Image Analysis, Classification and Change Detection in Remote Sensing: Errata

Page 13, second para.

the orthogonal matrix U in the keyword

Page 14, bottom

This becomes obvious if $f(x)$ is expanded in a *Taylor series* about x^*,

$$f(x) = f(x^*) + (x - x^*)\frac{d}{dx}f(x^*) + \frac{1}{2}(x - x^*)^2\frac{d^2}{dx^2}f(x^*) + \dots\ .$$

Page 15, second last equation

$$f(\boldsymbol{x}) \approx f(\boldsymbol{x}^*) + \frac{1}{2}(\boldsymbol{x} - \boldsymbol{x}^*)^\top \boldsymbol{H}(\boldsymbol{x} - \boldsymbol{x}^*).$$

Page 18, middle

The Lagrange function is

$$L(\boldsymbol{x}) = \boldsymbol{x}^\top \boldsymbol{C}\boldsymbol{x} - \lambda(\boldsymbol{x}^\top \boldsymbol{x} - 1).$$

Page 53, equation (3.10)

$$P(k,\ell) = |\hat{g}(k,\ell)|^2 = \hat{g}(k,\ell)\hat{g}^*(k,\ell).$$

Page 54, first equation

$$e^{\mathbf{i}2\pi(k_0 i/c + \ell_0 j/r)} = e^{\mathbf{i}\pi(i+j)} = (-1)^{i+j}.$$

Page 56, middle

shifts the basis function across the interval $[0,1]$.

Page 69, middle

A convenient constraint is $\boldsymbol{a}^\top\boldsymbol{a} = 1$. According to the discussion in Section 1.5, we can maximize the unconstrained Lagrange function

$$L = \boldsymbol{a}^\top \boldsymbol{\Sigma}\boldsymbol{a} - \lambda(\boldsymbol{a}^\top\boldsymbol{a} - 1).$$

Page 76, equation (3.41)

$$\ldots = \frac{1}{2}\boldsymbol{a}^\top((\boldsymbol{\Gamma}(\boldsymbol{\Delta}) + \boldsymbol{\Gamma}(-\boldsymbol{\Delta}))\boldsymbol{a}$$

Page 167, second equation

$$g_2 = -\frac{w_1}{w_2}g_1 - \frac{w_0}{w_2},$$

Page 167, figure caption

in the direction of class $k = 2$

Page 167, equation (6.19)

$$\begin{aligned} I(\boldsymbol{g}) &= w_0 + w_1 g_1 + \ldots + w_N g_N \\ &= \boldsymbol{w}^\top \boldsymbol{g} + w_0. \end{aligned}$$

Page 168, last equation

$$\begin{aligned} \Pr(1 \mid \boldsymbol{g}) &= \frac{p(\boldsymbol{g} \mid 1)\Pr(1)}{p(\boldsymbol{g} \mid 1)\Pr(1) + p(\boldsymbol{g} \mid 2)\Pr(2)} \\ &= \frac{1}{1 + p(\boldsymbol{g} \mid 2)\Pr(2)/(p(\boldsymbol{g} \mid 1)\Pr(1))} \\ &= \frac{1}{1 + \exp(-\frac{1}{2}[\|\boldsymbol{g} - \boldsymbol{\mu}_2\|^2 - \|\boldsymbol{g} - \boldsymbol{\mu}_1\|^2])(\Pr(2)/\Pr(1))}. \end{aligned}$$

Page 199, Exercise 2(d)

$$\Pr(1) \cdot \Phi\left(-\frac{1}{2}d + \frac{1}{d}\log\left(\frac{\Pr(2)}{\Pr(1)}\right)\right) + \Pr(2) \cdot \Phi\left(-\frac{1}{2}d - \frac{1}{d}\log\left(\frac{\Pr(2)}{\Pr(1)}\right)\right),$$

Page 325, middle

(default $6 \times 6 \times 6$)