# Binding Vision to Physics Based Simulation: The Case Study of a Bouncing Ball


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## PROBLEM STATEMENT

Given partial 2D or 3D trajectories of the motion of a uniformly colored bouncing ball, that is viewed by a single or multiple cameras, estimate its full 3D state, over time, i.e. location, orientation, angular and linear velocities.

## MOTIVATION

Scene understanding can benefit from exploiting the fact that a dynamic scene and its visual observations are invariably determined by the laws of physics.

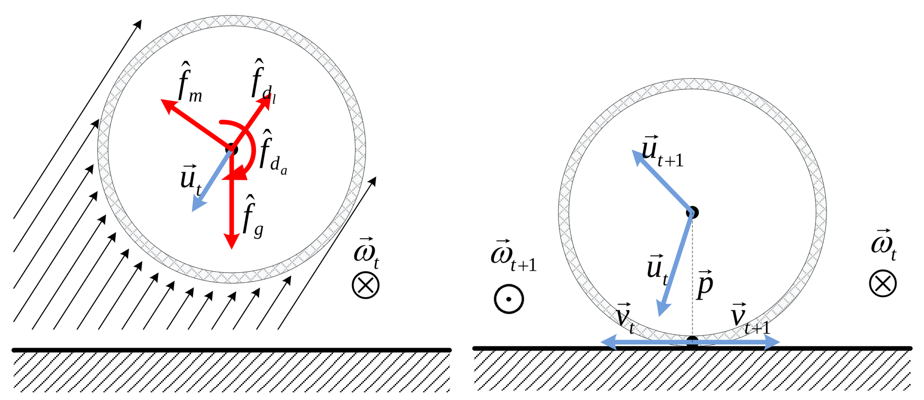
## MAIN IDEA

- Model the physics of the scene using physics-based simulation
- Acquire visual observations
- Define an objective function that connects the model to the observations
- Produce physically plausible interpretations of the scene by performing black-box optimization

## PHYSICS BASED SIMULATION

### (A) Dynamics of a bouncing ball

The bouncing ball is affected by gravity and air resistance while in flight and friction while in bounce with a surface.



### (B) Equations of motion

We assume standard equations of motion for the flight phase and add air resistance. We derive equations for the bounce phase by extending [1].

$$\begin{aligned} S_y \vec{u}_{t+1} &= -\beta S_y \vec{u}_t \\ S_y \vec{\omega}_{t+1} &= S_y \vec{\omega}_t \\ S_{xz} \vec{v}_{t+1} &= \alpha S_{xz} \vec{v}_t \\ m \cdot \vec{p} \times S_{xz} \Delta \vec{v} &= -I \cdot S_{xz} \Delta \vec{\omega} \end{aligned}$$

### (C) Simulation of a bouncing ball

We define a parameterized ball throwing simulation process $S$ that:

- receives a 21-D vector of scene properties and initial conditions
- at each point in time, produces a 12-D vector of location, orientation, linear and angular velocities
- is implemented by augmenting the Newton Game Dynamics simulator with our physics modeling
- performs at 500fps, but is sub-sampled to real acquisition rate (30fps), in order to account for aliasing effects

## PHYSICALLY PLAUSIBLE SCENE INTERPRETATION

We estimate the physically plausible explanation $e$ of the observed scene by formulating an optimization problem, where:

$$e = \arg\min_x \text{BackProjectionError}\left(o, S\left(x\right)\right)$$

- the hypothesis space of $x$ is defined over the domain of simulation process $S$
- the observation data $o$ are trajectories of a bouncing ball (potentially partial, 3D or 2D, from single or multiple cameras)
- the objective function quantifies the discrepancy between the result of an invocation to $S$ and the observations
- the objective function is optimized by means of Differential Evolution [5]

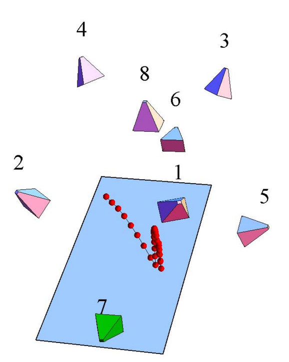
## CONTRIBUTIONS

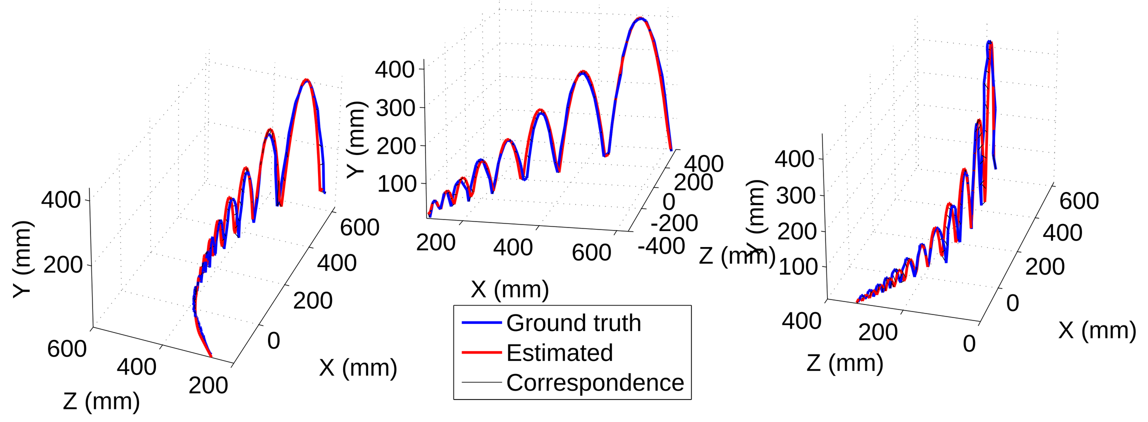
- First method to consider attributes of state that can only be estimated through physics-based simulation
- Extension to existing work [2–4] in exploiting physics based simulation in vision
- Proposal of an effective method that is clear, generic, top-down, simulation based
- Incorporation of realistic physics
- Selected generic and modular components allow for extension to other broader or different contexts

## EXPERIMENTAL RESULTS

### (A) Multiview estimation of 3D trajectories (synthetic/real)

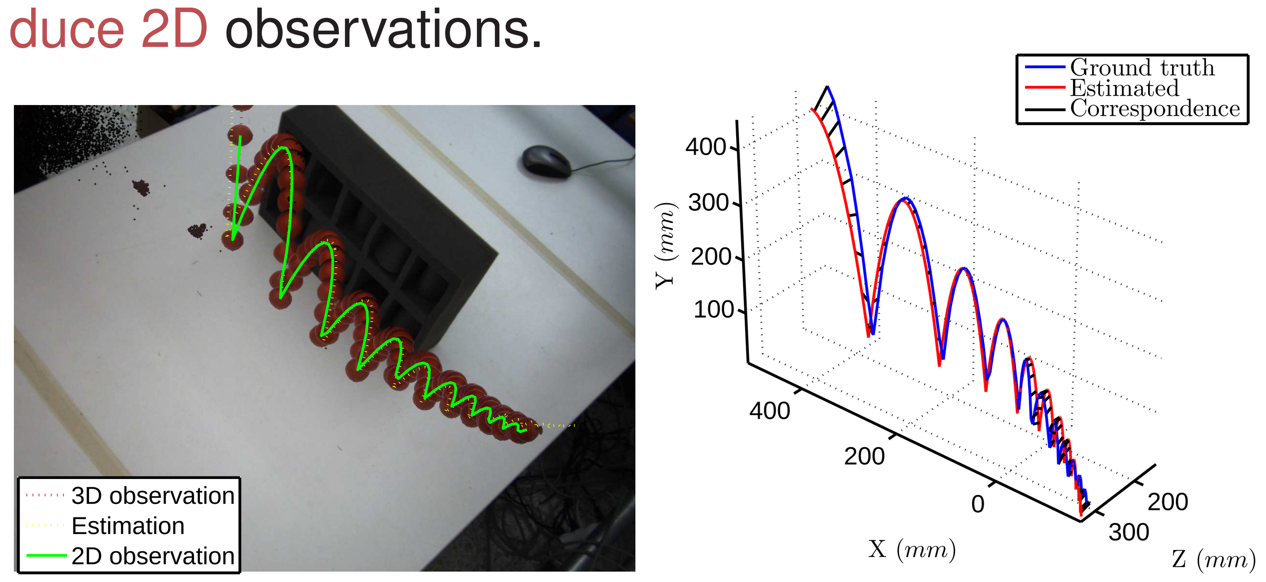
Finding ball throwing simulations that optimally reproduce 3D observations.





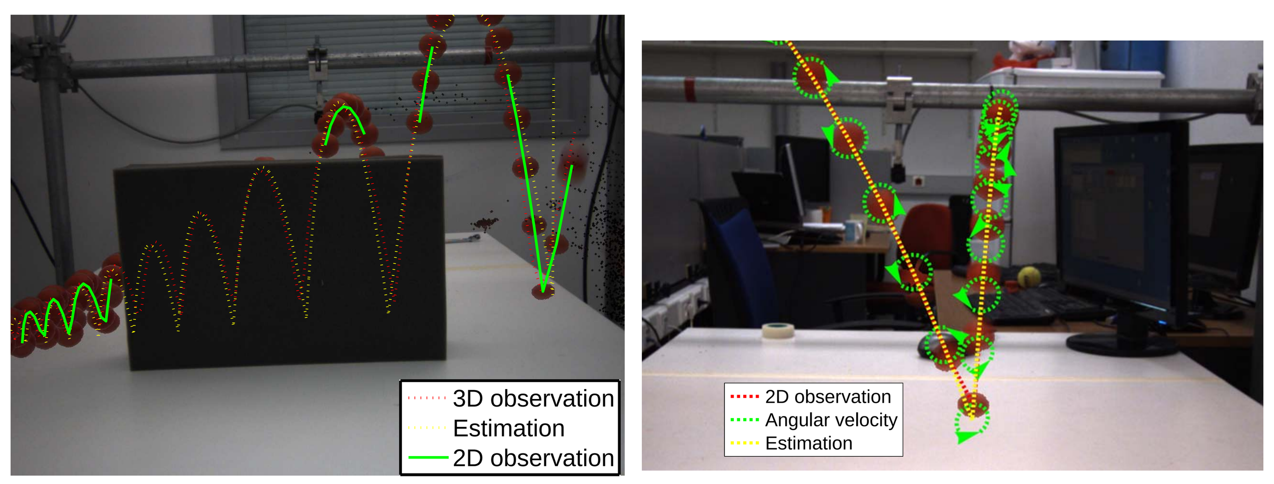

### (B) Single view estimation of 3D trajectories

Finding ball throwing simulations that optimally reproduce 2D observations.




### (C) Seeing the "invisible"

Implicit information, like the state of the ball while occluded (left) and the angular components of its 3D state (right), are computer based on a single camera.




## KEY REFERENCES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## MORE INFORMATION

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