Model Predictive Control for Robust Art-Directable Fluids

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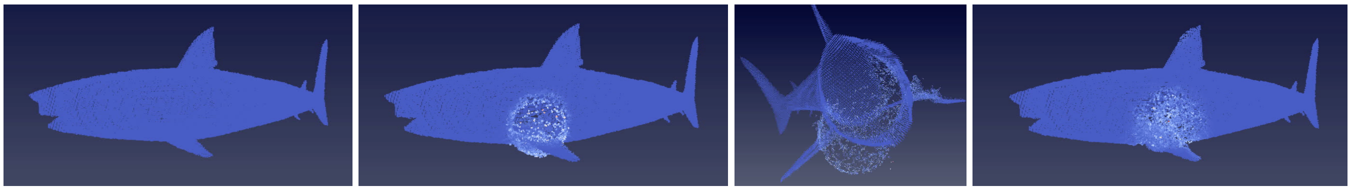

Figure 1: *A select number of stills from a controlled fluid simulation where a shark made out of fluid particles gets hit by an invisible cannonball. Before impact, the fluid maintains its shape, compensating gravity and other forces. After the collision with the sphere, the fluid swiftly and smoothly restores its shape in a fluid like manner thanks to the controller. The control forces were computed using a simplified model where only body forces and the pressure term are taken into account for predicting the particle positions.*

Keywords: Fluid Simulation, Fluid Control, Trajectory Tracking, Model Predictive Control

Concepts: •**Computing methodologies** → *Physical simulation;*

1 Introduction

Physics-based animation has become an important tool in computer graphics and is essential in recreating realistic looking natural phenomena. Researchers have been looking for tools to control passive simulations that allow artists to easily modify the simulation to best suit the artistic requirements. However, fluid motion is very hard to predict and it is very difficult, if not impossible, to achieve specific behavior just by altering the global variables. Active control of the simulation will be necessary to achieve this goal.

We present a model predictive controller (MPC) for fluid simulations that is able to achieve control with high precision based on an optimization process. The system has the potential to be used to control fluid simulations at run-time to deal with unforeseen user-interactions by controlling a simplified simulation using a sliding window to anticipate future changes. MPC is already being used extensively for controlling massive industrial processes. Likewise, the graphics community has applied this approach for generating bipedal locomotion. In the same vein, we hope that our method will provide artists with a robust and reliable tool to orchestrate complex simulations according to artistic needs and helps to obtain physically-plausible simulations with minimal effort.

2 Our Approach

At every time step in the simulation, MPC predicts the future by simulating an additional simplified fluid model for a fixed amount of frames H. We call H the prediction horizon. Based on this prediction, a suitable control force vector for every particle is computed that will be applied to the full simulation. Figure 2 shows a schematic overview of the force computation process.

Every particle is augmented with an individual time-varying control force $\mathbf{F}$ computed by the controller based on a user-defined goal function that measures the cost of any given fluid configuration. In order to make the fluid particle positions $\mathbf{x}[\mathbf{i}]$ reach a specific reference state given in $\mathbf{r}[\mathbf{i}]$ at time step i, the following cost function can be evaluated for every time step t:

$$\begin{aligned} \underset{\mathbf{F}}{\text{minimize}}\ J[t] &= \|\mathbf{x}[t+H] - \mathbf{r}[t+H]\|_C^2 \\ &+ \sum_{i=t}^{t+H-1} \left[\|\mathbf{x}[i] - \mathbf{r}[i]\|_Q^2 + \|\mathbf{F}[i]\|_R^2 \right] \end{aligned} \tag{1}$$

with $C \geq 0$ the terminal cost matrix, $Q \geq 0$ is the tracking error cost matrix. The control force are regularized thanks to a control cost matrix $R > 0$. The artists can control the trade-off between controller strength and natural fluid motion by tuning these matrices. This particular goal function only models keyframes on the particle positions but velocity keyframes can be added easily. Many other types of goal functions can also be used. The reference states can be defined by some mathematical formulation or it can easily be generated by sampling animated reference geometry.

Since this control vector is computed at every time step, the system can be used to control fluid simulations at run-time to deal with unforeseen circumstances such as unmodeled behavior like user interactions. Additionally, the predictive nature reduces artefacts and oscillations due to overshooting the goal state that are common with more simple control techniques.

Another advantage of MPC is that the control forces do not have to be computed based on the full fluid model as this might become too time-consuming. Approximations can be made to the fluid in order to improve the computation time. This simplified model does not have to produce the exact same behavior as the full fluid model because the controller takes the actual fluid state, computed with the full model and control forces, as the initial state for the prediction at every time step. This means that any mismatch between the control model and the full model are robustly handled.

In our implementation, we use the adjoint method to optimize the goal function using [McNamara et al. 2004] and [Wojtan et al. 2006] in order to keep the optimization tractable. The optimization can be performed iteratively until the optimal control force is

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found or a fixed number of iterations can be used to find a decent estimation in a fixed timeframe. The ability to provide the particle with a control force within a fixed amount of time is crucial in interactive settings.

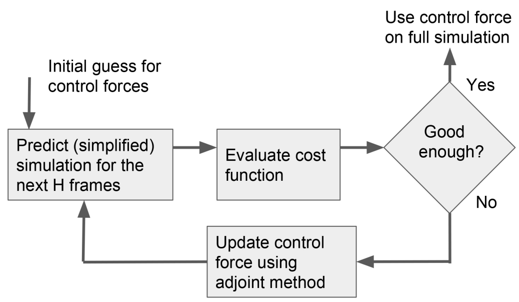

Figure 2: *MPC predictive simulation and optimization flowchart.*

3 Results

We implemented our control strategy in the multithreaded CPU code DualSPHysics SPH solver [Crespo et al. 2015] and constructed a simple scene to demonstrate some initial results. This particular example shows that the controller is able to maintain a specified shape, effectively counteracting external forces such as gravity. In a subsequent part in the simulation, a sphere is moved through the fluid at high velocity and the controller successfully restores the original shape after impact in a physically-plausible fashion. Figure 1 shows a few snapshots from said example scene. The results are obtained by using the cost function given in (1) with reference positions generated by sampling the boundary of the stationary shark geometry. The control forces are computed based on a simplified fluid model where only body forces and the pressure term are taken into account and with a prediction horizon of 5 frames. This example is computed with 28000 fluid particles and takes roughly one minute per frame to compute on an Intel Xeon E5-1607 CPU.

Although already useful for offline control, the implementation is still too slow to serve in interactive settings. In the future it might prove to be a valuable control strategy because of its robustness thanks to optimal control that is able to handle unforeseen and unmodeled behavior such as user interactions. The model can be sped-up relatively easily by a GPU implementation.

4 Future Research

In the future we would like to improve the control strategy further by researching the following aspects:

- **Adaptive Prediction Horizon** A prediction horizon might be chosen adaptively based on the goal function. Not every frame needs to be a keyframe in the goal function, the prediction horizon might be chosen to include the next keyframe. This means that H is chosen as the number of frames between two consecutive keyframes.

- **Simplified Fluid Models** We have obtained satisfying results by only incorporating the effects of body forces and the pressure term for relatively short prediction horizons. We will investigate whether we could simplify the model even further for short prediction horizons. More complex models will be needed for long horizons as the prediction will likely start to diverge from the real simulation. Combined with an adaptive prediction horizon, a good strategy for switching between control models needs to be investigated.

- **Goal Function Design** We would like to further investigate ways to formulate specific non-trivial keyframes in the goal function.

In conclusion, we successfully implemented a new control strategy for art-directable fluids and have obtained pleasing preliminary results. Although more test cases, research, convergence analysis and validation will be necessary to provide a method that can compete with the state-of-the-art, we believe that the use of predictive control based on an underlying simplified model provides many opportunities in both offline and online control for physics-based animation in general.

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