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

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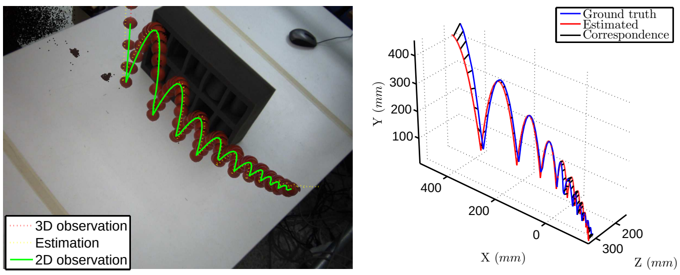
A dynamic scene and, therefore, its visual observations are invariably determined by the laws of physics. Based on the case-study of a uniformly colored bouncing ball, we demonstrate that *physical explanation*, as a vision prior, is not a commodity but a necessity. More specifically, by considering the problem of ball motion estimation we show how physics-based simulation in conjunction with visual processes can lead to the reduction of the visual input required to infer physical attributes of the observed world. Even further, we show that the proposed methodology manages to reveal certain physical attributes of the observed scene that are difficult or even impossible to extract by other means. A series of experiments on synthetic data as well as experiments with image sequences of an actual ball, support the validity of the proposed approach. The use of generic tools and the top-down nature of the proposed approach make it general enough to be a likely candidate for handling even more complex problems in larger contexts.



(a) (b)

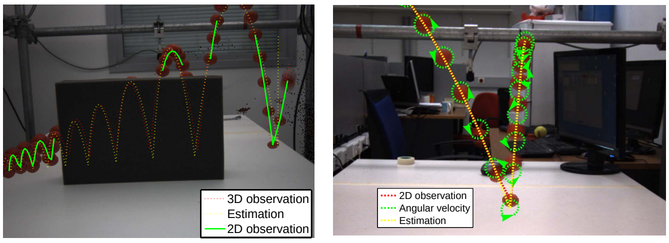
Figure 1: The proposed method employs the assumption of a given physical world in order to estimate the non-trivial 3D trajectory of a bouncing ball with spin and air resistance, from a *single camera* (a) with *high accuracy* (b).

This work is most closely related to [2, 3, 4]. We go further by proposing a top-down method that, at the same time, can be easily extended, exposes the full potential of employing physics in vision and, because of this, achieves an increase of the extracted information and a decrease of the required visual input.

By employing standard computer vision techniques, accounting for the position of the ball at each time step is not trivial. The possibly inadequate acquisition frame rate may lead to aliasing and the possibly large shutter time may lead to motion blur. Thus, single view ball 3D localization, which depends on the ability to accurately estimate the ball's projected shape and size, becomes problematic.

In our formulation of the problem, we consider a more reliable source of information, i.e. the physics governing the motion of the ball. Our method receives 2D (single camera) or 3D (multiple cameras) trajectories that represent the course of a bouncing ball and outputs the parameters of a simulated experiment that optimally matches the observations. These parameters can be used to reproduce/simulate the experiment anew, and thus gain access to a wealth of information, at almost arbitrary time resolution.

More specifically, we consider the *physical explanation* e of the bouncing of the observed ball. We assume that certain scene properties (mass, inertia, collision properties) and initial conditions (position and velocities of the throw), together with the laws of physics, generate a 3D trajectory, via simulation, which optimally projects back to all cameras and matches the observations o. We define the back-projection error as the quantity to be minimized in an optimization problem, whose hypothesis space involves both scene properties and initial conditions. The simulated experiment can be sub-sampled to match the acquisition rate of the actual camera set. This also accounts for the aliasing effects of the acquisition



(a) (b)

Figure 2: The top-down consideration of the scene dynamics enables the induction of otherwise unaccountable information, such as (a) the full state of the ball while it is not visible to the camera that observes it due to occlusions and (b) the spin of the uniformly coloured ball that makes it travel in curved trajectories (again from a single camera).

process. Since whatever is observed must be *physically plausible*, the *physical explanation* e is the minimizer parameter vector x of this objective function. In notation:

$$e = \arg\min_x \text{BackProjectionError}\left(o, \text{Simulation}\left(x\right)\right). \quad (1)$$

We extend the bouncing ball's dynamic behaviour described in [1] to the 3D case and also acknowledge air resistance as a factor that affects it. We inject these dynamics in the Newton Game Dynamics[1] physics simulator that, together with its basis, form the full dynamics modeling. We employ Differential Evolution [5] in order to perform the aforementioned optimization over the configuration of a simulated ball throwing experiment on the Newton Game Dynamics simulator.

The method has been thoroughly evaluated in both synthetic and real data that involved non trivial trajectories of a bouncing table-tennis ball, having been observed from single and multiple cameras. We were able to perform accurate motion estimation, from a single camera (Fig. 1), even despite occlusions (Fig. 2(a)). Interestingly, the requirement that "hidden" dynamics are forced to be in accordance with acquired observations, enables their inference (Fig. 2(b)). Overall, we demonstrated that accounting for physics does not simply constitute yet another complementary source of information but rather, a strong prior that permits the treatment of underconstrained vision problems. In fact, we demonstrated that by incorporating physics, we may require less cameras/observations to obtain the same type of information (Fig. 1) or even gain access to information that is otherwise "invisible" to a vision system (Fig. 2).

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