

As in the previous case, the confusion matrix must be normalized, but in this case to contain the conditional probabilities  $P(w_j | \mathcal{C}_k)$ , where  $w_j$  is the  $j$ -th component of the GMM in use and  $\mathcal{C}_k$  is the  $k$ -th target class.

This way,  $P(\mathcal{C}_k | x)$ , the *a posteriori* probability that the current period corresponds to target class  $\mathcal{C}_k$  when  $x$  has been observed, will be computed as follows according to the Bayes' rule:

$$P(\mathcal{C}_k | x) = \frac{\pi(\mathcal{C}_k) \cdot p(x | \mathcal{C}_k)}{\sum_c \pi(\mathcal{C}_c) \cdot p(x | \mathcal{C}_c)}$$

where

- $\pi(\mathcal{C}_k)$  is the *a priori* probability of the target class  $\mathcal{C}_k$ , and
- $p(x | \mathcal{C}_k)$  is the *conditional probability density* of generating  $x$  during the period in which the state of the patient corresponds to target class  $\mathcal{C}_k$ .

The *conditional probability density*  $P(x | \mathcal{C}_k)$  is computed as follows:

$$p(x | \mathcal{C}_k) = \sum_{j=1}^J \pi(w_j) \cdot p(x | w_j) \cdot P(w_j | \mathcal{C}_k)$$

where

- $J$  is the number of components in the GMM in use,
- $\pi(w_j)$  is the weight of Gaussian  $w_j$  in the mixture,
- $p(x | w_j) = \mathcal{N}(x | \mu_j, \Sigma_j)$  and
- $P(w_j | \mathcal{C}_k)$  is the conditional probability of observing samples generated by the Gaussian component  $w_j$  during a period corresponding to target class  $\mathcal{C}_k$ .