The image contains $n \times m$ pixels.

There are k features f_k observed at each pixels.

A reconstruction $z = \{z_i\}$ consists of a y–coordinate for each image column i. So each (i, z_i) is the coordinates of a pixel on the floor/wall intersection.

Hyper–parameters θ consist of (for each of k features):

- $\gamma_k \in \Re$, the "ideal" value of the feature f_k we expect to observe at the floor/wall intersection. This is the same for all columns.
- $\rho_k > 0$, the "fall-off" rate at which f_k diminishes as we move away from the floor/wall intersection (i, z_i) (is actually the variance of an un–normalized Gaussian).
- $\Sigma_k > 0$, the Gaussian variance for the noise model in feature f_k
- $\alpha_k \in [0, 1]$, the probability that the measurement f_k arose from the signal we're interested in as opposed to a background noise process.

In addition, θ contains the mean μ_0 and variance Σ_0 for the background noise process, which is shared by all k features.

A feature at row i, column j is then distributed as

$$P(\mathbf{f} \mid z, \theta) = \prod_k \alpha_k \mathcal{N}(f_k; \mu_k, \Sigma_k) + (1 - \alpha_k)\mathcal{N}(f_k; \mu_0, \Sigma_0) \tag{1}$$

where

$$\mu_k = \gamma_k \mathcal{N}(j; z_i, \rho_k) \tag{2}$$