

by plugging into (1), (2)

So $\frac{\partial \tilde{N}_i}{\partial x_j}|_{ap} = \frac{1}{a} \frac{\partial \tilde{N}_i}{\partial x_j}|_p$ So $\tilde{k}(v) = \frac{k(v)}{a}$, which is true at all (shared) stationary points.

But mean curvature H is the average of k at stationary points, thus $H(ap) = \frac{1}{a} H(p)$.

(d) K (Gauss-Kronecker curvature) is the product of $k(v)$ at stationary points

$$so \quad K(ap) = a^{-n} k(p)$$

Remark: Above argument based on stationary points is not strict enough, especially considering the multiplicity of L_p 's eigenvalues. A better proof is: $\forall v, w \in S_p$. As $\nabla g(ap) = \frac{1}{a} \nabla f(p)$

$$so \quad S_p = \mathcal{L}_{ap}, \quad \forall v, w \in S_p, \quad L_p(v) \cdot w = \frac{1}{2} [k(v+w) - k(v) - k(w)], \quad \text{as } \tilde{k}(v) = k(v)/a$$

$$\text{let } \tilde{L}_p \text{ be Weingarten map on } \tilde{S} \text{ at } ap \rightarrow \tilde{L}_p(v) \cdot w = \frac{1}{2} [\tilde{k}(v+w) - \tilde{k}(v) - \tilde{k}(w)] = \frac{1}{a} L_p(v) \cdot w$$

Since w is arbitrary in S_p , so $\tilde{L}_p(v) = \frac{1}{a} L_p(v)$, so each eigenvalue λ_i of \tilde{L}_p corresponds to the eigenvalue λ_i/a of L_p . As H and K are average / product of eigenvalues, we have

$$H(ap) = \frac{1}{a} H(p) \quad k(ap) = a^{-n} k(p) \quad \text{[if } \# \text{ eigenvalues of } L_p \text{ is even]}$$

$$\text{then one has } (\tilde{L}_p(v) - \frac{1}{a} L_p(v)) \cdot (\tilde{L}_p(v) - \frac{1}{a} L_p(v)) = 0. \text{ So } \tilde{L}_p(v) = \frac{1}{a} L_p(v)$$

13.1 If S is convex at p , then h_u ($u = N(p)$ Gauss map) attains local max/min at p .

so \mathcal{Q}_p is semi-definite, so $\mathcal{Q}_p = \pm \mathcal{D}_p$ is also semi-definite. But the Gauss-Kronecker curvature, which is equal to the product of all eigenvalues of \mathcal{Q}_p , is negative.

As S_p is even dimensional, there must be one positive and one negative eigenvalue, which contradicts the fact that \mathcal{Q}_p is semi-definite. So S is not convex at p .

13.2 $\forall v, w \in S_p, \quad \nabla_v(\text{grad } h) w = \nabla_v(\nabla h - (\nabla h \cdot N)N) w = \nabla_v(\nabla h) w - (\nabla h \cdot N)(\nabla_v N \cdot w)$

$$\nabla_w(\text{grad } h) v = \nabla_w(\nabla h - (\nabla h \cdot N)N) v = \nabla_w(\nabla h) v - (\nabla h \cdot N)(\nabla_w N \cdot v)$$

We know L_p is self-adjoint, i.e., $\nabla_v N \cdot w = \nabla_w N \cdot v$. Besides,

$$\nabla_v(\nabla h) w = v^T H w = w^T H v = \nabla_w(\nabla h) v \quad \text{so } \nabla_v(\text{grad } h) w = \nabla_w(\text{grad } h) v, \text{ so self-adjoint}$$

13.3. (a) \Rightarrow If \mathcal{Q} is posDef, then \forall eigenvector v , $\mathcal{Q}(v) = \lambda v$, $\mathcal{Q}(v) \cdot v = \lambda > 0$ as \mathcal{Q} is PosDef

\Leftarrow We know that the eigenvectors v_1, \dots, v_n make up an orthonormal basis on S_p . $\forall v \in S_p$.

$$\text{Let } v = \sum_{i=1}^n a_i v_i \quad \mathcal{Q}(v) \cdot v = \mathcal{Q}\left(\sum_{i=1}^n a_i v_i\right) \cdot \sum_{i=1}^n a_i v_i = \left(\sum_{i=1}^n a_i \mathcal{Q}(v_i)\right) \cdot \left(\sum_{i=1}^n a_i v_i\right) = \left(\sum_{i=1}^n a_i \lambda_i v_i\right) \cdot \left(\sum_{i=1}^n a_i v_i\right) = \sum_{i=1}^n a_i^2 \lambda_i \geq 0 \text{ because } \lambda_i \geq 0$$

\Leftarrow It is equal to 0 iff ~~$a_i = 0$~~ $a_i = 0$, i.e. $v = 0$.

(b) \Leftarrow Since \mathcal{L} is self-adjoint linear transformation, its associated matrix \mathcal{L} is symmetric. so it has two real valued eigenvalues λ_1, λ_2 . $\det \mathcal{L} > 0 \Rightarrow \lambda_1, \lambda_2 > 0$. But if $\lambda_1 < 0, \lambda_2 < 0$, then \mathcal{L} is negative definition, i.e., there can't be any $v : \mathcal{Q}(v) > 0$. thus $\lambda_1 > 0, \lambda_2 > 0$.

\Rightarrow by definition $Q(v) > 0$ for all $v \neq 0$. As Q is pos def. both eigenvalues are positive, thus $\det L = \lambda_1 \lambda_2 > 0$

- (5) L is non-singular $\Leftrightarrow \det L = \prod_{i=1}^n \lambda_i \neq 0 \Leftrightarrow \lambda_i \neq 0$ (λ_i are eigenvalues)
 L is non-degenerate \Leftrightarrow i.e. p is non-degenerate
 \mathcal{H}_p is non-degenerate $\Leftrightarrow L: V \mapsto \nabla_V(\text{grad } h)$ is non-singular $\Leftrightarrow \lambda_i \neq 0 \Leftrightarrow \forall v \quad \nabla_v(\text{grad } h) \neq 0$

(3.4) If h is height function or any function which has constant $\|\nabla h\|$, then

$$(h \circ \beta)(t) = \nabla h(\beta(t)) \cdot \dot{\beta}(t) \leq \|\nabla h(\beta(t))\| \cdot \|\dot{\beta}(t)\| = \|\nabla h(\alpha(t))\| \cdot \|\dot{\alpha}(t)\|$$

$$= \nabla h(\alpha(t)) \cdot \dot{\alpha}(t) = (h \circ \alpha)'(t).$$

$$\text{So } h(\alpha(b)) = h(\alpha(a)) + \int_a^b (h \circ \alpha)'(t) dt = h(\beta(b))$$

Equality holds iff $\nabla h(\beta(t)) = \lambda \dot{\beta}(t) \quad \lambda > 0$. But $\nabla h(\alpha(t)) = \nabla h(\beta(t))$.

$$\text{So } \|\nabla h(\alpha(t))\| = \lambda \|\dot{\beta}(t)\| = \lambda \|\dot{\alpha}(t)\|. \text{ But } \dot{\alpha}(t) = \nabla h(\alpha(t)). \text{ So } \lambda = 1$$

So $\nabla h(\beta(t)) = \dot{\beta}(t)$, i.e. β is also a gradient line passing thru $\alpha(a)$, but such a line is unique, so $\beta = \alpha$.

If $\|\nabla h\| = \text{const}$ is not guaranteed, WE FEEL that this proposition may not hold.

The following is a counter-example. Let $\tilde{h}(x_1, x_2) = h(x_1)$ $f(x_1, x_2) = x_2$

$$\text{then } \nabla \tilde{h} = (h'(x_1), 0) \quad \nabla f = (0, 1) \text{ so } S = f^{-1}(0) \text{ is a surface. } \nabla \tilde{h} \perp \nabla f \Rightarrow \frac{\text{grad } \tilde{h}}{\|\nabla \tilde{h}\|} = \nabla h$$

$$\alpha(t), \beta(t) \in S. \text{ So we can write in brief } \alpha(t) = (\alpha(t), 0), \beta(t) = (\beta(t), 0)$$

$$\text{So now } \dot{\alpha}(t) = h'(\alpha(t)) \quad \|\dot{\beta}(t)\| = |\dot{\alpha}(t)|$$

As $\beta(t)$ appears in the conclusion only inside $h(\beta(t))$, the only constraint on β

$$\text{is actually } \ell(\beta) = \int_a^b \|\dot{\beta}(t)\| dt = \int_a^b \|\dot{\alpha}(t)\| dt = \ell(\alpha). \text{ Now we } \overset{\text{plot } h(t)}{\text{plot } h(t)}$$

check function $h(t) = \frac{1}{t} \sin \frac{1}{t} \quad (t > 0)$ so \tilde{h} is

defined on (R^+, R) which is open. (let $\alpha(a) = t_0$, s.t. $\sin \frac{1}{t_0} = -1$)

the first peak to the left of t_0 is $t_0 - X$, where $\frac{1}{t_0 - X} = \frac{1}{t_0} + \pi$, $X = \frac{\pi t_0}{1 + \pi t_0}$.

$$h(t_0 - X) = \frac{1}{t_0} + \pi, \quad h(t_0 + X) = \frac{1 + \pi t_0}{t_0 + 2\pi t_0} \sin \frac{1 + \pi t_0}{t_0 + 2\pi t_0} < \frac{1 + \pi t_0}{t_0 + 2\pi t_0} < \frac{1 + \pi t_0}{t_0} = h(t_0 - X).$$

Besides, the first peak to the right of t_0 is $t_0 + S$, s.t. $\frac{1}{t_0 + S} = \frac{1}{t_0} - \pi$, $S = \frac{\pi t_0}{1 - \pi t_0} > X$

in $(t_0, t_0 + S)$ $\dot{\alpha}(t) \neq 0$. Now suppose $\alpha(t) = t_0 + \varepsilon$ where $\varepsilon > 0$ is sufficiently small,

for $t > a$, $\alpha(t)$ monotonically increases, and $\beta(t)$ is forced to decrease monotonically.

As ε can be arbitrarily small, by above discussion, $\beta(t)$ first reaches $t_0 - X$, while

$\alpha(t)$ hasn't reached $t_0 + S$, i.e. $\varepsilon = \frac{1}{t_0} \sin \frac{h'(t_0 + \varepsilon)}{t_0 + \varepsilon}$ guarantees that α has enough impetus to go right and meanwhile β reaches $t_0 - X$ while α only reaches $t_0 + X + 2\varepsilon$.

Suppose b is chosen at such a moment, then we have $h(\alpha(b)) < h(\beta(b))$

which contradicts the exercise assertion.

$$13.5 \quad h(\beta(t)) = c \Rightarrow \nabla h(\beta(t_1)) \cdot \dot{\beta}(t_1) = 0 \quad \left. \begin{array}{l} \alpha(t_0) = \beta(t_1) \\ \end{array} \right\} \Rightarrow \nabla h(\alpha(t_0)) \cdot \dot{\beta}(t_1) = 0 \quad \left. \begin{array}{l} \alpha(t_0) = (\text{grad } h)(\alpha(t_0)) \\ \end{array} \right\}$$

$$\Rightarrow (\text{grad } h)(\alpha(t_0)) \cdot \dot{\beta}(t_1) = 0 \Rightarrow \nabla h$$

$$\Rightarrow \alpha(t_0) \cdot \dot{\beta}(t_1) = (\text{grad } h)(\alpha(t_0)) \cdot \dot{\beta}(t_1) = (\nabla h(\alpha(t_0)) - (\nabla h(\alpha(t_1)) \cdot N(\alpha(t_0))) N(\alpha(t_0))) \cdot \dot{\beta}(t_1) = 0$$

$$\Leftrightarrow \nabla h(\alpha(t_0)) \cdot \dot{\beta}(t_1) = 0 \quad \text{As } N(\alpha(t_0)) \cdot \dot{\beta}(t_1) = N(\beta(t_1)) \cdot \dot{\beta}(t_1) = 0$$