

1 Objectives

The objective is to solve the mutual information calculation for the complex signal model and N tissue types.

2 Work

2.1 Probability Distribution Definitions

Calculate mutual information using numerical integration for a complex signal model $\mathbf{z}(\boldsymbol{\mu}, \mathbf{k})$.

$$\mathbf{z}(\boldsymbol{\mu}, \mathbf{k}) = \int_{\Omega} M(\mathbf{x}) e^{-s(\boldsymbol{\mu}, \mathbf{x})} e^{-2\pi i \mathbf{k} \cdot \mathbf{x}} d\mathbf{x} + \boldsymbol{\nu} = \mathcal{G}(\boldsymbol{\mu}, \mathbf{k}) + \boldsymbol{\nu} \quad (1)$$

$$s(\boldsymbol{\mu}, \mathbf{x}) = \frac{T_E}{T_2^*(\mathbf{x})} + i[2\pi\gamma\alpha B_0 T_E \Delta u(\boldsymbol{\mu}, \mathbf{x}) + T_E \Delta \omega_0(\mathbf{x})] \quad (2)$$

$$\boldsymbol{\nu} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\nu}) \quad \boldsymbol{\Sigma}_{\nu} = \begin{bmatrix} \sigma_{\nu,r}^2 & 0 \\ 0 & \sigma_{\nu,i}^2 \end{bmatrix} \quad (3)$$

Therefore, the probability distribution for $p(\mathbf{z}|\boldsymbol{\mu})$ is

$$p(\mathbf{z}|\boldsymbol{\mu}) = \mathcal{N}(\mathcal{G}(\boldsymbol{\mu}), \boldsymbol{\Sigma}_{\nu}) \quad (4)$$

The tissue properties can be described by the following piecewise functions.

$$\boldsymbol{\mu}(\mathbf{x}) = \sum_{n=1}^N \boldsymbol{\mu}_n U(\mathbf{x} - \Omega_n) \quad (5)$$

$$\bigcup_{n=1}^N \Omega_n = \Omega \quad \Omega_n \cap \Omega_m = \emptyset \quad (6)$$

$$U(\mathbf{x} - \Omega_n) = \begin{cases} 1, & x \in \Omega_n \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Assume normal distribution for the model parameter, optical attenuation coefficient $\boldsymbol{\mu}$.

$$p(\boldsymbol{\mu}) = \mathcal{N}(\mathbf{m}_{\mu}, \boldsymbol{\Sigma}_{\mu}) \quad (8)$$

$$\mathbf{m}_{\mu} = \begin{bmatrix} m_{\mu_1} \\ \vdots \\ m_{\mu_N} \end{bmatrix} \quad \boldsymbol{\Sigma}_{\mu} = \begin{bmatrix} \sigma_{\mu_1} & 0 & \cdots & 0 & 0 \\ 0 & \sigma_{\mu_2} & 0 & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \ddots & 0 & \sigma_{\mu_{N-1}} & 0 \\ 0 & 0 & \cdots & 0 & \sigma_{\mu_N} \end{bmatrix} \quad (9)$$

Also of note, because the real and imaginary components of \mathbf{z} are assumed independent, the covariance matrix $\boldsymbol{\Sigma}_z$ is diagonal, and the following simplification results.

$$p(\mathbf{z}|\boldsymbol{\mu}) = \mathcal{N}_{\mathbf{z}}(\mathcal{G}(\boldsymbol{\mu}), \boldsymbol{\Sigma}_{\nu}) = \mathcal{N}_{z_r}(\mathcal{G}_r(\boldsymbol{\mu}), \boldsymbol{\Sigma}_{\nu}) \mathcal{N}_{z_i}(\mathcal{G}_i(\boldsymbol{\mu}), \boldsymbol{\Sigma}_{\nu}) = p(z_r|\boldsymbol{\mu}) p(z_i|\boldsymbol{\mu}) \quad (10)$$

Similarly, the various tissue types are independent, and the covariance matrix $\boldsymbol{\Sigma}_{\mu}$ is also diagonal.

$$p(\boldsymbol{\mu}) = \mathcal{N}_{\boldsymbol{\mu}}(\mathbf{m}_{\mu}, \boldsymbol{\Sigma}_{\mu}) = \prod_{i=1}^N \mathcal{N}_{\mu_i}(m_{\mu_i}, \sigma_{\mu_i}) = \prod_{i=1}^N p(\mu_i) \quad (11)$$

2.2 Problem Statement

The most approachable way to solve mutual information is to begin with the difference of entropies definition.

$$I(\boldsymbol{\mu}; \mathbf{z}) = H(\mathbf{z}) - H(\mathbf{z}|\boldsymbol{\mu}) = \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\boldsymbol{\Sigma}_z| \right) - \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\boldsymbol{\Sigma}_\nu| \right) \quad (12)$$

Assuming $\sigma_{\nu,r}^2 = \sigma_{\nu,i}^2$, then

$$|\boldsymbol{\Sigma}_\nu| = \sigma_\nu^2 \sigma_\nu^2 - 0 = \sigma_\nu^4 \quad (13)$$

Calculation of $\boldsymbol{\Sigma}_z$ is less straightforward.

$$\boldsymbol{\Sigma}_z = \begin{bmatrix} \mathbb{E} \left[(z_r - \mathbb{E}[z_r])^2 \right] & \mathbb{E} \left[(z_r - \mathbb{E}[z_r]) (z_i - \mathbb{E}[z_i]) \right] \\ \mathbb{E} \left[(z_i - \mathbb{E}[z_i]) (z_r - \mathbb{E}[z_r]) \right] & \mathbb{E} \left[(z_i - \mathbb{E}[z_i])^2 \right] \end{bmatrix} \quad (14)$$

$\mathbb{E}[z_r]$, $\mathbb{E}[z_i]$, $\mathbb{E} \left[(z_r - \mathbb{E}[z_r])^2 \right]$, $\mathbb{E} \left[(z_i - \mathbb{E}[z_i])^2 \right]$, and $\mathbb{E} \left[(z_r - \mathbb{E}[z_r]) (z_i - \mathbb{E}[z_i]) \right]$ all need to be calculated numerically.

Alternatively, $\int p(z|\mu)p(\mu)$ can probably be calculated analytically using [Bromiley 2003]. The product of three normal distributions is a scaled normal distribution, so after converting N_{z_i} and N_{z_r} to distributions in terms of μ for the integration, the normal distribution integrates to 1, and the scaling factor comes out as a function of z_r and z_i , $S_{fgh}(z_r, z_i)$, for the remaining two integrals. This leaves potentially very difficult numerical integrations at this step.

2.3 Gauss-Hermite Quadrature

Gaussian quadrature:

$$\int_{-\infty}^{\infty} \exp^{-x^2} f(x) dx \approx \sum_{i=1}^N \omega_i f(x_i) \quad (15)$$

$$\omega_i = \frac{2^{n-1} n! \sqrt{\pi}}{n^2 [H_{n-1}(x_i)]^2} \quad (16)$$

where n is the number of sample points used, $H_n(x)$ is the physicists' Hermite polynomial, x_i are the roots of the Hermite polynomial, and ω_i are the associated Gauss-Hermite weights.

Substitution for normal distributions using Gauss-Hermite quadrature:

$$\mathbb{E}[h(y)] = \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right) h(y) dy \quad (17)$$

h is some function of y , and random variable Y is normally distributed.

$$x = \frac{y-\mu}{\sqrt{2}\sigma} \Leftrightarrow y = \sqrt{2}\sigma x + \mu \quad (18)$$

$$\mathbb{E}[h(y)] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{\pi}} \exp(-x^2) h(\sqrt{2}\sigma x + \mu) dx \quad (19)$$

$$\mathbb{E}[h(y)] \approx \frac{1}{\sqrt{\pi}} \sum_{i=1}^N \omega_i h(\sqrt{2}\sigma x_i + \mu) \quad (20)$$

2.4 Mutual Information Calculation

$$I(\boldsymbol{\mu}; \mathbf{z}) = H(\mathbf{z}) - H(\mathbf{z}|\boldsymbol{\mu}) = \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\boldsymbol{\Sigma}_z| \right) - \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\boldsymbol{\Sigma}_\nu| \right) \quad (21)$$

$$|\boldsymbol{\Sigma}_\nu| = \sigma_\nu^2 \sigma_\nu^2 - 0 = \sigma_\nu^4 \quad (22)$$

$$\boldsymbol{\Sigma}_z = \begin{bmatrix} \mathbb{E} \left[(z_r - \mathbb{E}[z_r])^2 \right] & \mathbb{E} \left[(z_r - \mathbb{E}[z_r]) (z_i - \mathbb{E}[z_i]) \right] \\ \mathbb{E} \left[(z_i - \mathbb{E}[z_i]) (z_r - \mathbb{E}[z_r]) \right] & \mathbb{E} \left[(z_i - \mathbb{E}[z_i])^2 \right] \end{bmatrix} \quad (23)$$

$$p(\mathbf{z}) = \int p(\mathbf{z}|\boldsymbol{\mu}) p(\boldsymbol{\mu}) d\boldsymbol{\mu} \quad (24)$$

$$p(\mathbf{z}|\boldsymbol{\mu}) = \mathcal{N}_{\mathbf{z}}(\mathcal{G}(\boldsymbol{\mu}), \boldsymbol{\Sigma}_\nu) = \mathcal{N}_{z_r}(\mathcal{G}_r(\boldsymbol{\mu}), \sigma_\nu) \mathcal{N}_{z_i}(\mathcal{G}_i(\boldsymbol{\mu}), \sigma_\nu) = p(z_r|\boldsymbol{\mu}) p(z_i|\boldsymbol{\mu}) \quad (25)$$

$$p(\boldsymbol{\mu}) = \mathcal{N}_{\boldsymbol{\mu}}(\mathbf{m}_\mu, \boldsymbol{\Sigma}_\mu) = \prod_{i=1}^N \mathcal{N}_{\mu_i}(m_{\mu_i}, \sigma_{\mu_i}) = \prod_{i=1}^N p(\mu_i) \quad (26)$$

The signal measurement probability distribution $p(\mathbf{z})$ can be approximated using Gauss-Hermite quadrature. The calculation is performed separately for the real and imaginary components, $p(z_r)$ and $p(z_i)$, because z_r and z_i are assumed independent.

$$p(z_r) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} p(z_r|\mu_1, \dots, \mu_N) \prod_{i=1}^N p(\mu_i) d\mu_1 \cdots d\mu_N \quad (27)$$

$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma_{\mu_i}} \exp \left(-\frac{(\mu_i - m_{\mu_i})^2}{2\sigma_{\mu_i}^2} \right) p(z_r|\mu_1, \dots, \mu_N) d\mu_1 \cdots d\mu_N \quad (28)$$

$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \prod_{i=1}^N \frac{1}{\sqrt{\pi}} \exp(-x_i^2) p \left(z_r \left| \left(\sqrt{2}\sigma_{\mu_1}x_1 + m_{\mu_1}, \dots, \sqrt{2}\sigma_{\mu_N}x_N + m_{\mu_N} \right) \right. \right) dx_1 \cdots dx_N \quad (29)$$

$$\approx \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p \left(z_r \left| \left(\sqrt{2}\sigma_{\mu_1}x_{1,q} + m_{\mu_1}, \dots, \sqrt{2}\sigma_{\mu_N}x_{N,q} + m_{\mu_N} \right) \right. \right) \quad (30)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(z_r|\mu_{1,q}, \dots, \mu_{N,q}) \quad (31)$$

$$\begin{cases} \mu_{1,q} = \sqrt{2}\sigma_{\mu_1}x_{1,q} + m_{\mu_1} \\ \vdots \\ \mu_{N,q} = \sqrt{2}\sigma_{\mu_N}x_{N,q} + m_{\mu_N} \end{cases} \quad (32)$$

An identical calculation for the imaginary component results in

$$p(z_i) = \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(z_i|\mu_{1,q}, \dots, \mu_{N,q}) \quad (33)$$

$$\begin{cases} \mu_{1,q} = \sqrt{2}\sigma_{\mu_1}x_{1,q} + m_{\mu_1} \\ \vdots \\ \mu_{N,q} = \sqrt{2}\sigma_{\mu_N}x_{N,q} + m_{\mu_N} \end{cases} \quad (34)$$

Calculate expectation values for real and imaginary components by definition and approximating $p(\mathbf{z})$ with Gauss-Hermite quadrature as shown above.

$$\mathbb{E}[z_r] = \int z_r p(z_r) dz_r \approx \int z_r \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(z_r | \mu_{1,q}, \dots, \mu_{N,q}) dz_r \quad (35)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int z_r p(z_r | \mu_{1,q}, \dots, \mu_{N,q}) dz_r \quad (36)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathbb{E}[z_r | \mu_{1,q}, \dots, \mu_{N,q}] \quad (37)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \quad (38)$$

Similarly for the imaginary component,

$$\mathbb{E}[z_i] \approx \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathbb{E}[z_i | \mu_{1,q}, \dots, \mu_{N,q}] = \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) \quad (39)$$

The variance can be calculated as follows:

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])^2] = \mathbb{E}[z_r^2] - (\mathbb{E}[z_r])^2 = \int z_r^2 p(z_r) dz_r - (\mathbb{E}[z_r])^2 \quad (40)$$

$$\approx \int z_r^2 \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(z_r | \mu_{1,q}, \dots, \mu_{N,q}) dz_r - (\mathbb{E}[z_r])^2 \quad (41)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int z_r^2 p(z_r | \mu_{1,q}, \dots, \mu_{N,q}) dz_r - (\mathbb{E}[z_r])^2 \quad (42)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int z_r^2 \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_r - \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}))^2}{2\sigma_\nu^2}\right) dz_r - (\mathbb{E}[z_r])^2 \quad (43)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int (x^2 \sigma_\nu^2 + 2x\sigma_\nu \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) + \mathcal{G}_r^2(\mu_{1,q}, \dots, \mu_{N,q})) \cdot \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx - (\mathbb{E}[z_r])^2 \quad (44)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} (\sigma_\nu^2 + \mathcal{G}_r^2(\mu_{1,q}, \dots, \mu_{N,q})) - (\mathbb{E}[z_r])^2 \quad (45)$$

$$= \pi^{-N/2} \sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_r])^2 \quad (46)$$

$$\begin{cases} \mu_{1,q} = \sqrt{2}\sigma_{\mu_1}x_{1,q} + m_{\mu_1} \\ \vdots \\ \mu_{N,q} = \sqrt{2}\sigma_{\mu_N}x_{N,q} + m_{\mu_N} \end{cases} \quad (47)$$

Again, an identical calculation for the imaginary component yields

$$\mathbb{E}[(z_i - \mathbb{E}[z_i])^2] = \pi^{-N/2} \sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_i^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_i])^2 \quad (48)$$

$$\begin{cases} \mu_{1,q} = \sqrt{2}\sigma_{\mu_1}x_{1,q} + m_{\mu_1} \\ \vdots \\ \mu_{N,q} = \sqrt{2}\sigma_{\mu_N}x_{N,q} + m_{\mu_N} \end{cases} \quad (49)$$

The off-diagonal elements of Σ_z are equal.

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i])] = \mathbb{E}[(z_i - \mathbb{E}[z_i])(z_r - \mathbb{E}[z_r])] \quad (50)$$

$$\mathbb{E}[(z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i])] = \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i])p(\mathbf{z})d\mathbf{z} \quad (51)$$

$$= \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \int p(\mathbf{z}|\boldsymbol{\mu})p(\boldsymbol{\mu})d\mathbf{z} \quad (52)$$

$$\approx \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(\mathbf{z}|\mu_{1,q}, \dots, \mu_{N,q}) d\mathbf{z} \quad (53)$$

$$= \int (z_r - \mathbb{E}[z_r])(z_i - \mathbb{E}[z_i]) \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} p(z_r|\mu_{1,q}, \dots, \mu_{N,q}) p(z_i|\mu_{1,q}, \dots, \mu_{N,q}) d\mathbf{z} \quad (54)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int (z_r - \mathbb{E}[z_r]) p(z_r|\mu_{1,q}, \dots, \mu_{N,q}) dz_r \cdot \int (z_i - \mathbb{E}[z_i]) p(z_i|\mu_{1,q}, \dots, \mu_{N,q}) dz_i \quad (55)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int (z_r - \mathbb{E}[z_r]) \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_r - \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}))^2}{2\sigma_\nu^2}\right) dz_r \cdot \int (z_i - \mathbb{E}[z_i]) \frac{1}{\sqrt{2\pi}\sigma_\nu} \exp\left(-\frac{(z_i - \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}))^2}{2\sigma_\nu^2}\right) dz_i \quad (56)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \int (\sigma_\nu x + \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r]) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx \cdot \int (\sigma_\nu y + \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_i]) \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y^2}{2}\right) dy \quad (57)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} ((\mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r])(\mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_i])) \quad (58)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} (\mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathbb{E}[z_i] - \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) \mathbb{E}[z_r] + \mathbb{E}[z_r] \mathbb{E}[z_i]) \quad (59)$$

$$= \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r] \mathbb{E}[z_i] \quad (60)$$

Thus, the numerical approximation to the covariance matrix Σ_z is then

$$\Sigma_z = \begin{bmatrix} \pi^{-N/2}\sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_r])^2 \\ \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r] \mathbb{E}[z_i] \end{bmatrix}$$

$$\left[\begin{array}{c} \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r] \mathbb{E}[z_i] \\ \pi^{-N/2} \sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_i^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_i])^2 \end{array} \right] \quad (61)$$

The determinant of the covariance matrix is easily calculated.

$$\begin{aligned} |\mathbf{\Sigma}_z| = & \left(\pi^{-N/2} \sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_r])^2 \right) \\ & \cdot \left(\pi^{-N/2} \sigma_\nu^2 + \pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_i^2(\mu_{1,q}, \dots, \mu_{N,q}) - (\mathbb{E}[z_i])^2 \right) \\ & - \left(\pi^{-N/2} \sum_{q_1=1}^{Q_1} \omega_{q_1} \cdots \sum_{q_N=1}^{Q_N} \omega_{q_N} \mathcal{G}_r(\mu_{1,q}, \dots, \mu_{N,q}) \mathcal{G}_i(\mu_{1,q}, \dots, \mu_{N,q}) - \mathbb{E}[z_r] \mathbb{E}[z_i] \right)^2 \end{aligned} \quad (62)$$

The mutual information calculation is straightforward once the value of $|\mathbf{\Sigma}_z|$ is known.

$$I(\boldsymbol{\mu}; \mathbf{z}) = H(\mathbf{z}) - H(\mathbf{z}|\boldsymbol{\mu}) = \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\mathbf{\Sigma}_z| \right) - \frac{1}{2} \ln \left((2\pi e)^2 \cdot |\mathbf{\Sigma}_\nu| \right) \quad (63)$$

2.5 The Nonlinear Signal Model Case

$z = \mathcal{G}(\boldsymbol{\mu}) + \nu$ where $\mathcal{G}(\boldsymbol{\mu})$ is nonlinear.

$$H(\mathbf{z}) = \int_{\mathbf{z}} p(\mathbf{z}) \ln(p(\mathbf{z})) d\mathbf{z} = \int_{\mathbf{z}} \left(\int_{\boldsymbol{\mu}} p(\mathbf{z}|\boldsymbol{\mu}) p(\boldsymbol{\mu}) d\boldsymbol{\mu} \right) \ln(p(\mathbf{z})) d\mathbf{z} \quad (64)$$

$$= \int_{\mathbf{z}} \sum_q \omega_q p(\mathbf{z}|\boldsymbol{\mu}_q) \ln(p(\mathbf{z})) d\mathbf{z} = \sum_q \omega_q \int_{\mathbf{z}} p(\mathbf{z}|\boldsymbol{\mu}_q) \ln(p(\mathbf{z})) d\mathbf{z} \quad (65)$$

$$= \sum_q^{N_\mu} \omega_q \sum_k^{N_z} \omega_k \ln \left(\sum_q \omega_q p(\mathbf{z}_k|\boldsymbol{\mu}_q) \right) \quad (66)$$

$$N_z = \text{number of quadrature points over } z \quad (67)$$

$$N_\mu = \text{number of quadrature points over } \mu \quad (68)$$