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Variational Bayesian PHD filter with Deep Learning Network Updating for Multiple Human Tracking

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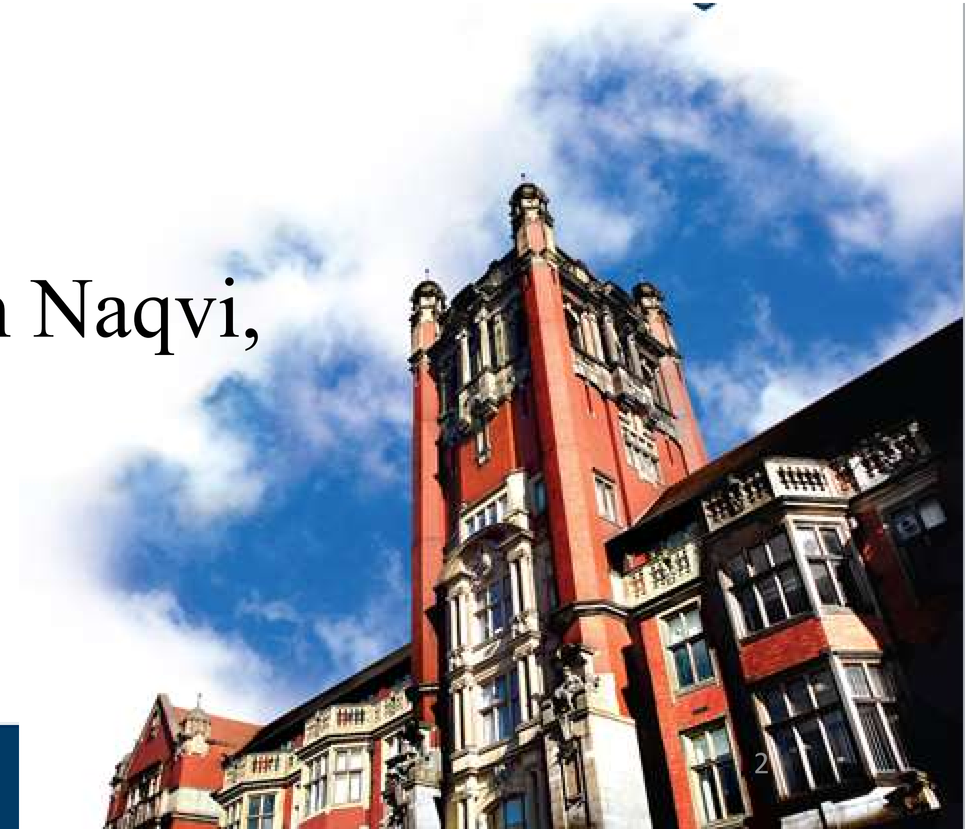
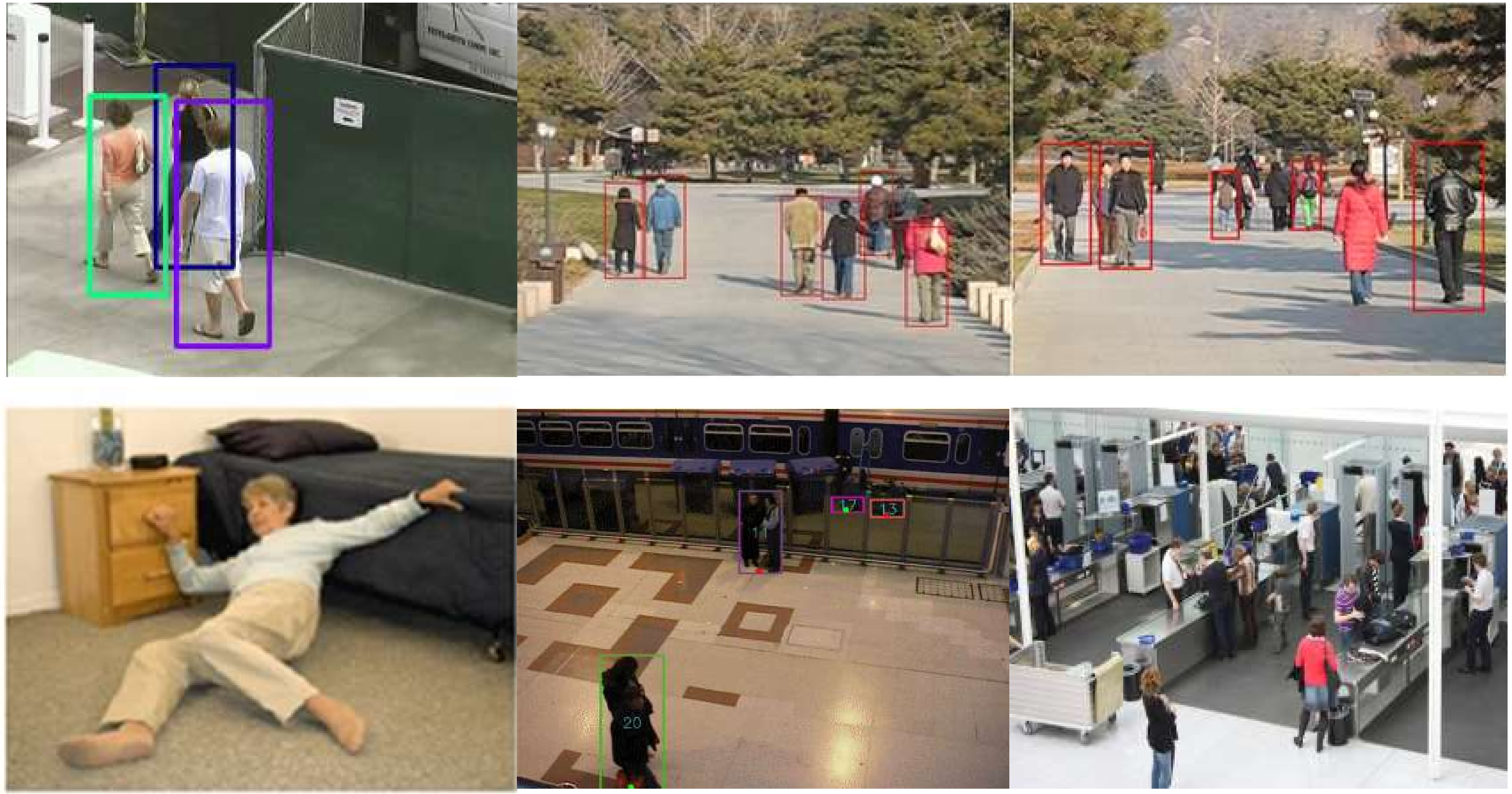


Motivation

Application of multiple human tracking work

- ➢ Monitoring
- ➢ Homeland Security
- ➢ Assistive Living



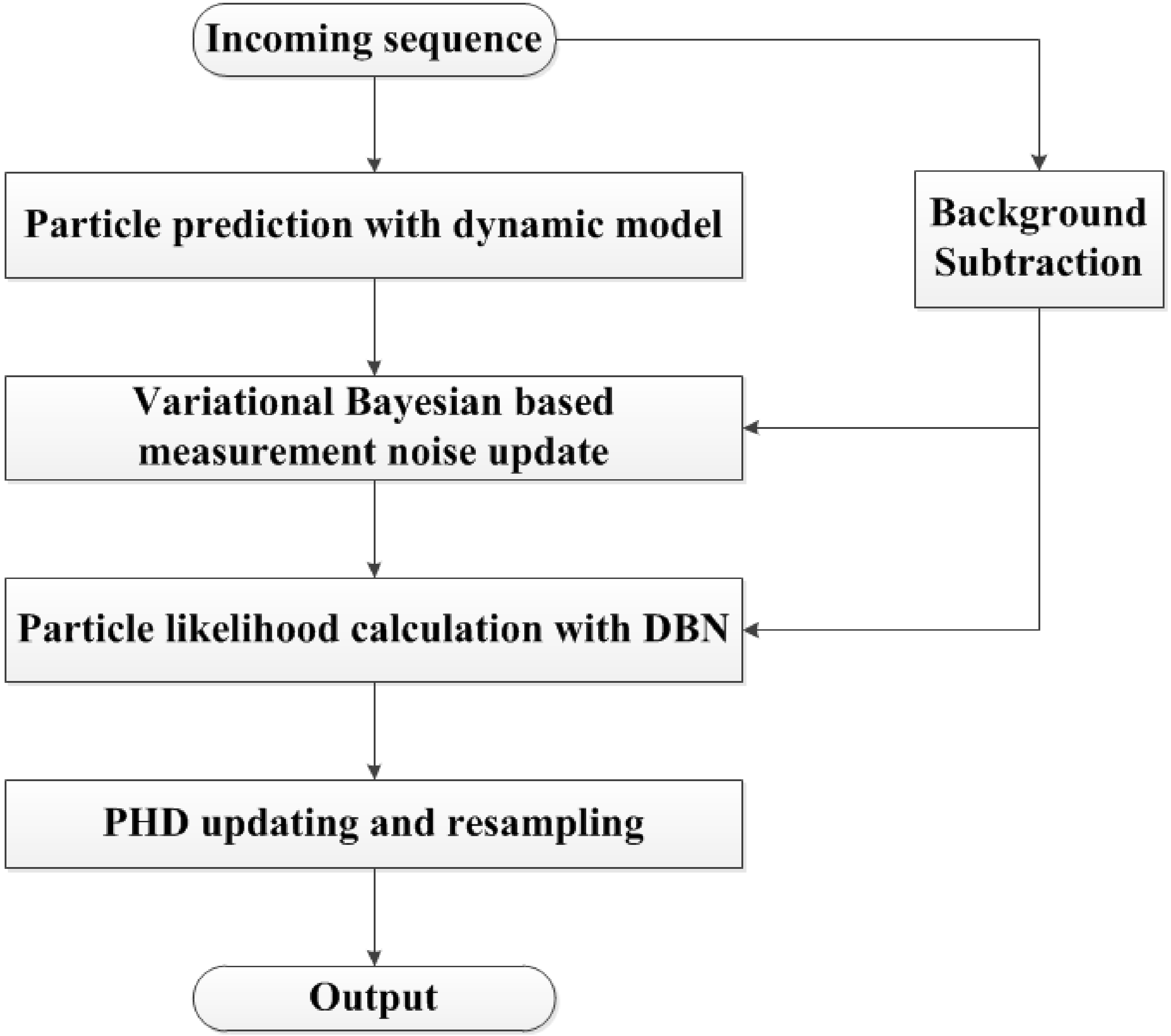
Challenges for Multiple Human Tracking

- Variable number of targets
- Targets appearing and disappearing randomly
- Occlusion
- Computational complexity
- Parameter selection

Outline of the presentation

- Overview of the proposed tracking system
- Fundamentals of particle PHD filter for multiple human tracking
- Variational Bayesian method for parameter updating
- Background subtraction and DBN likelihood calculation
- Simulation results
- Conclusions and future work

Overview of the proposed system



Background Subtraction

- Easier to identify new-born targets.
- Achieve measurement set.
- Code book method for background subtraction [7]

PHD filter for multiple human tracking

Random finite set (RFS)

An RFS provides a principled solution to the problem of uncertainty modeling to the cardinality of the state set and the measurement set [2].

Let Ξ_k be the RFS associated with the multi-target state

$$\Xi_k = \mathbf{S}_k(\mathbf{X}_{k-1}) \bigcup \mathbf{B}_k(\mathbf{X}_{k-1}) \bigcup \mathbf{\Gamma}_k$$

where S_k (X_{k-1}) denotes the RFS of survived targets, B_k (X_{k-1}) denotes the targets spawned from the previous set of targets X_{k-1} and Γ_k is the RFS of the new-born targets.

PHD filter for multiple human tracking

The PHD prediction step is defined as:

$$\mathbf{D}_{k|k-1}(x) = \int \phi_{k|k-1}(x,\xi)\mathbf{D}_{k-1|k-1}(\xi)d(\xi) + \Upsilon_k$$

where Υ_k is the intensity function of the new target birth RFS, $\phi_{k|k-1}(x,\xi)$ is the analogue of the state transition probability.

$$\phi_{k|k-1}(x,\xi) = e_{k|k-1}(\xi)f_{k|k-1}(x|\xi) + \beta_{k|k-1}(x|\xi)$$

in which $e_{k|k-1}(\xi)$ is the probability that the target still exists at time k and $\beta_{k|k-1}(x|\xi)$ is the intensity of the RFS that a target is spawned from the previous state ξ.

PHD filter for multiple human tracking

The PHD updating step is defined as:

$$\mathbf{D}_{k|k}(x) = \left[p_M(x) + \sum_{z \in \mathbf{Z}_k} \frac{\psi_{k,z}(x)}{\kappa_k + \langle \psi_{k,z}, \mathbf{D}_{k|k-1} \rangle} \right] \mathbf{D}_{k|k-1}(x)$$

where p_M is the missing detection probability, $\psi_{k,z}(x) = (1-p_M)g_k(z|x)$ is the single target likelihood defining the probability that a measurement z is generated by a target with state x, κ_k is the clutter intensity.

Types of PHD filter – GMM, Particle

A set of particles denotes the state of surviving targets at time k [3]

$$\{x_k^i, w_k^i\}_{i=1}^{N}$$

where N is the number of particles.

- Weights for new-born targets $w_k^{i-new-born} = 1/J_k$ where J_k is the number of the particles for new-born targets.
- We need measurement noise covariance information to update the particle PHD filter – in practice, its selection is difficult.

Variational Bayesian Approach

- The goal of the variational Bayesian approach is to **build a joint distribution** for the **state model and the measurement covariance** and compute the posterior distribution $p(x_k, R_k | Z_k)$.
- Prediction: Bayesian filtering state model [1]

$$x_k = F x_{k-1} + w_k$$

- Updating: Bayesian filtering measurement model

$$z_k = H x_k + v_k$$

where F and H are the transition functions of state and measurement model; w_k is the state noise with covariance P_k and v_k is the measurement noise with covariance R_k.

Variational Bayesian Approach

- The posterior distribution at time *k-1* can be represented by a product form, given the inverse-Gamma distribution is the conjugate prior distribution for the variance of a Gaussian distribution,

$$p(x_{k-1},R_{k-1}|Z_{k-1}) = N(x_{k-1},\mu_{k-1},P_{k-1}) \times \prod_{i=1}^{d} IG(\sigma_{k-1}^2|\alpha_{k-1},\beta_{k-1})$$

- By assuming the models of the state and measurement noise variances are independent, the joint prediction distribution remains as a factored form of a Gaussian and an inverse Gamma distribution

$$p_{k|k-1}(x_k,R_k|Z_k) = p_{k|k-1}(x_k|Z_{k-1})p_{k|k-1}(R_k|Z_{k-1}) = N(xk_{|k-1},\mu_{k|k-1},P_{k|k-1}) \times \prod_{i=1}^{d} IG(\sigma_{k|k-1}^2|\alpha_{k|k-1},\beta_{k|k-1})$$

- However, calculation of the posterior is coupled by the likelihood function, therefore, we use a factorized free form distribution

$$p(x_k,R_k|Z_k) \approx Qx(x_k)Q_R(R_k)$$

where

$$Q_{\mathbf{x}}(\mathbf{x}_k) = N(\mathbf{x}_k,\mu_k,\mathbf{P}_k)$$

$$Q_{\mathbf{R}}(\mathbf{R}_k) = IG(\sigma_{k,i}^2|\alpha_{k,i},\beta_{k,i})$$

Variational Bayesian Approach

➢ Then the approximate posterior density can be determined by minimizing the Kullback-Leibler (KL) divergence between the approximation and the true posterior density expressed as

$$KL\{Q_{\mathbf{x}}(\mathbf{x}_k)Q_{\mathbf{R}}(\mathbf{R}_k)||p(\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_k)\} = \int Q_{\mathbf{x}}(\mathbf{x}_k)Q_{\mathbf{R}}(\mathbf{R}_k)\log\frac{Q_{\mathbf{x}}(\mathbf{x}_k)Q_{\mathbf{R}}(\mathbf{R}_k)}{p(\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_k)}d\mathbf{x}_k d\mathbf{R}_k$$

➢ Using the alternating optimisation, the probability densities $Q_x(x_k)$ and $Q_R(\boldsymbol{R}_k)$ are calculated in turn, while keeping the other fixed, yielding

$$Q_{\mathbf{x}}(\mathbf{x}_k) \propto E\left\{\int \log p(\mathbf{z}_k,\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_{1:k-1})Q_{\mathbf{R}}(\mathbf{R}_k)d\mathbf{R}_k\right\}$$

$$Q_{\mathbf{R}}(\mathbf{R}_k) \propto E\left\{\int \log p(\mathbf{z}_k,\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_{1:k-1})Q_{\mathbf{x}}(\mathbf{x}_k)d\mathbf{x}_k\right\}$$

➢ Since the above two equations are coupled, they cannot be solved directly, by computing their expectations, which is of the form of a fixed point iteration: we obtain

$$\int \log p(\mathbf{z}_k,\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_{1:k-1})Q_{\mathbf{R}}(\mathbf{R}_k)d\mathbf{R}_k = -0.5(\mathbf{z}_k-\mathbf{H}_k\mathbf{x}_k)^T\langle\mathbf{R}_k^{-1}\rangle_{\mathbf{R}}(\mathbf{z}_k-\mathbf{H}_k\mathbf{x}_k) - 0.5(\mathbf{x}_k-\mathbf{F}_k\mathbf{x}_{k-1})^T(\mathbf{P}_k^{-1})(\mathbf{x}_k-\mathbf{F}_k\mathbf{x}_{k-1}) + C_1$$

$$\int \log p(\mathbf{z}_k,\mathbf{x}_k,\mathbf{R}_k|\mathbf{Z}_{k-1})Q_{\mathbf{x}}(\mathbf{x}_k)d\mathbf{x}_k = -\sum_{i=1}^{d}(\frac{3}{2}+\alpha_{k,i})\ln(\sigma_{k,i}^2) - \sum_{i=1}^{d}\frac{\beta_{k,i}}{\sigma_{k,i}^2} - \frac{1}{2}\sum_{i=1}^{d}\frac{\langle(\mathbf{z}_k-\mathbf{H}_k\mathbf{x}_k)_i^2\rangle_{\mathbf{x}_k}}{\sigma_{k,i}^2} + C_2$$

Variational Bayesian Approach

- In order to minimize the KL divergence, the parameters of the filter are the solutions to the following coupled set of equations

$$x_k = x_{k-1} + P_{k|k-1} {H_k}^T(\widehat{R_k} + H_k P_{k|k-1} {H_k}^T)^{-1} (zk - Hkx_{k|k-1})$$

$$P_{k|k} = P_{k|k-1} - P_{k|k-1} {H_k}^T(\widehat{R_k} + H_k P_{k|k-1} {H_k}^T)^{-1} H_k P_{k|k-1}$$

$$\alpha_{k,i} = \widehat{\alpha_{k,i}} + \frac{1}{2}$$

$$\beta_{k,i} = \widehat{\beta_{k,i}} + \frac{1}{2}[(z_k - Hk\widehat{x_k})_i{}^2] + \frac{1}{2} \mathrm{H_k P_k H_k}^{\mathrm{T}}$$

and the estimated measurement covariance matrix $\widehat{R_k}$ is

$$\hat{\mathbf{R}}_k = diag\left\{\frac{\beta_{k,1}}{\alpha_{k,1}}, \ldots, \frac{\beta_{k,m}}{\alpha_{k,m}}\right\}$$

Extra Steps for VB-Particle PHD Filtering

- Additional steps for the variational Bayesian approach for particle PHD filter
  - Prediction: the measurement noise parameters are predicted as

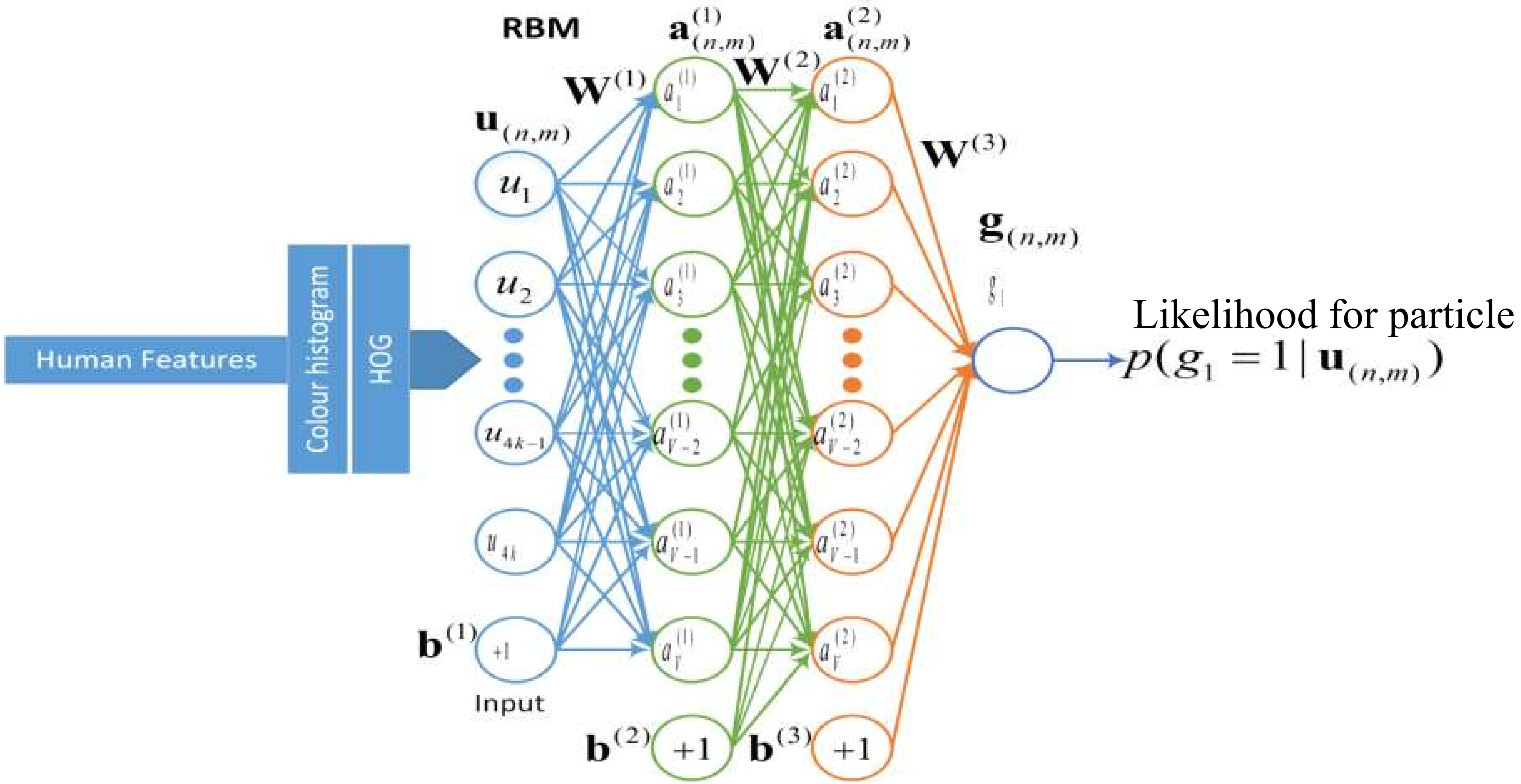
$$\hat{\alpha}_{k-1,i} = \rho\alpha_{k-1,i}$$
$$\hat{\beta}_{k-1,i} = \rho\beta_{k-1,i}$$

where $\rho \in (0,1]$ is a scalar.

  - Updating: employing fixed point iteration to compute the parameters as the solution of the equations described in previous slide for l steps, then compute the covariance matrix R_k as

$$R_k = diag\{\frac{\beta_{k,1}}{\alpha_{k,1}}, \ldots, \frac{\beta_{k,m}}{\alpha_{k,m}}\}$$

Particle likelihood calculation with DBN



Particle PHD Updating

After particle sampling step, we can obtain a set of predicted particles with predicted weights:

$$\{\widetilde{x_k^i}, \widetilde{w_k^i}\}_{i=1}^{N+J_k}$$

The PHD updating step can be defined as [8]:

$$w_k^i = \left[P_M(x_k^i) + \sum_{\forall z \in Z_k} \frac{(1 - P_M(x_k^i))\varphi_{k,z}(x_k^i)}{k_k(z) + C_k(z)} \right] \widetilde{w_k^i}$$

where

$$C_k(z) = \sum_{j=1}^{N} (1 - P_M(x_k^i))\varphi_{k,z}(x_k^i)\,\widetilde{w_k^i}$$

and $\varphi_{k,z}(x_k^i)$ is the likelihood of particle from both background subtraction and DBN.

Target Number Calculation & Particle Resampling

The number of targets is calculated by the sum of all weights for particles and the particles are resampled as Algorithm 2 in order to avoid the degeneracy problem.

Algorithm 2 Resampling step of the particle PHD filter

$\{\{\tilde{w}_k^i, \tilde{\mathrm{x}}_k^i\}_{i=1}^{N+J_k}\} \to \{w_k^i, \mathrm{x}_k^i\}_{i=1}^{N}$

Compute the target number at time k

$$\hat{N}_k = \sum_{i=1}^{N+J_k} \tilde{w}_k^i$$

Initialize the cumulative probability $c_1 = 0$

$$c_i = c_{i-1} + \frac{\tilde{w}_k^{(i)}}{\hat{N}_k},\ i = 2, ..., N + J_k$$

Draw a starting point $\mu_1 \sim [0, N^{-1}]$

For $j = 1, ..., N$

$$\mu_j = \mu_1 + N^{-1}(j-1)$$

while $\mu_j > c_i$, $i = i + 1$. End while

$$w_k^{(i)} = \tilde{w}_k^{(i)}$$

$$\mathrm{x}_k^{(i)} = \tilde{\mathrm{x}}_k^{(i)}$$

End for

Rescale the weights by $\hat{N}_k$ to get $\{\mathrm{x}_k^{(i)}, \frac{\hat{N}_k}{N}\}$

Simulation & Results

In order to evaluate the proposed variational Bayesian particle PHD filter with DBN updating step for multiple human tracking, two sequences from the CAVIAR dataset are employed for simulations.

The comparison of mean of error and standard deviation between the traditional and our proposed particle PHD filter from the two scenarios are shown as

	Scenario 1		Scenario 2	
	Traditional	Proposed	Traditional	Proposed
Mean of error	13.45	11.89	34.54	22.26
Standard deviation	16.68	12.85	19.87	11.85

Simulation & Results

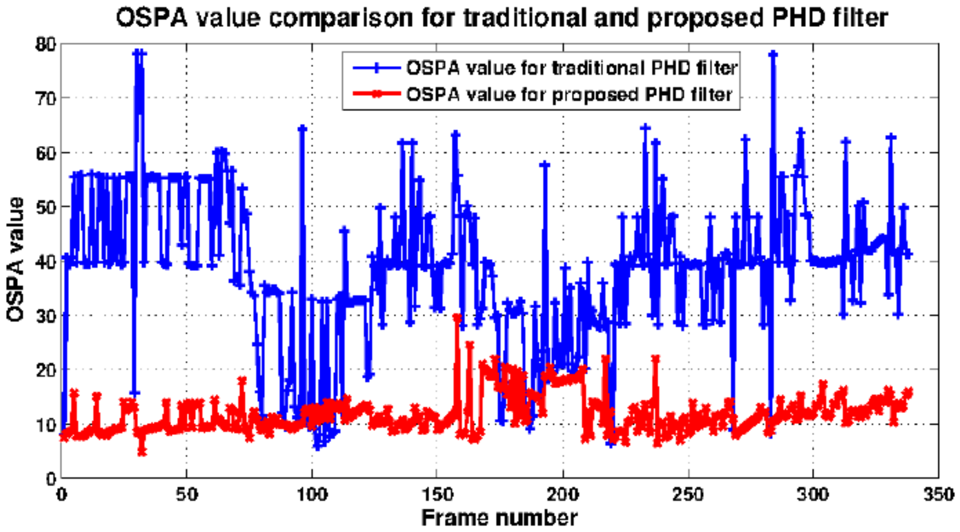
Tracking results comparison: OSPA (Optimal Subpattern Assignment) [9]

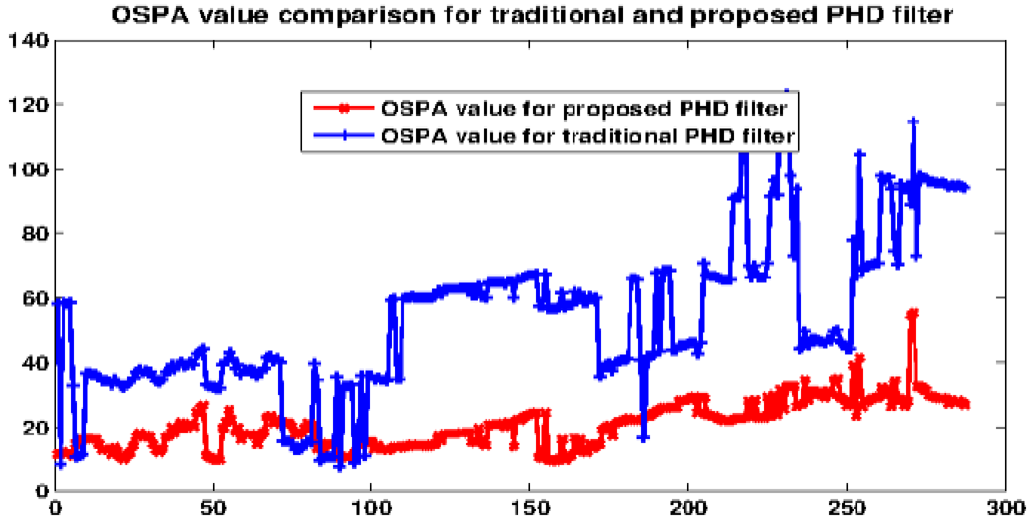
$$d_p^c(\mathbf{X},\mathbf{Y}) := \left(\frac{1}{n}\left(\min_{\pi\in\prod_n}\sum_{i=1}^{m} d^c(\mathbf{x}_i,\mathbf{y}_{\pi(i)})^p + c^p(n-m)\right)\right)^{\frac{1}{p}}$$

- X is the results from the tracker with m targets
- Y is ground truth information with n targets
- c is the cut-off value
- p is the metric order
- Both the localization error and the cardinality value are both considered to evaluate the accuracy of the tracking system.

Simulation & Results

Comparison of OSPA





Conclusions & Future work

- Variational Bayesian approach is employed to estimate more accurate measurement covariance parameters for the particle PHD filter.
- A DBN classifier which is trained by colour and HOG histogram features to mitigate measurement noise and calculate the likelihood for particles, and thereby reduce the probability of false alarms and hence improve the performance of the PHD filter.
- Simulation results show the improvement from the proposed particle PHD filter in both localization and cardinality as well.
- Ongoing work: more datasets will be employed to make comprehensive evaluations; and find a way to reduce the computational complexity.

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