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Real Examples based Natural Phenomena Synthesis

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Abstract

Current physics-based simulation is an important tool in the fluid animation. However some problems require a new change to current research trends which depend only on the simulation. The ultimate goal of this project is to obtain information of flow example, analyze an example through machine learning and the novel fluid animation reconfigure without physical simulation.

Key words : Example-based, Physical simulation, Computational efficiency, Vector potential, Tensor

1. INTRODUCTION

1.1 Motivations

Current physics-based simulation is an important tool in the fluid animation, but the two problems listed below require a new change to current research trends which depend only on the simulation. First, a physics-based method is inefficient in economic terms. Fluid scene used in movies and advertising requires realism level of actual image.

To do this, the huge computation time and computing resources are required. The scene which pours water into a cup for about 10 seconds requires a day or more simulation time. Various studies [6,11] are conducted to calculate efficiency. But variables which are proportional to the resolution of the simulation are woven by the global calculation. There are obvious limitations in efficiency improvements. Second, the current physics-based studies are limitations of representation the subject. Smoke, water, fire, and many of the fluids had the development which makes it incredibly similar to the actual image in terms of the quality of a scene. But at the same time dealing with two or more fluid multi-phase flow [7], such as cigarette smoke, fine fluid diffusion, and other physical objects and interactions [3] and is still considered to be a challenging

problem. Even in the field of computational fluid dynamics, it is true that above problem's physical solutions are on the level of toddlers.

The subject of this study, based on the example fluid animation, is little research that is closely related. Example-based research is an active field of character animation. Various studies [10, 8] using motion capture attracted the attention of many researchers in the last dozen years and in recent years, articulated body dynamics by applying the example of the behavior have been attempted to control character [17]. To reduce the computational load for realistic rendering, studies using examples had been carried out [15] and for the effective deformation calculation, there were studies which analyze simulation in the direction of a particular force in preprocessing step [1]. Example-based idea is spread to fluid simulation, study is carried out that the smoke example which is simulated is simplify the simulation process through data analysis [16]. However, grid resolution to possibly perform real-time is not large enough, as well as, other than smoke such as water it has limitation to extend to fluid.

1.2 Prospect in the field of fluid animation

Unlike the main goal that had high-quality output and efficiency improvements fluid results, in the future fluid animation fields are expected to receive attention following the research of three areas. First, in the field of fluid, convergence studies which combine example based ideas will be tried. For the computational efficiency and expand

the representation of the area, it will be developed from actual image or fluid example consist of simulation result to new animation reconstruction area. Second, the fluid control problems which reflect the diverse needs of users will attract more attention. Like other areas of graphics, fluid field is also advanced form of research that produces results which meet the designer's needs. A high level of control such as specific features added in detail, the appearance of the flow field constrained in a specific time will be carried out by research. Third, parallel computing research is expected to be more prevalent. The methodology [9] which are performed universal calculations on the GPU as theme of the research called GPGPU(General-Purpose computation on Graphics Processing Units) is already spread as CUDA, OpenCL structure. A simulation algorithm which is only consist of region calculation is already performed by GPU and in the future, studies which are even global calculation performed by GPU will be spotlight.

2. OBJECTIVE

The ultimate goal of this project is to obtain information of flow example, analyze an example through machine learning and the new fluid animation reconfigure without physical simulation. Fluid data as an example use all data which are video images captured actual fluid and the data which is calculated by captured actual fluid[5] and physics simulation. Depending on user's needs, fluid style selection, the source position, guiding path changing, and the reconstruction of a high-quality video as the same level of example seems more than the ability to perform real-time at 30 frames per second.

3. OUR METHOD

As machine learning target, the vector potential [2] for the example velocity field is used. Learning the example velocity field is basic approach. But it can be failed to extract meaningful result. The conservation of mass about incompressible flow is equivalent to $\nabla \cdot \boldsymbol{u} = 0$. But if learning only velocity field, it is hard to see reconstructed velocity field is satisfied this condition. After a given velocity field $\boldsymbol{u}$ to the $\boldsymbol{u} = \nabla \times \boldsymbol{p}$ and obtain numerically the vector potential $\boldsymbol{p}$. If this is the object of study, reconstructed velocity field by arbitrary vector field $\boldsymbol{q}$ to the properties of $\nabla \cdot (\nabla \times \boldsymbol{q}) = 0$ will be always satisfied incompressible fluid field condition.

To overcome the difficulty of high-level examples process, it is attempted to tensor based dimension reduction.

The flow data is proportional to resolution of the sample. So in the case of three-dimensional has generally more millions dimensions. It is common idea in machine learning that if learning these high-level data simply, it is difficult to produce effective result. The flow data can be represented as a multi-dimensional tensor. Therefore it is more effective to apply a tensor-based technology than to apply vector-based dimension reduction such as Principal component analysis.

It is modeling the learning input and output based on the example of time correlation. The decisive viewpoint which is the status change of next time depends only on the current state is the basic principle of physics-based simulation. The model which is approximated from simulation example is Navier-Strokes method so the learning algorithm is tried which is regarded the current frame and the next frame of physics values as features. From the point of machine learning, deterministic perspective can be modeled using the Markov property. Assuming the dimension of derived physical value is properly reduced, the following conditions only depend on current state of feature according to Marko property. That is, Probability which transferred the given current state to the next state is defined as $\mathcal{P}(s_{t+1}|s_t, \alpha)$. The next state s_{t+1} and the current state s_t became the derived physics values from the example, factors that contribute to the prior state are separately extracted and suppose as α, it can learn given example through optimization method of machine learning, and then the next state fluid which is about arbitrary input state can be stochastic selected based on Markov properties.

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