

(HW 4)

(7.4)

$$\gamma_{k_n}^{(H)} := P(Z_n = k | x_n; \theta^{(H)})$$

$$= \frac{P(Z_n = k; \theta^{(H)}) P(x_n | Z_n = k; \theta^{(H)})}{P(x_n; \theta^{(H)})}$$

(Bayes formula)

$$= \frac{P(Z_n = k; \theta^{(H)}) P(x_n | Z_n = k; \theta^{(H)})}{\sum_{i=1}^K P(Z_n = i; \theta^{(H)}) P(x_n | Z_n = i; \theta^{(H)})}$$

(Total prob formula since $\{Z_n = i\}_{i=1}^K$ is a partition of the prob space)

$$\Rightarrow \gamma_{k_n}^{(H)} = \frac{\pi_k^{(H)} \mathcal{N}(x_n; \mu_k^{(H)}, \Sigma_k^{(H)})}{\sum_{i=1}^K \pi_i^{(H)} \mathcal{N}(x_n; \mu_i^{(H)}, \Sigma_i^{(H)})}$$

(9.2) Let us suppose the family $(P_\mu)_{\mu \in \mathcal{P}}$ is independent. Thus, one can write:

$$EPLL(\mu) = \sum_{P \in \mathcal{P}} \log(P(P_\mu))$$

$$= \log\left(\prod_{P \in \mathcal{P}} P(P_\mu)\right)$$

$$= \log\left(P\left(\bigcap_{P \in \mathcal{P}} P_\mu\right)\right)$$

representing the likelihood of the image μ since $(P_\mu)_{\mu \in \mathcal{P}}$ forms \mathcal{M} .

Hence, indeed, EPLL can be considered as a log-likelihood of the image μ . Nevertheless, we should point out this is only true for independent patches. This may not be true in practice since patches may overlap.

(9.3)

$$\min_{Q_P} E(Q_P)$$

$$\Leftrightarrow \min_{Q_P} -\log\left(e^{-\frac{\|P_\mu - Q_P\|^2}{2\sigma^2}} P(Q_P)\right)$$

$$\Leftrightarrow \max_{Q_P} \underbrace{e^{-\frac{\|P_\mu - Q_P\|^2}{2\sigma^2}} P(Q_P)}_{\propto P(P_\mu | Q_P) \rightarrow \text{constant independent of } Q_P}$$

$$\Leftrightarrow \max_{Q_P} P(P_\mu | Q_P) P(Q_P)$$

$$\text{Bayes} \quad \Leftrightarrow \max_{Q_P} P(Q_P | P_\mu) \underbrace{P(P_\mu)}_{\text{independent of } Q_P}$$

$$\Leftrightarrow \max_{Q_P} P(Q_P | P_\mu)$$

Indeed, minimizing $E(Q_P)$ is \Leftrightarrow to maximizing $P(Q_P | P_\mu)$ which is a MAP among Q of class a GMM.