Fire Simulation in CG: A Survey

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Abstract

In recent years, fire simulation has gained significant attention due to its importance in video games, VR/AR, film-making, and security applications. There are many approaches to simulate fire, and these approaches serve for different purposes. This paper reviews fire simulation methods from 2016 to 2025, categorizing them into physics-based, data-driven, visual-effects oriented, hybrid, and other related approaches. We also provide a clear comparison of the advantages and disadvantages of each method. Finally, we discuss current challenges and outline potential directions for future research in fire simulation.

Keywords

Fire simulation, Visualization, Virtual reality, Neural network, Visual effect, Texture mapping.

1. Introduction

With the development of video games and VR/AR applications, the demand for simulation of real things has increased significantly. Fire simulation, which is known for its high requirements in real-time performance and realism, has been extensively studied in recent years. Researchers have proposed a wide range of approaches from physics-based approaches (modeling the thermodynamics and fluid dynamics of flames) to visual-oriented approaches (focusing on perceived realism and rendering efficiency) .In recent years, data-driven methods, especially those based on machine learning and neural networks, have been introduced to further improve realism while reducing computational costs. However, there are still several challenges such as the interaction between the flames and the environment, the cost for generating a more realistic flame, and the parameter settings when simulating flames. Therefore, a comprehensive review of fire simulation methods is necessary to summarize the progress, analyze their strengths and limitations, and identify promising directions for future research.

Nevertheless, with the growth of demand for the complexity of the environment for fire simulation, the number of methods has raised rapidly. These methods involve many subjects and need to be integrated. To provide a clear understanding of the existing methods, this paper provides an overview of the existing methods in the past ten years(2016-2025). The content of this paper focuses on the following sections: Section 2 introduces physics-based simulations, which include particle-based, grid-based, DNS/LES, and application-specific models such as indoor, outdoor, and marine fire scenarios. This approach concentrates on the physical accuracy of the fire. Therefore, it is suitable for simulating the real-world flames. Section 3 discusses data-driven and neural network-based methods, which utilize large-scale data for learning and prediction. Section 4 reviews visual effects-oriented simulations, including particle-based effects and sprite-based animation, which are widely used in games and films. Section 5 demonstrates the hybrid methods that combine different approaches to realize the simulation. Section 6 briefly covers the other related methods such as texture mapping and numerical simplifications. Section 7 discusses the advantages and disadvantages of different approaches. Finally, section 8 presents the conclusion.

2. Physics-based Simulation

2.1. Particle-based Simulation

Wei et al. proposed that the gravitational field and wind force are important in the dynamic effects of flame simulation, so the Gyarmathy model and Perlin noise function were introduced in the simulation based on particle systems. Each particle was textured and rendered at the same time to solve the problem of simulating the realism and real-time aspect of fire particles[1].Wong et al. proposed the use of basis fire to simulate and preserve its streamline trajectory and temperature information and then use this information to fit the user input data to generate flames of specified shapes and movements [2].

2.2. Grid-based Simulation

Huang et al. proposed using a base state with an amendment model to improve data update efficiency in situations where the flame scale is large and generates a large amount of grid data[3].Mukai et al. divided the flame burning state into three stages and introduced the effect of environmental temperature changes on air density to make the flame shape closer to the real candle flame[4].

2.3. DNS / LES

Vanbersel et al. proposed a feature-based adaptive mesh refinement method TFP-AMR to efficiently and accurately simulate the flame propagation and vortex structure dynamics in turbulent deflagration. The method automatically adjusts the mesh resolution, avoids the user's manual parameter adjustment, and ensures the high accuracy of the calculation area[5].

2.4. Application-specific Simulation

2.4.1. Outdoor fire simulation

Andrews et al. reviewed the Rothermel surface fire spread model and its extended equations, analyzes the impact of input variables such as fuel, wind direction, and terrain on wildfire spread prediction, and provides a unified reference for system development and fuel model customization[6].Hädrich et al. proposed using branch modules to simulate the geometric shapes of trees, allowing for the representation of structures ranging from simple trees to complex forests. Through this simulation, a combustion model related to plants can be defined, capturing various effects including carbon insulation, mass loss, and heat transfer. Additionally, the team employs a fluid dynamics model of the atmosphere to simulate the spread of flames over terrain to enhance realism[7].Like the previous article, Kokosza et al. also adopted branch modules to represent trees and forests. The difference is that a new mathematical framework is defined in this paper to implement the horizontal and vertical spread of flames in different fuel domains. This is mainly achieved by dynamically tracking the humidity of different fuels[8]. (Figure 1)

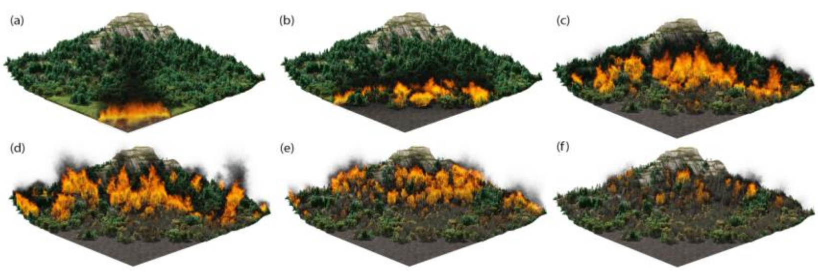

Figure 1. The model of fire interacting with the environment[8].

2.4.2. Indoor fire simulation

Menzemer et al. summarized various training methods for building fire evacuation and points out that fire simulations using VR/AR have certain potential, but there is an urgent need to establish a scientific quantitative system to verify their value[9].Li et al. produced a fire evacuation simulation model called FREEgress. The model can simulate heat, temperature, toxic gases, and smoke particles in the event of an indoor fire and assess their impact on evacuees[10].Valasek et al. uses a physics-based grid CFD model FDS to simulate fires in cinemas with inclined floors and curved ceilings. The results show that the model can capture the main trends of smoke diffusion and predict associated safety risks quite accurately[11]. (Figure 2)

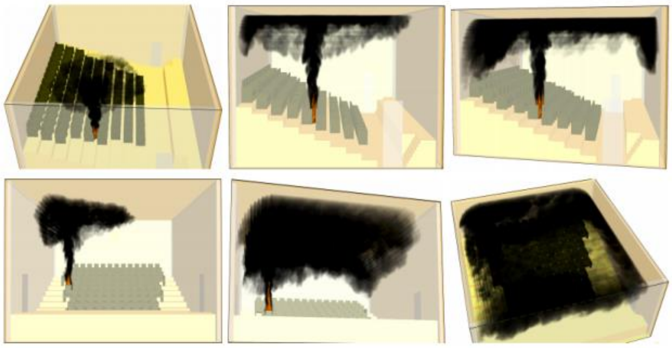

Figure 2. The simulation of fire and smoke propagation in indoor environment[11].

2.4.3. Marine fire simulation

Tao et al. suggested a unified particle method based on vortex dynamics for real-time fluid simulation in ship fire scenarios, balancing velocity field accuracy and simulation stability. By optimizing computation with a local summation operation, the method demonstrates efficient and effective simulation results in complex scenarios involving smoke, carbon dioxide, and water mist[12].Tao et al. aimed to address the issues arising from the Eulerian smoke simulation method, achieving high-fidelity simulation of low-resolution grids through vortex particles. It can capture turbulence details while maintaining real-time performance[13].

3. Data-driven / Neural Network-based Simulation

Chu et al. proposed an efficient data-driven fluid simulation method that can generate high-resolution, non-dissipative, and reusable fluid datasets through descriptor learning and patch translation tracking techniques, providing a new solution for flame and smoke simulation in visual effects[14].Ntinas et al. Proposed a wildfire simulation method based on Fuzzy Cellular Automata and data-driven evolution optimization to improve the accuracy of fire spread prediction by combining real data. Through parallel implementation on GPUs and FPGAs, the method enables efficient simulations on heterogeneous terrain[15].Choi et al. adopted a neural network model that reduces the computational load of flame simulation while maintaining visual quality. The fire-flake generator in the neural network determines the location of flame generation, and the velocity modifier deduces the speed of the fire-flake, allowing the state of the fire-flake to align with the environment[16].Sengupta et al. focused on parameter estimation methods when simulating flames, using a heteroscedastic Bayesian Neural Network trained with anchored ensembling. Compared to Ensemble Kalman Filter-based tools, this method is more efficient in terms of data[17].Croci et al. also used the Bayesian data-driven machine learning method to achieve on-line parameter inference and uncertainty evaluation of experimental flames[18].Shui et al. introduced a flame modeling method based on 3D Gaussians, with a ray-tracing-based initialization that reduces overfitting under sparse viewpoints resulting in the optimization of computation time and memory usage[19].Tong et al. Used the datasets generated with a simplified coupled fire-atmosphere model to train a neural network to predict the time of first arrival of fire and study the corresponding inverse problem. The findings suggest that machine learning has potential in fire science[20].Bissantz et al. proposed using artificial neural network to learn the Quenching Flamelet-Generated Manifold(QFM), and to simulate the sidewall extinguishing process of methane-air premixed flame in CFD simulation. The results show that the method is in good agreement with detailed chemistry and QFM methods in capturing flame propagation and wall extinguishing characteristics[21].

3.1. Neural Style Transfer

Kanyuk et al. proposed to use Neural Style Transfer to ensure that the whole body and movement of the flame character should be like real flames, but not so frenetic. One of the great advantages of this approach is that the final formation of the flame is separated from the underlying simulation: the simulation can focus on low-frequency motion and stability, and NST focuses on detail shaping[22]. Aurand et al. took an upgrade on the basis of the traditional NST technology and solved the problem of the energy minimization requiring a camera in the previous method. This is mainly achieved through a simple feed-forward neural network architecture, which greatly improves the speed of stylization[23]. (Figure 3-4)

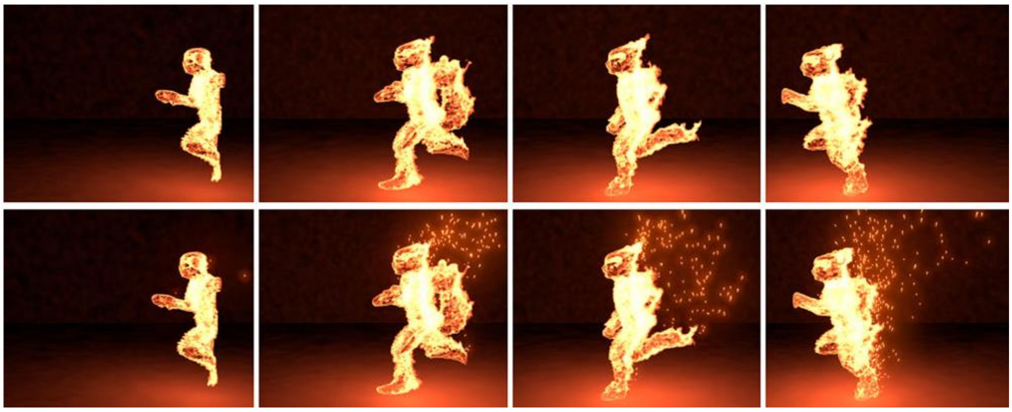

Figure 3. A neural network-based fire-flake simulation model that is used to generate natural fire-flake animations of flames and their surrounding environment at proper locations[16].

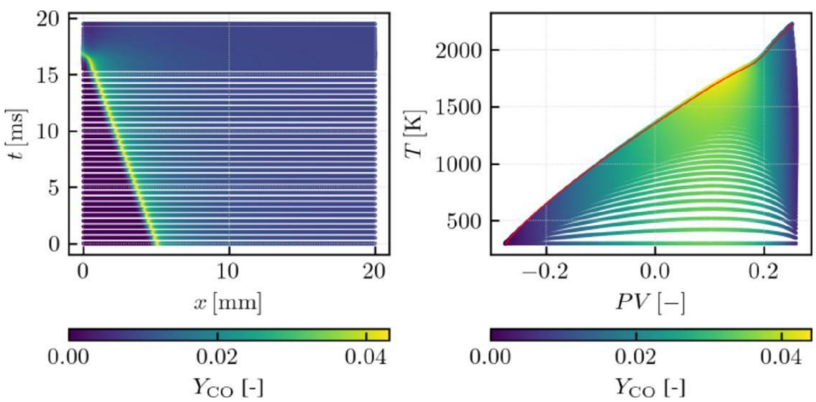

Figure 4. On the left, a scatter plot is shown for the head-on quenching flame in physical space (x) versus time (t), with points colored according to the CO mass fraction. On the right, the same dataset is represented in terms of progress variable (PV) and temperature (T). The additional preheated flamelets included in the manifold are displayed above the red line [21].

4. Visual Effects-Oriented Simulation

Wang et al. presented Volumetric Neural Cellular Automata (VNCA) to achieve artistic stylization of 3D volumetric smoke data. The self-emerging motion of the underlying cellular automaton significantly accelerates the training time[24].

4.1. Particle-based Effects

Kim et al. first proposed a fire-flake motion model to simulate the movement behavior of fire-flakes coordinating dynamically with flames. The target shape is achieved by gathering the fire-flakes and maintaining their inherent motion without relying on external forces[25]. Romu et al. produced an ARPG BOSS battle demonstration themed around flames using the Unity engine, focusing on the design of real-time visual effects and component reuse[26]. (Figure 5) Ong explored the application of AI in visual effects, focusing on improving efficiency, reducing labor intensity, and potentially transforming traditional production processes. At the same time, the question is further raised: is it possible for AI to allow non-professionals to create high-quality film special effects in the future[27]?

Figure 5. A flamethrower generated by Unity[26].

4.2. Sprite-based Simulation

Kim et al. adoptted a method to synthesize the fire-flake effect by inputting real or virtual flame videos. By capturing vectors in the video, the buoyancy field is calculated using the NS equations, and artificial motion blur is applied based on the buoyancy direction to complete the production. Because the output is in sprite animation format, it can be used by current game engines[28]. (Figure 6)

Figure 6. Zoom-in results of sprite-based fire-flake effect[28].

5. Hybrid Methods

Horvath et al. proposed a flame simulation method that combines coarse-grained particle mesh simulation and fine-grained view-oriented refinement on GPU to achieve high-resolution, controllable and photorealistic flame rendering. This approach leverages parallel GPU technology and perceptual optimization strategies to improve rendering efficiency and reduce implementation costs[29]. Nielsen et al. used a level set equation, which includes a physics-based term that can fit natural results, as well as a procedural term to artificially control the height and thickness of the flames. This combination is used to model soot oxidation, balancing the realism of simulating flames with controllability[30]. Fei achieved real-time fire animation generation and recognition by combining depth stripping algorithm, texture mapping, and an improved N-S equation with a particle system. The efficiency and stability of this method both perform well, but it can still be optimized[31]. Kim et al. introduced a fire-flake simulation method based on chaotic advection and various buoyant flow techniques. At the same time, a fire-flake dataset was generated through numerical simulations, and a neural network-based solver was utilized to learn the motion characteristics of spark particles. Compared to the typical random walk approach, this method can consistently represent fire-flake particles in most scenarios without the need for frequent parameter adjustments[32]. Dorta et al. used RGB cameras to capture flames in reality and estimate the physical properties associated with the flames, such as air density and combustion temperature. Unlike traditional image-based flame modeling tools, this method produces global illumination effects[33]. Faghihi et al. proposed a robust real-time hybrid fire simulation (HFS) method to physically test unknown or difficult-to-model fire heating sites and numerically simulate the rest. This approach effectively improves the accuracy and practicality of the overall simulation[34]. Selle et al. proposed a hybrid method combining Lagrangian vortex particles with the Euler grid method to enhance the detail of small-scale eddy currents in simulated smoke and flames. This method effectively generates a high degree of turbulence that is difficult to achieve with traditional grid methods and is suitable for the simulation of complex fluid phenomena such as smoke, water and explosion[35]. Kala et al. introduced a hybrid method combining Euler/FLIP fluid solver and material point solid simulation to simulate the combustion process of combustible solids. At the same time, a novel particle sampling strategy is introduced to apply the realistic flame effect of complex 3D scenes[36]. (Figure 7-9)

Figure 7. Real-time smoke rendering in Unity[30].

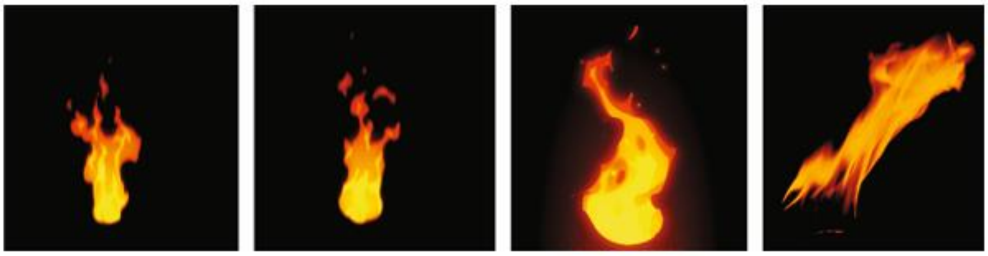

Figure 8. Simulated flame animation effect[31].

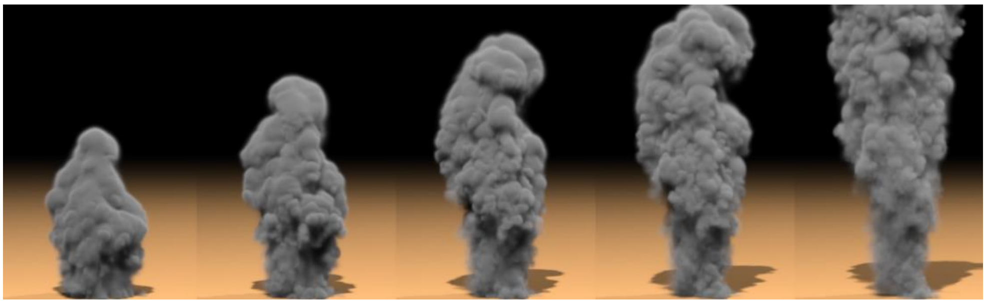

Figure 9. The temporal development of a smoke explosion, augmented by vortex particles introduced during the expansion process at the source. The simulation employs a 180 × 260 × 180 uniform grid with roughly 6000 vortex particles[35].

6. Other Method

Meng et al. presented a numerical simulation method for simplifying the fire test of aeroengines, which can accelerate the simulation speed while ensuring accurate prediction of the surface temperature distribution and temperature variation trends of the test components[37]. Koniaris et al. systematically reviewed the development of volumetric texture mapping techniques, focusing on evaluating content representation, storage, parameterization, and rendering performance. The paper also proposes future research directions and opportunities in real-time dynamic surface rendering[38]. Zhou et al. compared the advantages and disadvantages of forward texture mapping and backward texture mapping. Forward texture mapping is less dependent on graphic display algorithms, but it may cause holes and reduce image fidelity. Backward texture mapping is not prone to holes, but it requires higher capacity of computers[39]. Ramírez et al. proposed a structured methodology for guiding the artistic creation of real-time VFX in the gaming sector, emphasizing the importance of basing creation on art[40].

7. Discussion

The review of existing fire simulation methods highlights that each approach has its own strengths and weaknesses depending on the target application.

Physics-based methods provide the most accurate representation of thermodynamics and fluid dynamics, but they are often limited by high computational costs and reliance on the physical models to provide the data related to the simulation. In particular, particle-based approaches are efficient for providing flames that lack physical authenticity because of their relatively lower computational costs requirement. Grid-based methods capture more realistic fluid dynamics and heat transfer processes, yet their computational demands grow rapidly with resolution. DNS/LES can provide the most accurate physical simulation, but they face extremely high computational costs and the challenge of real-time performance.

Application-oriented simulations are often extensions of physics-based approaches. These simulations are designed to meet the requirements of specific scenarios such as wildfires, indoor evacuations, or marine fire incidents. Therefore, these methods focus on simulating realistic physical phenomena under different scenarios. For example, terrain and vegetation for wildfires, toxic gas diffusion in indoor fires, or fluid–fire interaction in shipboard environments. At the same time, highly customized models often lack generality, making cross-scenario transfer difficult.

Data-driven and neural network-based methods significantly improve efficiency and adaptability, but they heavily rely on the availability of large-scale datasets and may face challenges in generalizing unseen scenarios. While most data-driven approaches aim to approximate physical dynamics, Neural Style Transfer (NST), as a complemntary technique, emphasizes achieving realism. By enhancing visual details without physical modeling, NST bridges the gap between data-driven simulation and visual-oriented approaches.

Visual effects-oriented simulations prioritize efficiency and controllability, so they are widely adopted in games, films, and VR/AR applications.

Particle-based visual simulations generate convincing motion effects by reproducing the dynamic behavior of flame particles, such as sparks or flame fragments. Their main strengths are flexibility and the ability to capture complex, emergent visual effects with relatively low computational costs. However, because these methods rely on heuristic rules and simplified dynamics, the results may vary depending on parameter tuning and artistic design.

Sprite-based simulations, on the other hand, generate fire effects by reusing 2D images or video frames of flames and mapping them into animations. This approach is highly efficient and integrates easily with existing rendering pipelines, providing a fast solution for stylized or background fire. Its limitation lies in reduced adaptability to dynamic environments: the lack of physical interaction makes sprite-based flames less convincing in scenarios requiring close integration with surrounding airflow or objects.

Hybrid methods aim to balance realism, efficiency, and controllability by combining physics-based accuracy with data-driven adaptability or visual refinements. A common strategy for hybrid methods is to generate a rough flame using a physics-based model and then add details through a data-driven or visually oriented approach to achieve the desired effect for the creator. The challenge remains while maintaining consistency across different approaches and managing the complexity of integration. However, as the demand for increasingly refined fire simulation continues to grow, hybrid methods hold significant research value because they offer a promising balance between physical accuracy and computational efficiency.

Other methods focus on accelerating computation, texture mapping, and artistic VFX design. These methods emphasize efficiency and visual presentation over physical accuracy, making them suitable for engineering simplification, real-time rendering, and stylized effects, but they often lack generality and struggle with complex physical interactions. (Table 1)

Table 1: Category-based Comparison of Fire Simulation Methods.

Method Category	Representative Techniques	Advantages	Disadvantages	Typical Applications
Physics-based	Particle system, Grid-based, DNS/LES	High physical accuracy; suitable for scientific research	High computational cost; limited real-time performance	Scientific studies, engineering simulation
Data-driven	Bayesian NN, Fuzzy CA, NST	Efficient; can learn complex dynamics	Requires large datasets; poor generalization to unseen cases	Prediction, model optimization
Visual effects-oriented	Particle effects, Sprite animation	High efficiency; controllable; fast rendering	Lack of physical interaction; reduced realism	Games, films, VR/AR
Hybrid	Physics + Neural networks, Physics + Visual effects	Balance between accuracy and efficiency	Complex integration; parameter tuning challenges	Real-time applications, mixed environments
Other	Texture mapping, Numerical simplification	Fast computation; easy integration	Limited realism; narrow applicability	Engineering, stylized VFX

8. Conclusion

This paper reviewed different fire simulation methods, categorizing them into physics-based, data-driven, visual effects, hybrid, and related approaches. Each method has strengths and limitations, balancing realism, efficiency, and controllability. Looking ahead, future research should emphasize the integration of physics-based accuracy with the efficiency of data-driven or visual-effects oriented techniques, while also addressing the challenge of achieving real-time performance in complex and dynamic environments.

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