Combining Visual and Behavioural Models for Pedestrian Tracking

aka Behavioural Pedestrian Tracking (III)

Javier Cruz

École Polytechnique Fédérale de Lausanne

Some Results

(Visual Tracking - Simulated Column)

Some Results

(Visual+Behavioural Tracking - Simulated Column)

Agenda

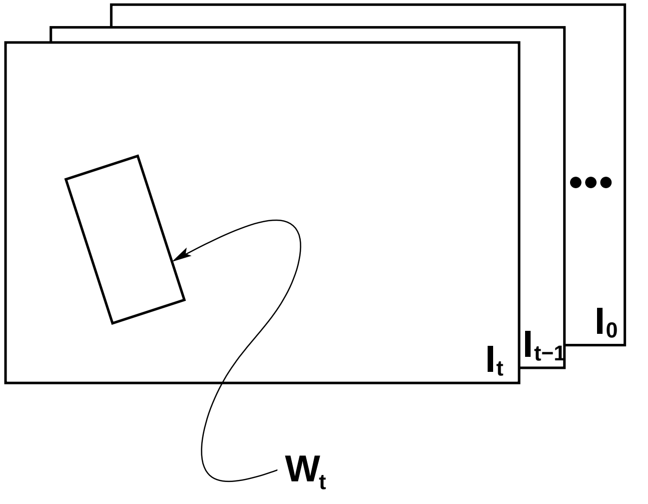
- Visual Tracking & Pedestrian Model Overview
- Old Approach $\longrightarrow$ New Approach
- Occlusion Detection
- Behavioural Probability
- General Algorithm
- Some More Results
- Conclusions and Future Work

Visual Tracking & Pedestrian Model Overview

Ross, D., Lim, J. and Lin, R.-S. (2008), *Incremental Learning for Robust Visual Tracking*. International Journal of Computer Vision 77:125-141.

Definitions:

- I_t: frame t
- $X_t = (x_t, y_t)$: position
- $\theta_t = (\varphi_t, \gamma_t, s_t, r_t)$: rotation, skewness, scale and aspect ratio
- $\Psi_t = \{X_t, \theta_t\}$: state
- $W_t = f(I_t, \Psi_t)$: a patch in I_t



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Visual Tracking & Pedestrian Model Overview

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- Particle filter with both importance density and state evolution probability, equal and Gaussian.
- Particle weights given by on-line PCA.

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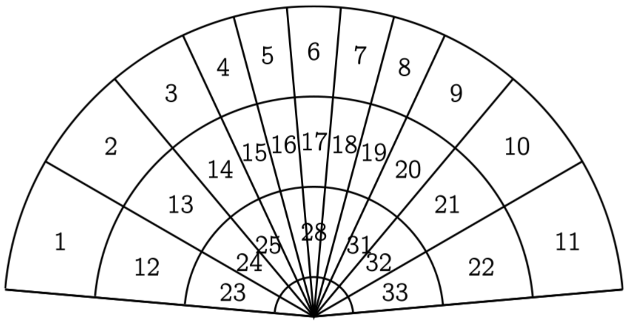
Visual Tracking & Pedestrian Model Overview

Robin, T., Antonini, G., Bierlaire, M., and Cruz, J. (2009), *Specification, estimation and validation of a pedestrian walking behavior model*. Transportation Research Part B, 43(1):36-56.

Next step model (cross-nested logit) taking into account:

- Direction
- Destination
- Speed
- “Leader-follower”
- “Collision avoidance”



Choice Set

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Visual Tracking & Pedestrian Model Overview

$$
\begin{aligned}
V_{vdn} = {} & \left.\begin{aligned}
&\beta_{\text{dir\_central}} \text{dir}_{dn} I_{\text{d,central}} && + \\
&\beta_{\text{dir\_side}} \text{dir}_{dn} I_{\text{d,side}} && + \\
&\beta_{\text{dir\_extreme}} \text{dir}_{dn} I_{\text{d,extreme}} && +
\end{aligned}\right\} \quad \textit{keep direction} \\
& \left.\begin{aligned}
&\beta_{\text{ddist}} \text{ddist}_{vdn} && + \\
&\beta_{\text{ddir}} \text{ddir}_{dn} && +
\end{aligned}\right\} \quad \textit{toward destination} \\
& \left.\begin{aligned}
&\beta_{\text{dec}} I_{\text{v,dec}} (v_n / v_{\text{max}})^{\lambda_{\text{dec}}} && + \\
&\beta_{\text{accLS}} I_{\text{n,LS}} I_{\text{v,acc}} (v_n / v_{\text{maxLS}})^{\lambda_{\text{accLS}}} && + \\
&\beta_{\text{accHS}} I_{\text{n,HS}} I_{\text{v,acc}} (v_n / v_{\text{max}})^{\lambda_{\text{accHS}}} && +
\end{aligned}\right\} \quad \textit{free flow acceleration} \\
& \left.\begin{aligned}
&I_{\text{v,acc}} I^L_{\text{d,acc}} \alpha^L_{\text{acc}} D_L^{\rho^L_{\text{acc}}} \Delta v_L^{\gamma^L_{\text{acc}}} \Delta \theta_L^{\delta^L_{\text{acc}}} && + \\
&I_{\text{v,dec}} I^L_{\text{d,dec}} \alpha^L_{\text{dec}} D_L^{\rho^L_{\text{dec}}} \Delta v_L^{\gamma^L_{\text{dec}}} \Delta \theta_L^{\delta^L_{\text{dec}}} && +
\end{aligned}\right\} \quad \textit{leader-follower} \\
& \left.\begin{aligned}
&I_{\text{d},d_n} I_{d,C} \alpha_C e^{\rho_C D_C} \Delta v_C^{\gamma_C} \Delta \theta_C^{\delta_C}
\end{aligned}\right\} \quad \textit{collision avoidance}
\end{aligned}
$$

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Visual Tracking & Pedestrian Model Overview

We want to use both models $\Rightarrow$ assumptions:

- Camera is calibrated
- Camera is fixed
- Pedestrians walking in normal conditions
- Destination known!

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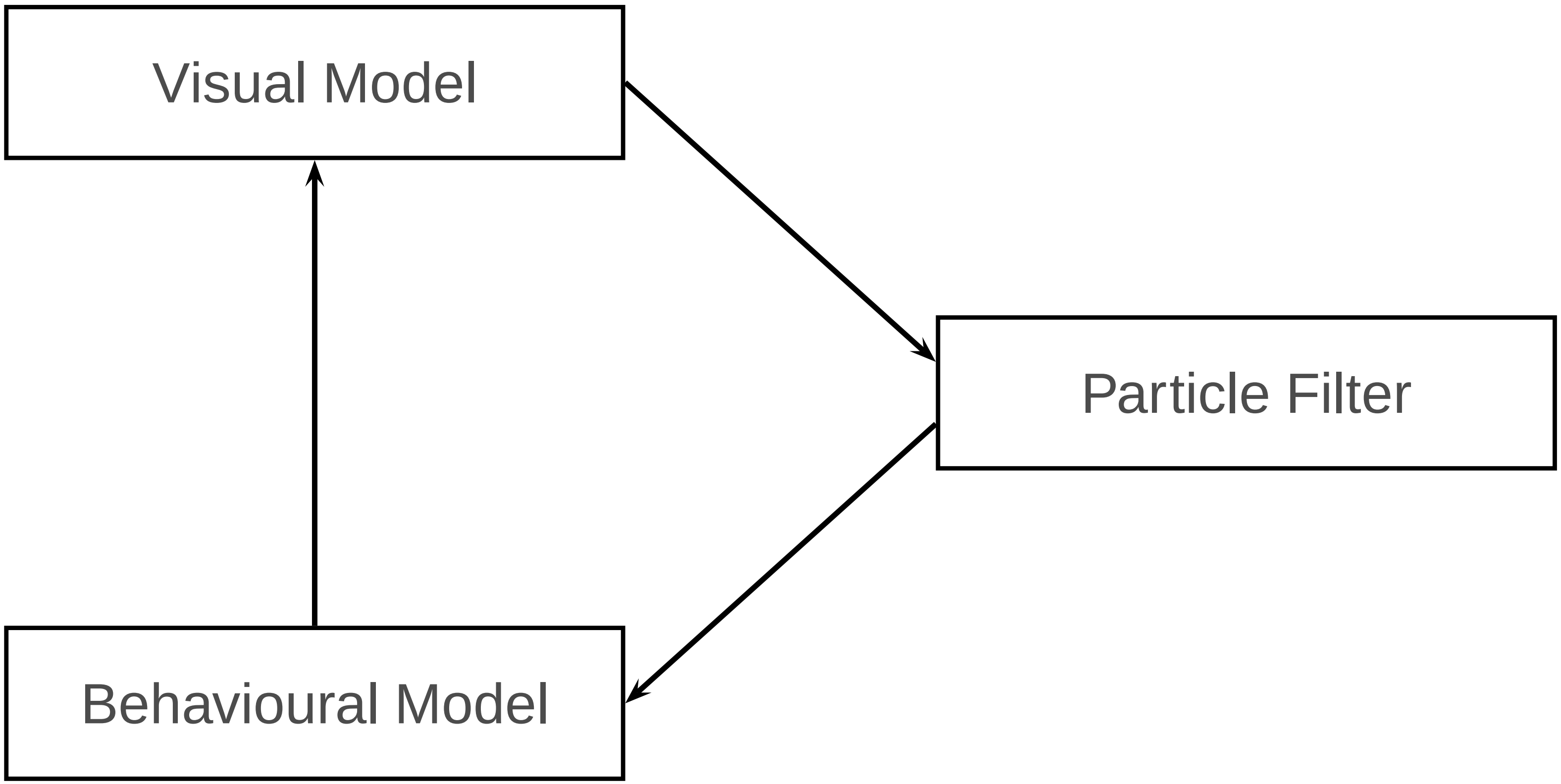
Old Approach $\longrightarrow$ New Approach

Old Approach:



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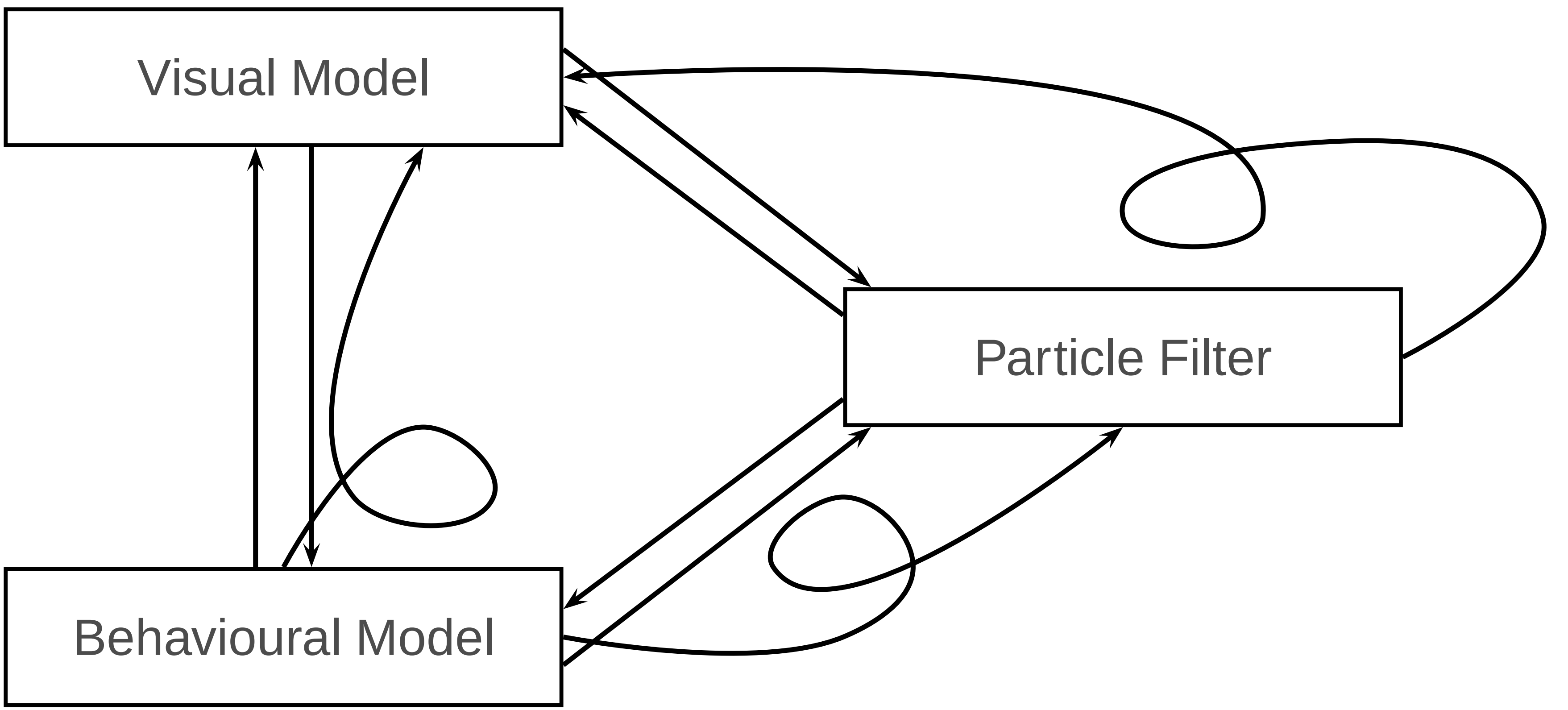
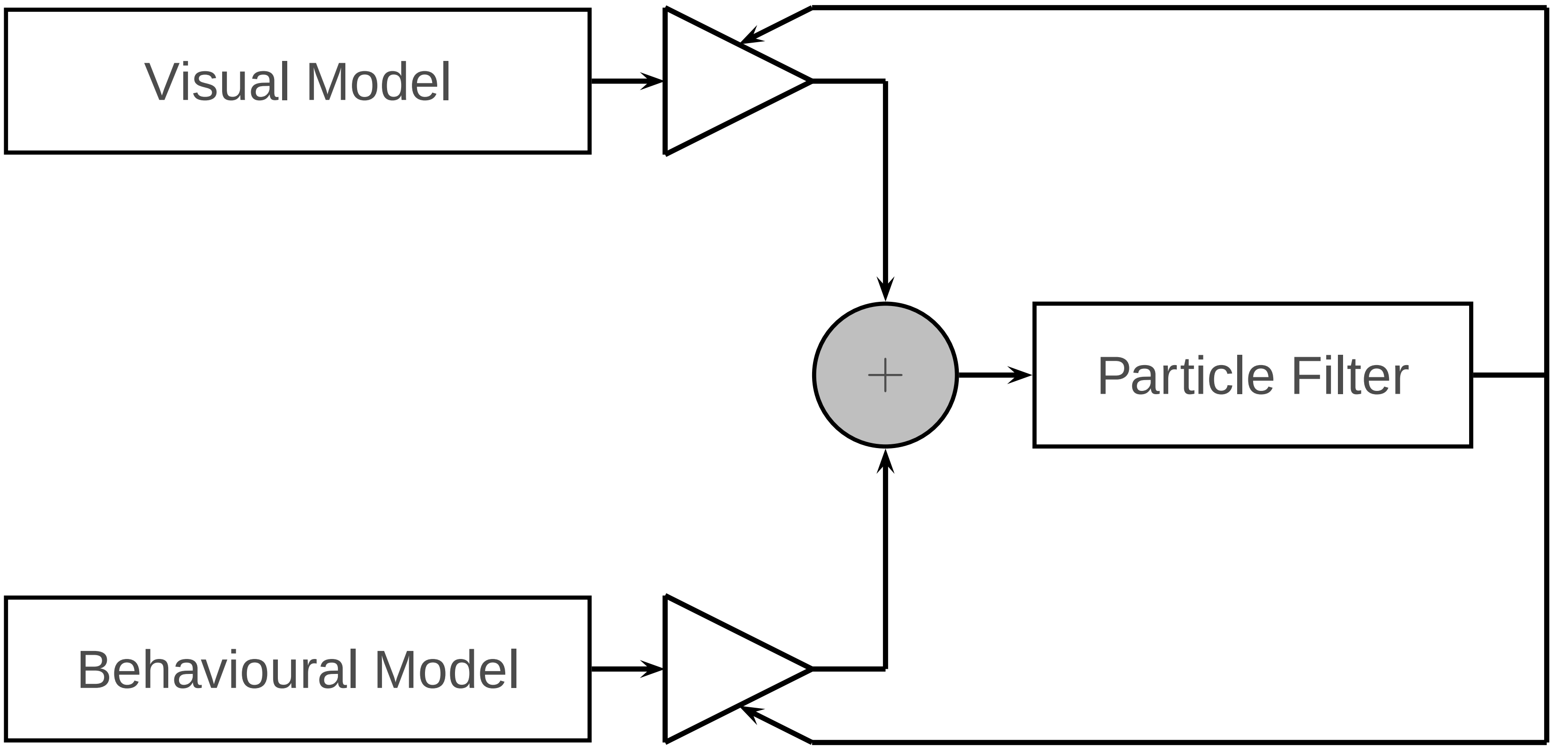
Old Approach $\longrightarrow$ New Approach

Intermediate Approach:



Old Approach $\longrightarrow$ New Approach

New Approach:



Occlusion Detection

Remember that in the visual case, $\omega_t^i \propto \omega_{t-1}^i P_{\text{VM}}(I_t|\Psi_t^i)$

Occlusion Detection

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Particle weights, given by the Visual Model, provide information about possible occlusions.

Ideally:

- $\text{Var}_i(\omega_{t|\text{VM}}^{*i}) \upuparrows$
- $\sum_i(\tilde{\omega}_{t|\text{VM}}^i) \upuparrows$

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$$\left.\begin{array}{ll} N_{eff} = & \dfrac{N_s}{1+\mathsf{Var}_i(\omega_{t|\mathsf{VM}}^{*i})} \\ \widehat{N_{eff}} = & \dfrac{1}{\sum_i(\omega_{t|\mathsf{VM}}^i)^2} \end{array}\right\} \Rightarrow \mathsf{Var}_i(\omega_{t|\mathsf{VM}}^{*i}) \simeq N_s \sum_i (\omega_{t|\mathsf{VM}}^i)^2 - 1$$

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Ideally:

- $\mathsf{Var}_i(\omega_{t|\mathsf{VM}}^{*i}) \upuparrows$
- $\sum_i(\tilde{\omega}_{t|\mathsf{VM}}^i) \upuparrows$

$$P_{Oc|\mathsf{VM}} = e^{-K \mathsf{Var}_i(\omega_{t|\mathsf{VM}}^{*i}) \sum_i(\tilde{\omega}_{t|\mathsf{VM}}^i)} \in (0,1]$$

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Behavioural Probability

In the case of the behavioural model, the observation is Ψ_t^i, and the prior is all the behavioural information (historical data of X_t^i and computed trajectories of other pedestrians).

$$P_{\text{BM}}(\Psi_t^i|\text{BI}) = P_{\text{DCM}}(X_t^i|\text{BI})e^{-|\text{size}_0 - \text{size}(\Psi_t^i)|}$$

General Algorithm

Apply Visual Tracker during $1.5 \cdot$ FPS
for every new frame **do**
    Compute $\omega^i_{t|\mathsf{VM}}, i = 1 \ldots N_s$
    Compute $P_{Oc|\mathsf{VM}}$
    $\omega^i_t \propto \omega^i_{t-1}((1 - P_{Oc|\mathsf{VM}})P_{\mathsf{VM}}(I_t|\Psi^i_t) + P_{Oc|\mathsf{VM}}P_{\mathsf{BM}}(\Psi^i_t|\mathsf{BI}))$
    if $P_{Oc|\mathsf{VM}} < P_{\mathsf{Th}}$ **then**
        Update PCA with winning window
    end if
end for

Some More Results

(Visual Tracking)

Some More Results

(Visual+Behavioural Tracking)

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Some More Results

(Visual Tracking - Simulated Column)

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Some More Results

(Visual+Behavioural Tracking - Simulated Column)

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Some More Results

(Visual Tracking - Lost Signal Simulation)

Some More Results

(Visual+Behavioural Tracking - Lost Signal Simulation)

Conclusions

- Occlusion detection allows to combine efficiently both models
- Visual+Blind approach overcomes typical problems of tracking algorithms
- Slow! (A lot of computations for each particle)

Future Work

- Improve occlusion measure and probability of BM
- Weighted PCA
- Implement more robust features
- Record videos with real occlusions