

Homework 4:Exercise 3.1

$P$  obeys a GMM.

$\tilde{P}$  is a noisy observation of  $P$ , of size  $w \times w$ , with noise  $\sigma^2$

$$P(\tilde{P} | P) = \frac{1}{(2\pi\sigma^2)^{\frac{w^2}{2}}} \exp \left[ -\frac{\|\tilde{P} - P\|^2}{2\sigma^2} \right]$$

$$P(P) = \sum_{k=1}^K \mu_k \mathcal{N}(P | \mu_k, \Sigma_k)$$

$\mu_k$  and  $\Sigma_k$  were obtained in the GMM training.

Thus, our current problem is

$$\min_P E(P | \tilde{P}) \Leftrightarrow \min_P \frac{\|P - \tilde{P}\|^2}{2\sigma^2} - \log(P(P))$$

$$\Leftrightarrow \max_P \log \left( P(P) \times e^{-\frac{\|P - \tilde{P}\|^2}{2\sigma^2}} \right)$$

$$\Leftrightarrow \max_P P(P) \times e^{-\frac{\|P - \tilde{P}\|^2}{2\sigma^2}}$$

$$\Leftrightarrow \max_P P(P) \times \frac{1}{(2\pi\sigma^2)^{\frac{w^2}{2}}} e^{-\frac{\|P - \tilde{P}\|^2}{2\sigma^2}}$$

$$\Leftrightarrow \max_P P(P) \times P(\tilde{P} | P)$$

$$\Leftrightarrow \max_P P(P | \tilde{P}) \times P(\tilde{P}) \quad \text{Bayes rule}$$

$$\Leftrightarrow \max_P P(P | \tilde{P})$$

This means that minimizing the energy is the same as solving a MAP problem.



### Exercice 9.2.

Let  $\mathcal{P}$  the set of patch projector

The likelihood of the image is the probability of each patch  $P_U$ , so that they all compose the image  $\mathcal{U}$  ie

$$\mathcal{L} = P \left( \bigcap_{P \in \mathcal{P}} \{P_U\} \right).$$

Thus,

$$\log(\mathcal{L}) = \log \left( P \left( \bigcap_{P \in \mathcal{P}} \{P_U\} \right) \right)$$

if all patches projectors are independent  
ie  $\log(\mathcal{L}) = \log \left( \prod_{P \in \mathcal{P}} P(P_U) \right)$

$$\text{ie } \boxed{\log(\mathcal{L}) = \sum_{P \in \mathcal{P}} \log P(P_U) = \text{EPPL}}$$

This is why the EPPL can be considered as the log likelihood of an image.

However, the patches are often not independent. Indeed, most of the patches are simply shifted from other patches.