Online multi-model particle filter-based tracking to study bedload transport

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ONLINE MULTI-MODEL PARTICLE FILTER-BASED TRACKING TO STUDY BEDLOAD TRANSPORT

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1. Context & Objectives

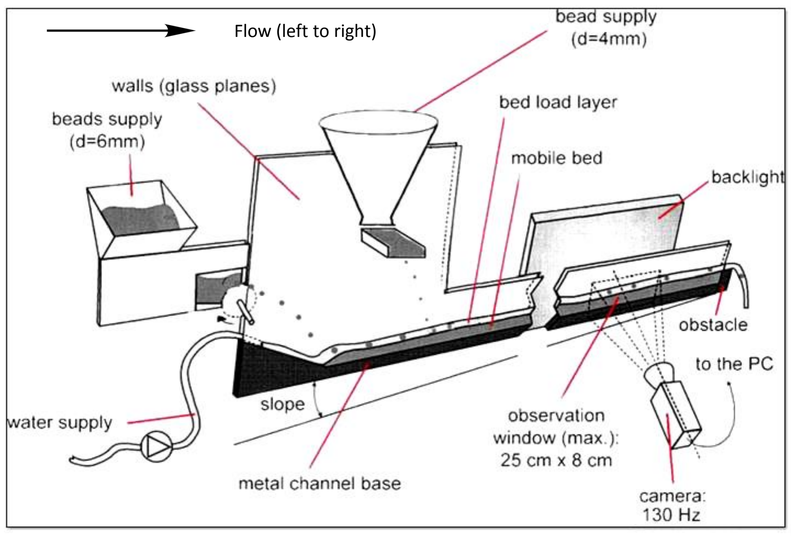
Global aim: studying bedload transport thanks to experiments with two-size beads in a water flow.

➥ **Main objective: track beads over long time sequences to better understand size segregation responsible for complex morphology structures.**

The idea: propose an **online particle filter-based algorithm** integrating several improvements

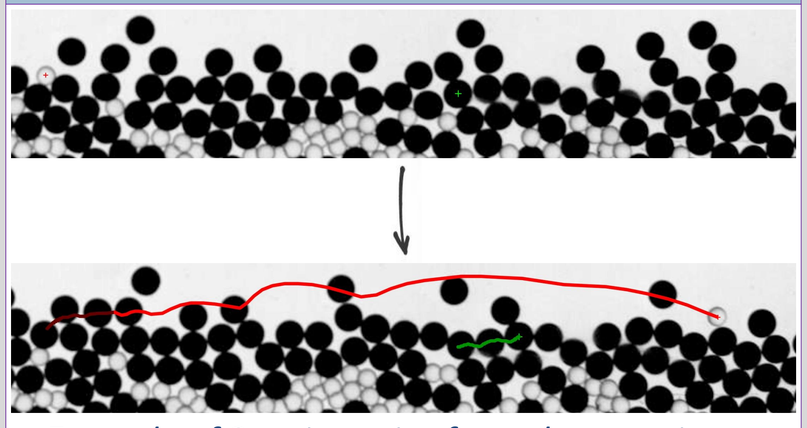
1. **Include an adapted multiple motion models** with known mechanical dynamics to better anticipate bead locations.
2. Exploit detector confidence to handle missing detections.

2a. Experimental setup



Sketch of the experimental arrangement (modified from [1])

2b. Tracking & bedload transport



Example of 2 trajectories from the experiment

Tracking bedload sediment transport to study:

- Velocities and concentrations
- Bedload granular rheology
- Size segregation and associated morphology

3. Multi-model tracking algorithm

Stage 1: Object detector

- Use specific morphological operations (hconvex, cross-correlation, …)
- Exploit detector confidence to handle miss-detections (based on [2])

$$d_c(\boldsymbol{x}) = \frac{1}{k_D}\sum\nolimits_{d\in D} \mathrm{xcorr}(d)\exp(-\lambda\|\boldsymbol{x}-\boldsymbol{x}_d\|)$$

Stage 2: Data association

- Perform greedy algorithm on matching costs

$$c(tr,d) = \underbrace{\alpha\frac{\|\boldsymbol{x}_d - \boldsymbol{x}_{\widehat{tr}}\|}{r_s}}_{\text{distance term}} + \underbrace{\beta\frac{|\boldsymbol{v}_d|}{|\boldsymbol{v}_{max}|}}_{\text{velocity term}}$$

Stage 3: Particle filtering

Principle: use Sequential Importance Resampling (SIR) with an internal state including motion state, position (x, y) and velocity (u, v):

1. Draw a new state according to conditional probability table
2. Propagate the particles using a motion-based stochastic tracking (as in [3]) with 3 motion models:
   - Resting - *not moving* - $(x,y)_t = (x,y)_{t-1} + \varepsilon^{rest}_{(x,y)}$
   - Rolling - *sliding on other* - $(x,y)_t = (x,y)_{t-1} + (u)_{t-1}\Delta t + \varepsilon^{roll}_{(x,y)}$, $(u)_t = (u)_{t-1} + \varepsilon^{roll}_{(u)}$
   - Saltating - *bouncing on others* - $(x,y)_t = (x,y)_{t-1} + (u,v)_{t-1}\Delta t + \varepsilon^{salt}_{(x,y)}$, $(u,v)_t = (u,v)_{t-1} + \varepsilon^{salt}_{(u,v)}$
3. Compute particle weighting

$$w_{tr,p} = \mathcal{I}(tr)\big(\underbrace{\delta p_{\mathcal{N}}(\boldsymbol{x}_p - \boldsymbol{x}_{d^*})}_{\text{particle position}} + \underbrace{\gamma p_{\mathcal{N}}(\boldsymbol{v}_p - \boldsymbol{v}_{d^*})}_{\text{particle velocity}}\big) + \underbrace{\eta d_c(\boldsymbol{x}_p)}_{\text{det. conf}}$$

4. Normalize weights and resample particles with SIR method
5. Estimate position and velocity by averaging resampled particles

4. Results

➢ **Creation of a ground truth dataset of 1000 images for the tests**

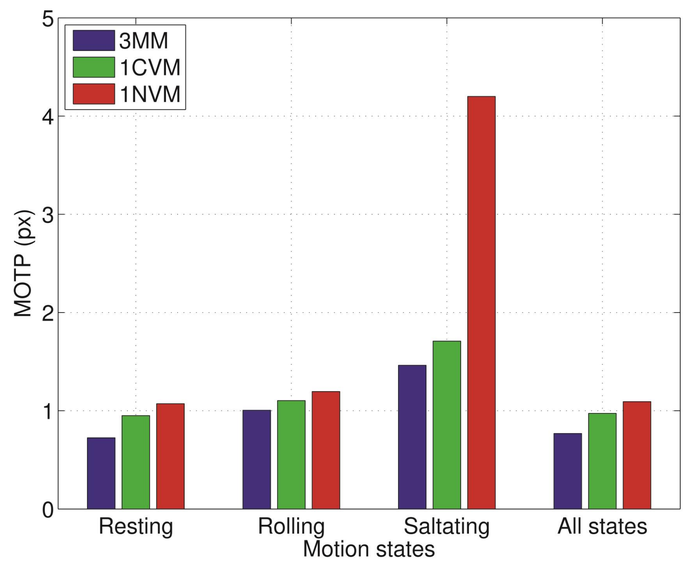
➥ Parameters are fixed on half of the dataset

➢ **Tracking evaluation results on 3 algorithm configurations:**

Algo. Models	% Correct Tracks	MOTP	FN	FP	Id Sw.	MOTA
3MM	**98.35%**	**0.64px**	**0.07%**	**0.16%**	**4**	**99.77%**
1CVM [2]	95.05%	0.77px	0.09%	0.17%	23	99.72%
1NVM	89.90%	0.89px	0.14%	0.54%	84	99.28%

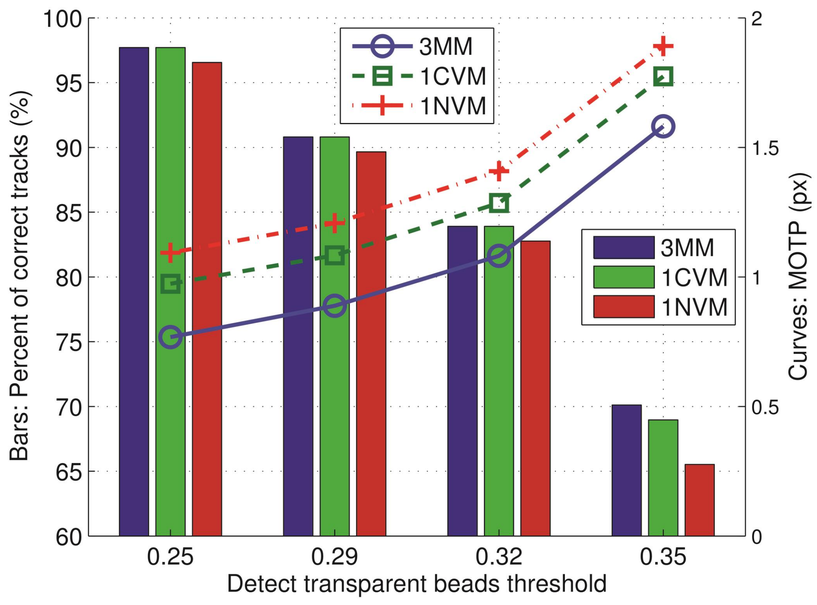
3MM = 3 motion models ; 1CVM = 1 constant velocity model ; 1NVM = 1 null velocity model

➢ **Precision score MOTP according to motion state:**



MOTP: precision to ground truth in pixels

➢ **Correct tracks and MOTP for different detection thresholds:**



Correct track: >95% of the track without FN or mismatches

5. Conclusions & Perspectives

➢ **New online particle filter-based tracking algorithm based on multiple dynamic models**:

- **Input of object mechanical dynamics** helps approaching real trajectories.
- Allows studying bedload transport with higher confidence.

➢ **Our multiple motion model based algorithm provides high tracking precision and accuracy with different detector qualities**:

- Outperforms single dynamic models.
- Effect of inaccurate detections reduced by detector confidence.

Perspectives: Use configuration and state of neighboring objects as an information to help choosing between motion states.

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