}(w) - \text{Exp}_x^{-1}(u))\| \\ & \leq \|\text{Exp}_x^{-1}(w_+) - (\text{Exp}_x^{-1}(u_+) + \Gamma_{u_+}^x \text{Exp}_{u_+}^{-1}(w_+))\| \\ & \quad + \|\text{Exp}_x^{-1}(w) - (\text{Exp}_x^{-1}(u) + \Gamma_u^x \text{Exp}_u^{-1}(w))\| \\ & \quad + \|\Gamma_{u_+}^x \text{Exp}_{u_+}^{-1}(w_+) - \Gamma_u^x \text{Exp}_u^{-1}(w) - \nabla v(x)\Gamma_u^x \text{Exp}_u^{-1}(w)\| \\ & \quad + \|\nabla v(x)(\Gamma_u^x \text{Exp}_u^{-1}(w) - (\text{Exp}_x^{-1}(w) - \text{Exp}_x^{-1}(u)))\| \\ & \leq (1 + c_3(K)R^2)(D_+ + D) + D_1 + \eta\|H(x)\|D. \end{aligned}$$

82 D, D_+ and D_1 are defined in Eq. (10), Eq. (11) and Eq. (6), they are all order $d(u, w)(d(u, w) +$
83 $d(u, x) + d(w, x))$ so we get the correct order in Eq. (7). \square

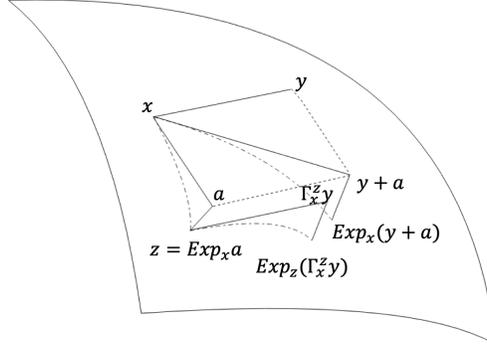


Figure 2: Lemma 3 bounds the difference of two steps starting from x : (1) take $y + a$ step in $\mathcal{T}_x\mathcal{M}$ and map it to manifold, and (2) take a step in $\mathcal{T}_x\mathcal{M}$, map to manifold, call it z , and take $\Gamma_x^z y$ step in $\mathcal{T}_x\mathcal{M}$, and map to manifold. $\text{Exp}_z(\Gamma_x^z y)$ is close to $\text{Exp}_x(y + a)$.

84 B.3 Control of two-steps iteration

85 In the following lemma we control the distance between the point obtained after moving along the
 86 sum of two vectors in the tangent space, and the point obtained after moving a first time along the first
 87 vector and then a second time along the transport of the second vector. This is illustrated in Fig. 2.

88 **Lemma 3.** *Let $x \in \mathcal{M}$ and $y, a \in T_x\mathcal{M}$. Let us denote by $z = \text{Exp}_x(a)$ then under Assumption 3*

$$d(\text{Exp}_x(y + a), \text{Exp}_z(\Gamma_x^z y)) \leq c_1(K) \min\{\|a\|, \|y\|\}(\|a\| + \|y\|)^2. \quad (12)$$

89 This lemma which is crucial in the proofs of Lemma 2 and Lemma 1 tightens the result of Karcher
 90 (1977, C2.3), which only shows an upper-bound $O(\|a\|(\|a\| + \|y\|)^2)$.

91 *Proof.* We adapt the proof of Karcher (1977, Eq. (C2.3) in App C2.2), the only difference being
 92 that we bound more carefully the initial normal component. We restate here the whole proof for
 93 completeness.

94 Let $x \in \mathcal{M}$ and $y, a \in T_x\mathcal{M}$. We denote by $\gamma(t) = \text{Exp}_x(ta)$. We want to compare the point
 95 $\text{Exp}_x(r(y + a))$ and $\text{Exp}_\gamma(1)(\Gamma_x^{\gamma(1)}y)$. These two points, for a fixed r are joined by the curve

$$t \mapsto c(r, t) = \text{Exp}_{\gamma(t)}(r\Gamma_x^{\gamma(t)}(y + (1 - t)a)).$$

96 We note that $\frac{d}{dt}c(r, t)$ is a Jacobi field along the geodesic $r \mapsto c(r, t)$, which we denote by $J_t(r)$.
 97 We importantly remark that the length of the geodesic $r \mapsto c(r, t)$ is bounded as $\|\frac{d}{dr}c(r, t)\| \leq$
 98 $\|y + (1 - t)a\|$. We denote this quantity by $\rho_t = \|y + (1 - t)a\|$. The initial condition of the Jacobi
 99 field J_t are given by:

$$\begin{aligned} J_t(0) &= \frac{d}{dt}\gamma(t) = \Gamma_x^{\gamma(t)}a \\ \frac{D}{dr}J_t(0) &= \frac{D}{dr}\Gamma_x^{\gamma(t)}(y + (1 - t)a) = -\Gamma_x^{\gamma(t)}a. \end{aligned}$$

100 These two vectors are linearly dependent and it is therefore possible to apply Karcher (1977, Proposi-
 101 tion A6) to bound J_t^{norm} . Moreover, following Karcher (1977, App A0.3), the tangential component
 102 of the Jacobi field is known explicitly, independent of the metric, by

$$J_t^{\text{tan}}(r) = \left(J_t^{\text{tan}}(0) + r \frac{D}{dr}J_t^{\text{tan}}(0) \right) \frac{d}{dr}c(r, t)$$

103 where the initial conditions of the tangential component of the Jacobi fields are given by $J_t^{\text{tan}}(0) =$
 104 $\langle J_t(0), \frac{\frac{d}{dr}c(r, t)}{\|\frac{d}{dr}c(r, t)\|} \rangle$ and $\frac{D}{dr}J_t^{\text{tan}}(0) = \langle \frac{D}{dr}J_t(0), \frac{\frac{d}{dr}c(r, t)}{\|\frac{d}{dr}c(r, t)\|} \rangle = -J_t^{\text{tan}}(0)$. Therefore

$$J_t^{\text{tan}}(r) = (1 - r)J_t^{\text{tan}}(0) \frac{d}{dr}c(r, t),$$

105 and $J_t^{\text{tan}}(1) = 0$.

106 We estimate now the distance $d(\text{Exp}_x(y + a), \text{Exp}_z(\Gamma_x^z y))$ by the length of the curve $t \mapsto c(r, t)$ as
 107 follows:

$$d(\text{Exp}_x(y + a), \text{Exp}_z(\Gamma_x^z y)) \leq \int_0^1 \left\| \frac{d}{dt} c(1, t) \right\| dt = \int_0^1 \|J_t^{\text{norm}}(1)\| dt,$$

108 where we use crucially that $J_t^{\text{an}}(1) = 0$.

109 We utilize (Karcher, 1977, Proposition A.6) to bound $\|J_t^{\text{norm}}(1)\|$ as

$$\|J_t^{\text{norm}}(1)\| \leq \|J_t^{\text{norm}}(0)\| \left(\cosh(\sqrt{K}\rho_t) - \frac{\sinh(\sqrt{K}\rho_t)}{\sqrt{K}\rho_t} \right)$$

110 using (Karcher, 1977, Equation (A6.3)) with $\kappa = 0$, $f_\kappa(1) = 0$ and recalling that the geodesics
 $r \mapsto c(r, t)$ have length ρ_t .

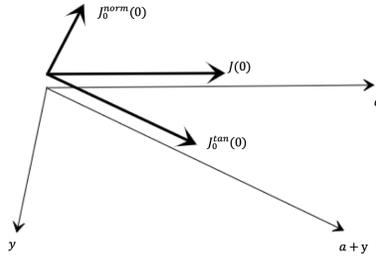


Figure 3: Figure for Lemma 3.

111

112 In particular for small value $\|a\| + \|y\|$ we have for some constant $c_1(K)$,

$$\|J_t^{\text{norm}}(1)\| \leq \|J_t^{\text{norm}}(0)\| c_1(K) \rho_t^2.$$

113 We bound $\|J_t^{\text{norm}}(0)\|$ now. This is the main difference with the original proof of Karcher (1977)
 114 who directly bounded $\|J_t^{\text{norm}}(0)\| \leq \|J_t(0)\| = \|a\|$ and $\rho_t \leq \|a\| + \|y\|$. Therefore his proof does
 115 not lead to the correct dependence in $\|y\|$.

116 We have $J_t^0 = \Gamma_x^{\gamma(t)} a$, and the tangential component (velocity of $r \rightarrow c(r, t)$) is in the $\Gamma_x^{\gamma(t)}(y + (1 -$
 117 $t)a)$ direction. Let $\tilde{z} = \Gamma_x^{\gamma(t)}(y + (1 - t)a)$ and $\mathcal{P}_{\tilde{z}^\perp}$ and \mathcal{P}_{a^\perp} denote the projection onto orthogonal
 118 complement of \tilde{z} and a .

$$\begin{aligned} \|J_t^{\text{norm}}(0)\|^2 &= \|\mathcal{P}_{\tilde{z}^\perp}(a)\|^2 \\ &= \|a\|^2 - \frac{(a^T \tilde{z})^2}{\|\tilde{z}\|^2} \\ &= \frac{\|a\|^2}{\|\tilde{z}\|^2} \left(\|\tilde{z}\|^2 - \frac{(a^T \tilde{z})^2}{\|\tilde{z}\|^2} \right) \\ &\leq \frac{\|a\|^2}{\|\tilde{z}\|^2} \|\mathcal{P}_{a^\perp}(\Gamma_x^{\gamma(t)}(y + (1 - t)a))\|^2 \\ &\leq \frac{\|a\|^2}{\|\tilde{z}\|^2} \|\mathcal{P}_{a^\perp}(\Gamma_x^{\gamma(t)}((1 - t)a) + \mathcal{P}_{a^\perp}(\Gamma_x^{\gamma(t)}y))\|^2 \\ &= \frac{\|a\|^2}{\|\tilde{z}\|^2} \|\mathcal{P}_{a^\perp}(\Gamma_x^{\gamma(t)}y)\|^2 \\ &\leq \frac{\|a\|^2 \|y\|^2}{\|\tilde{z}\|^2}. \end{aligned}$$

119 So

$$\begin{aligned} \|J_t^{\text{norm}}(1)\| &\leq \|J_t^{\text{norm}}(0)\|c_1(K)\rho_t^2 \\ &\leq \frac{\|a\| \cdot \|y\|}{\|\tilde{z}\|}c_1(K)\|\tilde{z}\|^2 \\ &\leq c_1(K)\|a\| \cdot \|y\|(\|a\| + \|y\|), \end{aligned}$$

120 and

$$d(\text{Exp}_x(y+a), \text{Exp}_z(\Gamma_x^z y)) \leq c_1(K)\|a\| \cdot \|y\|(\|a\| + \|y\|).$$

121

□

122 B.4 Auxilliary lemmas

123 In the proofs of Lemma 1 and Lemma 2 we needed numerous auxiliary lemmas we are stating here.

124 We needed the following lemma which shows that both the exponential map and its inverse are
125 Lipschitz.

126 **Lemma 4.** *Let $x, y, z \in M$, and the distance of each two points is no bigger than R . Then under
127 Assumption 3*

$$(1 + c_2(K)R^2)^{-1}d(y, z) \leq \|\text{Exp}_x^{-1}(y) - \text{Exp}_x^{-1}(z)\| \leq (1 + c_3(K)R^2)d(y, z).$$

128 Intuitively this lemma relates the norm of the difference of two vectors of $\mathcal{T}_x\mathcal{M}$ to the distance
129 between the corresponding points on the manifold \mathcal{M} and follows from bounds on the Hessian of the
130 square-distance function (Sakai, 1996, Ex. 4 p. 154).

131 *Proof.* The upper-bound is directly proven in Karcher (1977, Proof of Cor. 1.6), and we prove the
132 lower-bound via Lemma 3 in the supplement. Let $b = \text{Exp}_y(\Gamma_x^y(\text{Exp}_x^{-1}(z) - \text{Exp}_x^{-1}(y)))$. Using
133 $d(y, b) = \|\text{Exp}_y^{-1}(b)\|$ and Lemma 3,

$$\begin{aligned} d(y, z) &\leq d(y, b) + d(b, \text{Exp}_x(\text{Exp}_x^{-1}(z))) \\ &\leq \|\text{Exp}_x^{-1}(y) - \text{Exp}_x^{-1}(z)\| \\ &\quad + c_1(K)\|\text{Exp}_x^{-1}(y) - \text{Exp}_x^{-1}(z)\|(\|\text{Exp}_x^{-1}(y) - \text{Exp}_x^{-1}(z)\| + \|\text{Exp}_x^{-1}(y)\|)^2 \end{aligned}$$

134

□

135 The following contraction result is fairly classical and is proven using the Rauch comparison theorem
136 from differential geometry (Cheeger & Ebin, 2008).

137 **Lemma 5.** (Mangoubi et al., 2018, Lemma 1) *Under Assumption 3, for $x, y \in \mathcal{M}$ and $w \in T_x\mathcal{M}$,*

$$d(\text{Exp}_x(w), \text{Exp}_y(\Gamma_x^y w)) \leq c_4(K)d(x, y).$$

138 Eventually we need the following corollary of the famous Ambrose-Singer holonomy theorem (Am-
139 brose & Singer, 1953).

140 **Lemma 6.** (Karcher, 1977, Section 6) *Under Assumption 3, for $x, y, z \in \mathcal{M}$ and $w \in T_x\mathcal{M}$,*

$$\|\Gamma_y^z \Gamma_x^y w - \Gamma_x^z w\| \leq c_5(K)d(x, y)d(y, z)\|w\|.$$

141 C Proof of Lemma 7 and 8

142 In this section we prove two important lemmas from which the proof of our main result mainly comes
143 out. Then we show, in the last subsection, how to combine them to prove this main result.

144 **Lemma 7.** *Assume Assumptions 1, 2, 3 hold, and*

$$\epsilon \leq \min \left\{ \frac{\hat{\rho}}{56 \max\{c_2(K), c_3(K)\}\eta\beta} \log \left(\frac{d\beta}{\sqrt{\hat{\rho}\epsilon\delta}} \right), \left(\frac{\Im\hat{\rho}}{12\hat{c}\sqrt{\eta\beta}} \log \left(\frac{d\beta}{\sqrt{\hat{\rho}\epsilon\delta}} \right) \right)^2 \right\} \quad (14)$$

145 from the main theorem. There exists a constant c_{\max} , $\forall \hat{c} > 3, \delta \in (0, \frac{d\kappa}{e}]$, for any u_0 with $d(\tilde{x}, u_0) \leq$
 146 $2\mathcal{S}/(\kappa \log(\frac{d\kappa}{\delta}))$, $\kappa = \beta/\gamma$.

$$T = \min \left\{ \inf_t \left\{ t | \tilde{f}_{u_0}(u_t) - f(u_0) \leq -3\mathcal{F} \right\}, \hat{c}\mathcal{S} \right\},$$

147 then $\forall \eta \leq c_{\max}/\beta$, we have $\forall 0 < t < T$, $d(u_0, u_t) \leq 3(\hat{c}\mathcal{S})$.

148 **Lemma 8.** Assume Assumptions 1, 2, 3 and Eq. (14) hold. Take two points u_0 and w_0 which
 149 are perturbed from approximate saddle point, where $d(\tilde{x}, u_0) \leq 2\mathcal{S}/(\kappa \log(\frac{d\kappa}{\delta}))$, $\text{Exp}_{\tilde{x}}^{-1}(w_0) -$
 150 $\text{Exp}_{\tilde{x}}^{-1}(u_0) = \mu e_1$, e_1 is the smallest eigenvector¹ of $H(\tilde{x})$, $\mu \in [\delta/(2\sqrt{d}), 1]$, and the algorithm
 151 runs two sequences $\{u_t\}$ and $\{w_t\}$ starting from u_0 and w_0 . Denote

$$T = \min \left\{ \inf_t \left\{ t | \tilde{f}_{w_0}(w_t) - f(w_0) \leq -3\mathcal{F} \right\}, \hat{c}\mathcal{S} \right\},$$

152 then $\forall \eta \leq c_{\max}/l$, if $\forall 0 < t < T$, $d(\tilde{x}, u_t) \leq 3(\hat{c}\mathcal{S})$, we have $T < \hat{c}\mathcal{S}$.

153 C.1 Proof of Lemma 7

154 Suppose $f(u_{t+1}) - f(u_t) \leq -\frac{\eta}{2} \|\text{grad}f(u_t)\|^2$.

$$\begin{aligned} d(u_{\hat{c}\mathcal{S}}, u_0)^2 &\leq \left(\sum_0^{\hat{c}\mathcal{S}-1} d(u_{t+1}, u_t) \right)^2 \\ &\leq \hat{c}\mathcal{S} \sum_0^{\hat{c}\mathcal{S}-1} d(u_{t+1}, u_t)^2 \\ &\leq \eta^2 \hat{c}\mathcal{S} \sum_0^{\hat{c}\mathcal{S}-1} \|\text{grad}f(u_t)\|^2 \\ &\leq 2\eta \hat{c}\mathcal{S} \sum_0^{\hat{c}\mathcal{S}-1} f(u_t) - f(u_{t+1}) \\ &= 2\eta \hat{c}\mathcal{S} (f(u_0) - f(u_{\hat{c}\mathcal{S}})) \\ &\leq 6\eta \hat{c}\mathcal{S} \mathcal{F} = 6\hat{c}\mathcal{S}^2. \end{aligned}$$

155 C.2 Proof of Lemma 8

156 Note that, for any points inside a region with diameter R , under the assumption of Lemma 8, we have
 157 $\max\{c_2(K), c_3(K)\}R^2 \leq 1/2$.

158 Define $v_t = \text{Exp}_{\tilde{x}}^{-1}(w_t) - \text{Exp}_{\tilde{x}}^{-1}(u_t)$, let $v_0 = e_1$ be the smallest eigenvector of $H(\tilde{x})$, then let $\hat{y}_{2,t}$
 159 be a unit vector, we have

$$\begin{aligned} v_{t+1} &= (I - \eta H(\tilde{x}))v_t + C(K, \rho, \beta)d(u_t, w_t) \\ &\quad \cdot (d(u_t, \tilde{x}) + d(w_t, \tilde{x}) + d(\tilde{x}, u_0))\hat{y}_{2,t}. \end{aligned} \tag{16}$$

160 Let $C := C(K, \rho, \beta)$. Suppose lemma 8 is false, then $0 \leq t \leq T$, $d(u_t, \tilde{x}) \leq 3\hat{c}\mathcal{S}$, $d(w_t, \tilde{x}) \leq 3\hat{c}\mathcal{S}$,
 161 so $d(u_t, w_t) \leq 6\hat{c}\mathcal{S}$, and the norm of the last term in Eq. (16) is smaller than $14\eta C \hat{c}\mathcal{S} \|v_t\|$.

162 Lemma 4 in the main paper indicates that

$$\|v_t\| \in [1/2, 2] \cdot d(u_t, w_t) = [3/2, 6] \cdot \hat{c}\mathcal{S}. \tag{17}$$

163 Let ψ_t be the norm of v_t projected onto e_1 , the smallest eigenvector of $H(0)$, and φ_t be the norm of
 164 v_t projected onto the remaining subspace. Then Eq. (16) is

$$\begin{aligned} \psi_{t+1} &\geq (1 + \eta\gamma)\psi_t - \mu\sqrt{\psi_t^2 + \phi_t^2}, \\ \phi_{t+1} &\leq (1 + \eta\gamma)\phi_t + \mu\sqrt{\psi_t^2 + \phi_t^2}. \end{aligned}$$

¹“smallest eigenvector” means the eigenvector corresponding to the smallest eigenvalue.

165 Prove that for all $t \leq T$, $\phi_t \leq 4\mu t\psi_t$. Assume it is true for t , we have

$$4\mu(t+1)\psi_{t+1} \geq 4\mu(t+1) \cdot \left((1+\eta\gamma)\psi_t - \mu\sqrt{\psi_t^2 + \phi_t^2} \right),$$

$$\phi_{t+1} \leq 4\mu t(1+\eta\gamma)\phi_t + \mu\sqrt{\psi_t^2 + \phi_t^2}.$$

166 So we only need to show that

$$(1+4\mu(t+1))\sqrt{\psi_t^2 + \phi_t^2} \leq (1+\eta\gamma)\psi_t.$$

167 By choosing $\sqrt{c_{\max}} \leq \frac{1}{56\hat{c}^2}$ and $\eta \leq c_{\max}/\beta$, we have

$$4\mu(t+1) \leq 4\mu T \leq 4\eta C\mathcal{S} \cdot 14\hat{c}^2 \mathcal{T} = 56\hat{c}^2 \frac{C}{\hat{\rho}} \sqrt{\eta\beta} \leq 1.$$

168 This gives

$$4(1+\eta\gamma)\psi_t \geq 2\sqrt{2\psi_t^2} \geq (1+4\mu(t+1))\sqrt{\psi_t^2 + \phi_t^2}.$$

169 Now we know $\phi_t \leq 4\mu t\psi_t \leq \psi_t$, so $\psi_{t+1} \geq (1+\eta\gamma)\psi_t - \sqrt{2\mu}\psi_t$, and

$$\mu = 14\hat{c}\eta C\mathcal{S} \leq 14\hat{c}\sqrt{c_{\max}}\eta\gamma C \log^{-1}\left(\frac{d\kappa}{\delta}\right)/\hat{\rho} \leq \eta\gamma/2,$$

170 so $\psi_{t+1} \geq (1+\eta\gamma/2)\psi_t$.

171 We also know that $\|v_t\| \leq 6\hat{c}\mathcal{S}$ for all $t \leq T$ from Eq. (17), so

$$\begin{aligned} 6\hat{c}\mathcal{S} &\geq \|v_t\| \geq \psi_t \geq (1+\eta\gamma/2)^t \psi_0 \\ &= (1+\eta\gamma/2)^t \frac{\mathcal{S}}{\kappa} \log^{-1}\left(\frac{d\kappa}{\delta}\right) \\ &\geq (1+\eta\gamma/2)^t \frac{\delta\mathcal{S}}{2\sqrt{d}\kappa} \log^{-1}\left(\frac{d\kappa}{\delta}\right). \end{aligned}$$

172 This implies

$$\begin{aligned} T &< \frac{\log(12\frac{\kappa\sqrt{d}}{\delta}\hat{c}\log(\frac{d\kappa}{\delta}))}{2\log(1+\eta\gamma/2)} \\ &\leq \frac{\log(12\frac{\kappa\sqrt{d}}{\delta}\hat{c}\log(\frac{d\kappa}{\delta}))}{\eta\gamma} \\ &\leq (2+\log(12\hat{c}))\mathcal{T}. \end{aligned}$$

173 By choosing \hat{c} such that $2+\log(12\hat{c}) < \hat{c}$, we have $T \leq \hat{c}\mathcal{T}$, which finishes the proof.

174 C.3 Proof of function value decrease at an approximate saddle point

175 With Lemma 7 and 8 proved, we can lower bound the function value in $O(\mathcal{T})$ iterations
176 decrease by $\Omega(\mathcal{F})$, thus match the convergence rate in the main theorem. Let $T' :=$

177 $\inf_t \left\{ t | \tilde{f}_{u_0}(u_t) - f(u_0) \leq -3\mathcal{F} \right\}$. Let $\check{\cdot}$ denote the operator $\text{Exp}_{u_0}^{-1}(\cdot)$. If $T' \leq T$,

$$\begin{aligned} &f(u_{T'}) - f(u_0) \\ &\leq \nabla f(u_0)^T (u_{T'} - u_0) + \frac{1}{2}H(u_0)[\check{u}_{T'} - u_0, \check{u}_{T'} - u_0] \\ &\quad + \frac{1}{2}(\Gamma_{\tilde{x}}^{u_0} H(\tilde{x})\Gamma_{u_0}^{\tilde{x}} - H(u_0))[\check{u}_{T'} - u_0, \check{u}_{T'} - u_0] \\ &\quad + \frac{\rho}{6}\|\check{u}_{T'} - u_0\|^3 \\ &\leq \tilde{f}_{u_0}(u_t) - f(u_0) + \rho d(u_0, \tilde{x})\|\check{u}_{T'} - u_0\|^2 \\ &\leq -3\mathcal{F} + O(\rho\mathcal{S}^3) \leq -2.5\mathcal{F}. \end{aligned}$$

178 If $T' > T$, then $\inf_t \left\{ t | \tilde{f}_{w_0}(w_t) - f(w_0) \leq -3\mathcal{F} \right\} \leq T$, and we know $f(w_T) - f(w_0) \leq -2.5\mathcal{F}$.

179 **Remark 1.** What is left is bounding the volume of the stuck region, to get the probability of getting
 180 out of the stuck region by the perturbation. The procedure is the same as in Jin et al. (2017). We
 181 sample from a unit ball in $\mathcal{T}_x\mathcal{M}$, where x is the approximate saddle point. In Lemma 7 and 8, we
 182 study the inverse exponential map at the approximate saddle point x , and the coupling difference
 183 between $\text{Exp}_x^{-1}(w)$ and $\text{Exp}_x^{-1}(u)$. The iterates we study and the noise are all in the tangent space
 184 $\mathcal{T}_x\mathcal{M}$ which is a Euclidean space, so the probability bound is same as the one in Jin et al. (2017).

185 D Experiment with retraction

186 In the main algorithm and its proof, we use the exponential map in the algorithm. The exponential map
 187 is easy to compute for many manifolds, but one may also use *retraction* as a first order approximation
 188 of exponential map. We do not theoretically study retraction, but the experiment below shows that
 189 replacing exponential by a smooth retraction works well practically.

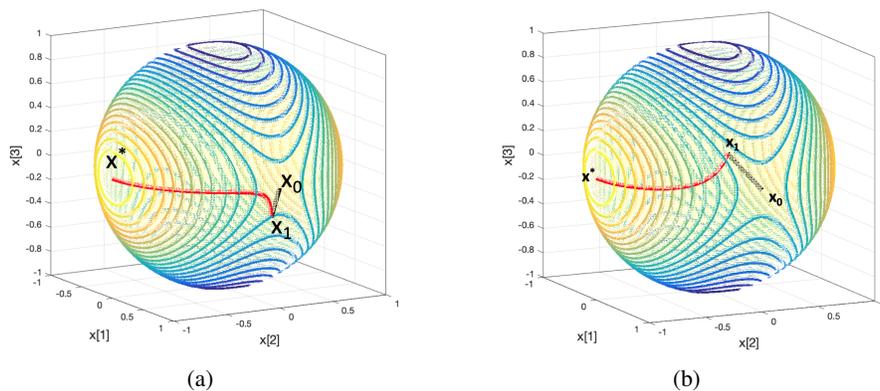


Figure 4: (a) Function f with saddle point on a sphere. $f(x) = x_1^2 - x_2^2 + 4x_3^2$. We plot the contour of this function on unit sphere. The main algorithm initializes at $x_0 = [1, 0, 0]$ (a saddle point), perturbs it towards x_1 and runs Riemannian gradient descent, and terminates at $x^* = [0, -1, 0]$ (a local minimum). We amplify the first iteration to make saddle perturbation visible. (b) We replace exponential map by retraction $R_x(v) = (x + v) / \|x + v\|_2$ and do the same experiment, which addresses the generality of the result. We do not provide in this paper proof for algorithm with retraction, but practically the iterates converge to an approximate saddle point.

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