Seismic imaging aims to recover physical properties of the Earth’s interior based on surface measurements. Seismic sources (as airguns in a marine environment, or vibrator trucks on land) are placed at the surface, and seismic waves are excited, propagate through the Earth, and transmitted/reflected back to the surface, where data are recorded (by hydro- or geophones), yielding information about the subsurface.

\[ \text{d} = F(q, m) + \varepsilon, \]
\[ m = G_\varepsilon(q, \theta). \]

We exploit the remarkable ease of deep convolutional networks to generate natural images, as added implicit regularization [4]. We consider the parameterized data model

\[ \log p(q, d, z, m) = \int \int \log p(q, d, z) p(z) p(z, d) \, \text{d} z \, \text{d} m, \]
\[ \text{and maximum-likelihood estimation problem} \]
\[ \min_\theta \mathbb{E}_{(q, d) \sim P_{\text{data}}(q, d)} \log p(q, d). \]

Note that the latent variables \( (z, m) \) are jointly distributed (coupled) with data \( (q, d) \).

The expectation maximization method (EM) is based on the identity:

\[ \log p(q, d) = \mathbb{E}_{(z, m) \sim P_{(z, m) q (d)}} \bigg[ \log p(q, d, z, m) \bigg] \]

Having set the loss \( L_\theta = -\log p(q, d, z, m) \),

\[ L_\theta(q, d, z, m) = \frac{1}{m^2} \| d - F(q, m) \|^2 \]
\[ + \frac{1}{q^2} \| m - G_\varepsilon(q) \|^2 + \frac{2}{q^2} \| z \|^2, \]

we alternate the following steps:

- (E) update \( m \) via (6) applied to (11) (\( z \) fixed), and sample \( z \sim p(z | m) \) with Langevin dynamics (\( m \)'s fixed);
- (M) update \( \theta \) by \( \theta = \arg \min_{\theta} L_\theta \sum_{z, m} \| m - G_\varepsilon(q) \|^2 \)

not accounting for the dependency of the sampled \( z \), \( m \) wrt \( \theta \), according to (10).

**REFERENCES**


