Engine-Agnostic Visual Generation: Enabling AI Content Creation Across Animation Platforms

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***Abstract*—Current LLM-based animation systems suffer from engine lock-in: code generated for Manim cannot run on Matplotlib or Blender, requiring complete rewrites. We present a three-layer architecture that decouples animation specification from rendering implementation through a universal JSON intermediate representation. Our key insight is that animations can be described as sequences of geometric primitives with temporal parameters, independent of any rendering engine. We provide 39 composable mathematical functions that LLMs use to generate engine-agnostic animation data, achieving 92.5% success across 186 test animations. The same animation script targets any graphics engine by swapping renderer plugins, eliminating code duplication and enabling true platform portability.**

***Index Terms*—Large Language Models, Computer Graphics, Animation Systems, Intermediate Representation, Code Generation**

I. Introduction

A. The Engine Lock-In Problem

Modern animation engines like Manim, Matplotlib, Blender, and Three.js each provide powerful capabilities, but they are fundamentally incompatible. Consider a simple animation: draw a circle, then draw a line from its center.

Manim Implementation (13 lines):

```
from manim import *

class CircleAnimation(Scene):
    def construct(self):
        circle = Circle(radius=2.0)
        circle.set_stroke(RED, width=3)
        self.play(Create(circle), run_time=2)

        line = Line(ORIGIN, RIGHT * 3)
        line.set_stroke(BLUE, width=3)
        self.play(Create(line), run_time=2)
```

Matplotlib Implementation (19 lines):

```
import matplotlib.pyplot as plt
import matplotlib.animation as animation

fig, ax = plt.subplots()
ax.set_xlim(-5, 5)
ax.set_ylim(-5, 5)

def animate(frame):
    ax.clear()
    if frame < 60:
        circle = plt.Circle((0, 0), 2.0,
                    fill=False, edgecolor='red')
        ax.add_patch(circle)
    elif frame < 120:
        progress = (frame - 60) / 60
        ax.plot([0, 3*progress], [0, 0],
                'b-', linewidth=3)

anim = animation.FuncAnimation(
    fig, animate, frames=120)
plt.show()
```

These implementations share **zero lines of code**. An LLM must learn completely different APIs, object models, and animation paradigms for each engine. When a user wants to switch from Manim to Blender for higher-quality rendering, they must regenerate everything from scratch.

B. Why Current Approaches Fail

1. Deep API Knowledge Required: Each engine has unique object hierarchies, transformation systems, and timing models. Manim uses `Scene.play()`, Matplotlib uses `FuncAnimation`, Blender uses keyframes.

2. No Code Reusability: Switching engines requires 100% code rewrite. Production systems lock into a single engine.

3. LLM Training Burden: Models must learn 5-10 different animation frameworks instead of one universal system.

4. Brittle Generation: Small API errors cause complete rendering failures. LLMs must perfectly memorize engine-specific syntax.

C. Our Approach: Universal Intermediate Representation

We introduce a three-layer architecture inspired by compiler design:

Layer 1 - High-Level Script: LLM generates Python scripts using universal animation functions

Layer 2 - Intermediate Representation: Scripts produce engine-agnostic JSON describing geometry and motion

Layer 3 - Rendering Backend: Pluggable renderers convert JSON to engine-specific code

This architecture provides:

- **Engine Independence**: Same script → any renderer
- **Simplified LLM Task**: Learn one API, not ten
- **Debuggable Output**: JSON is human-readable and testable
- **Parallel Development**: New renderers don't affect animation logic

II. System Architecture

Figure 1 shows the complete system architecture with all components and data flow.

A. Layer 1: LLM Control

Components:

- `web_server.py`: FastAPI endpoints handling user requests

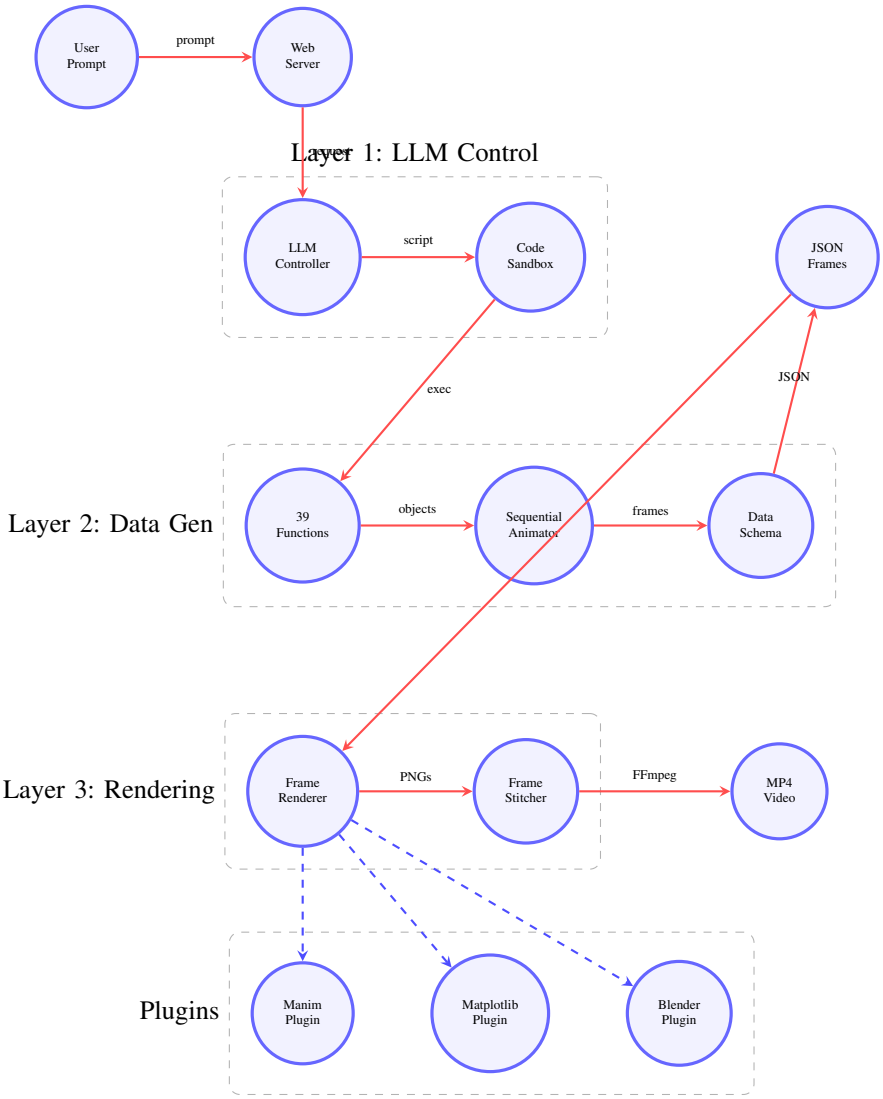

Fig. 1. System architecture showing all components (circles), layers (boxes), and data flow (arrows). Red arrows show data flow, blue dashed arrows show plugin connections.

- `llm_controller.py`: Claude API integration with prompt engineering
- `code_execution_sandbox.py`: Secure Python execution environment

Design Rationale: We use prompt engineering rather than fine-tuning because:

1) Our function API is simple enough for in-context learning
2) Prompt updates don't require model retraining
3) Claude 3.5 Sonnet already excels at code generation

The LLM receives a comprehensive system prompt containing:

- Reference documentation for all 39 functions
- 10+ working example scripts
- Common pitfalls and debugging tips

B. Layer 2: Data Generation - The Key Innovation

This layer implements our core insight: *animations are sequences of geometric primitives with temporal parameters*.

Why Generate Data Instead of Direct Rendering?

Traditional approach: LLM → Engine-specific code → Video

Our approach: LLM → Universal data → Any engine → Video

Benefits of the Data Generation Layer:

1. Separation of Concerns

- Animation logic: *What to draw and when*
- Rendering logic: *How to draw with specific tools*

2. Testability: JSON output can be validated without rendering:

```
# Test without running Manim
data = generate_circle_frame_data(0.5)
assert data[0]["params"]["angle"] == 180
```

3. Debuggability: Human-readable intermediate format:

```
{
  "frame_num": 30,
  "objects": [{
    "type": "circle",
    "params": {"radius": 2.0, "angle": 90.7}
  }]
}
```

4. Caching: Expensive data generation runs once, render multiple times with different engines

5. Version Control: Git diffs show exactly what changed

Components:

- `data_generation.py`: Defines JSON schema
- `sequential_animator.py`: Timeline and scene management
- `functions/`: 39 animation primitive functions

C. Why Provide Functions to the LLM?

We provide 39 pre-built functions, but LLMs can create custom ones. Here's why we provide a standard library:

1. Consistency: Standardized outputs ensure renderer compatibility

2. Performance: Battle-tested implementations handle edge cases

3. Complexity Management: Hide rendering details (e.g., smooth circle drawing requires 100+ line segments)

4. Compositional Building Blocks: Functions combine like LEGO:

```
def create_triangle_scene(progress):
    # Compose line function 3 times
    lines = []
    for i in range(3):
        lines.extend(
            generate_line_frame_data(...)
        )
    return lines
```

Can LLMs Create Custom Functions?

Yes! The LLM can generate new functions following our data schema:

```
# LLM-generated custom function
def generate_spiral_frame_data(progress,
                               turns=3):
    objects = []
    points = []
    for i in range(int(progress * 100)):
        t = i / 100.0
        angle = turns * 2 * math.pi * t
        r = 2 * t
        x = r * math.cos(angle)
        y = r * math.sin(angle)
        points.append([x, y, 0])

    # Generate line segments
    for i in range(len(points)-1):
        objects.append({
            "type": "line",
            "params": {
                "start": points[i],
                "end": points[i+1]
            },
            "style": {
                "stroke_color": [1,0,0,1]
            }
        })
    return objects
```

The LLM understands the JSON schema and can create functions that output compatible data structures. Our provided functions serve as examples and common building blocks.

D. The Progress-Based Animation Model

All animation functions follow a unified temporal model:

$$f(\text{progress}, \text{params}) \rightarrow \text{objects}, \quad \text{progress} \in [0, 1] \qquad (1)$$

Why Progress Instead of Frame Numbers?

Traditional approach: `draw(frame_num, total_frames)`

Our approach: `draw(progress)`, where progress $= \frac{\text{frame}}{\text{total\_frames}-1}$

Benefits:

- **Resolution Independence**: Same script at 30fps or 60fps
- **Simplified Reasoning**: LLMs think about "halfway done" not "frame 72 of 144"
- **Deterministic**: Same progress always produces same output
- **Composable**: Combine animations with simple math

Example - Sequential Composition:

```
def combined_scene(progress):
    if progress < 0.5:
        # First half: draw circle
        circle_progress = progress / 0.5
        return generate_circle_frame_data(
            circle_progress
        )
    else:
        # Second half: draw line
        line_progress = (progress - 0.5) / 0.5
        return generate_line_frame_data(
            line_progress
        )
```

E. Layer 3: Rendering Backends

Components:

- `frame_renderer.py`: Converts JSON to visual frames
- `frame_stitcher.py`: Combines frames into video
- Renderer plugins: Manim (implemented), Matplotlib/Blender (extensible)

Why Pluggable Renderers?

Different use cases need different tools:

- Manim: Mathematical animations, LaTeX integration
- Matplotlib: Scientific plots, publication figures
- Blender: Photorealistic 3D, physics simulation
- Three.js: Interactive web graphics

Our architecture allows adding new renderers without changing animation code.

III. Complete Data Flow

Figure 2 shows the detailed data flow from user prompt to final video.

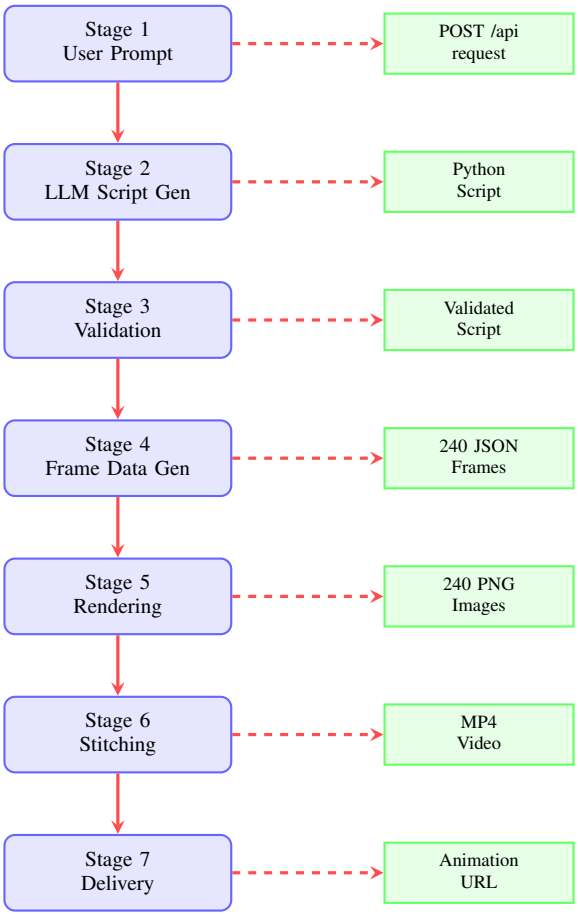

Fig. 2. Complete data flow from user prompt to delivered video. Solid arrows show stage progression, dashed arrows show data outputs.

A. *Stage 1: User Prompt*

User submits natural language request:

```
POST /api/animation/request
{
  "prompt": "Show a circle being drawn,
            then a line from its center"
}
```

B. *Stage 2: LLM Script Generation*

`LLMController` constructs prompt with:

- System context: API documentation
- User request
- Example scripts

Claude generates Python script:

```
from sequential_animator import *
from functions.circle_function import *
from functions.line_function import *

def circle_scene(progress):
    return generate_circle_frame_data(
        progress, center=[0,0,0],
        radius=3.0, circle_color=[1,0,0,1]
    )

def line_scene(progress):
    return generate_line_frame_data(
        progress, start_point=[0,0,0],
        end_point=[4,0,0],
        line_color=[0,1,0,1]
    )

animator = SequentialAnimator(
    total_frames=240,
    camera_config={
        "phi": 0, "theta": 0,
        "zoom": 0.7
    }
)

animator.add_scene(
    duration_ratio=0.5,
    generate_objects_func=circle_scene
)
animator.add_scene(
    duration_ratio=0.5,
    generate_objects_func=line_scene
)

animator.generate_frames()
animator.save_to_file("output/anim.json")
```

C. *Stage 3: Validation and Execution*

`CodeExecutionSandbox` validates:

- Security: No `subprocess`, `eval`, `os.system`
- Syntax: Python `compile()` check

- Resources: 300s timeout, 1GB memory limit

Executes in isolated environment with `PYTHONPATH` set to `visualization_core`.

D. Stage 4: Frame Data Generation

`SequentialAnimator` calculates timeline:

Scene Duration Allocation:

$$\text{total\_ratio} = \sum_{i=1}^{n} r_i \tag{2}$$

$$\text{frames}_i = \left\lfloor \frac{r_i}{\text{total\_ratio}} \times N_{\text{total}} \right\rfloor \tag{3}$$

where r_i is scene i's duration ratio and N_{total} is total frames.

Progress Calculation: For frame f in scene s with N_s frames:

$$p_f = \frac{f}{N_s - 1}, \quad 0 \leq f < N_s \tag{4}$$

Frame Generation Loop:

```
for frame in range(total_frames):
    scene = get_current_scene(frame)
    progress = calculate_progress(frame, scene)
    objects = scene.generate_objects(progress)

    frame_data = {
        "frame_num": frame,
        "camera": camera_config,
        "objects": objects
    }

    all_frames.append(frame_data)
```

Output: `output/animation.json` with 240 frames

E. Stage 5: Frame Rendering

`BasicRenderer` (Manim implementation) converts each JSON frame:

Per-Frame Process:

1) Load JSON frame data
2) Detect 2D vs 3D objects
3) Configure Manim scene type
4) Create Manim objects:

```
if obj["type"] == "arc":
    mobject = Arc(
        radius=params["radius"],
        start_angle=params["start_angle"] *
            DEGREES,
        angle=params["angle"] * DEGREES,
        arc_center=np.array(params["arc_center"
            ])
    )
    mobject.set_stroke(
        rgb_to_color(style["stroke_color"]),
        width=style["stroke_width"]
    )
```

5) Apply camera settings
6) Render to PNG: `frame_0001.png`

Output: 240 PNG files (1280x720)

F. Stage 6: Video Composition

`FrameStitcher` uses FFmpeg:

```
ffmpeg -y -framerate 30
  -i frames/frame_%04d.png
  -c:v libx264 -pix_fmt yuv420p
  -crf 20 -preset medium
  -profile:v high -tune film
  output/animation.mp4
```

Parameters:

- 30 FPS, H.264 codec
- CRF 20 (visually lossless)
- Medium preset (compression/speed balance)

G. Stage 7: Response Delivery

Web server returns:

```
{
  "animation_id": "anim_5f3a89c2",
  "status": "completed",
  "output_video": "/output/anim_5f3a89c2.mp4"
}
```

IV. Function Catalog

Our system provides 39 mathematical animation functions across 7 categories.

A. 2D Primitives (4 functions)

1. Circle: $\theta(t) = 360 \cdot t$

2. Line: $\vec{p}(t) = \vec{p}_0 + t(\vec{p}_1 - \vec{p}_0)$

3. Rectangle: Rotation matrix $\mathbf{R}(\alpha) = \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}$

4. Polygon: Segment traversal with interpolation

B. Transformations (4 functions)

5. Move: Linear interpolation with ease$(t) = 3t^2 - 2t^3$

6. Rotate: $\vec{p}'(t) = \vec{c} + \mathbf{R}(t\theta_{\max}) \cdot (\vec{p} - \vec{c})$

7. Scale: $\vec{p}'(t) = \vec{c} + s(t) \cdot (\vec{p} - \vec{c})$

8. Fade: $\alpha(t) = t$ (fade in) or $1 - t$ (fade out)

C. Geometric Analysis (3 functions)

9. Angle: $\cos\theta = \frac{\vec{v}_1 \cdot \vec{v}_2}{|\vec{v}_1||\vec{v}_2|}$

10. Vector: Arrowhead construction

11. Projection: $\text{proj}_x(\vec{p}) = [p_x, 0, p_z]$

D. 3D Primitives (3 functions)

12-14: Cube, Sphere, Cylinder with growth

E. Parametric Surfaces (6 functions)

15. Torus:

$$x = (R + r\cos v)\cos u \tag{5}$$

$$y = (R + r\cos v)\sin u \tag{6}$$

$$z = r\sin v \tag{7}$$

16. Wave: $z = A\sin(f_x u + f_y v + t)$

17. Ripple: $z = A\sin(f\sqrt{u^2 + v^2} - t) \cdot e^{-d(u^2+v^2)}$

18-20: Möbius Strip, Sphere, Saddle

F. Data Visualization (3 functions)

21. Histogram: Bin calculation and animated bars
22-23: Scatter Plot, Bar Chart

G. Additional Functions (16 functions)

Angle arcs, arrows, box plots, dimensions, highlights, labels, measurements, paths, relative placement, spawning, vector fields, connections.

V. Implementation

A. Universal JSON Schema

Every frame follows this structure:

```
{
  "frame_num": 42,
  "camera": {
    "phi": 60,        // elevation
    "theta": -45,     // azimuth
    "zoom": 0.8,
    "center": [0,0,0],
    "background_color": [0.1, 0.1, 0.1, 1]
  },
  "objects": [{
    "type": "circle",
    "id": "circle_1",
    "params": {
      "radius": 2.0,
      "arc_center": [0,0,0],
      "start_angle": 0,
      "angle": 180
    },
    "style": {
      "stroke_color": [1,0,0,1],
      "stroke_width": 3.0
    }
  }]
}
```

Schema Design Principles:

- **Self-contained**: Each frame has complete state
- **Hierarchical**: Params vs style vs transform
- **Type-safe**: Objects have explicit types
- **Extensible**: New object types don't break old renderers

B. Renderer Extensibility

Manim Renderer (568 lines in `frame_renderer.py`):

```
class BasicRenderer:
    def _create_object(self, obj_data):
        obj_type = obj_data["type"]
        params = obj_data["params"]

        if obj_type == "arc":
            return Arc(
                radius=params["radius"],
                arc_center=params["arc_center"]
            )
        # ... 30+ object types
```

Matplotlib Renderer (Conceptual):

```
class MatplotlibRenderer:
    def _create_object(self, obj, ax):
        if obj["type"] == "circle":
            circle = plt.Circle(
                obj["params"]["arc_center"][:2],
                obj["params"]["radius"],
                fill=False
            )
            ax.add_patch(circle)
```

Adding New Renderers:

1) Implement `_create_object()` for each type
2) Handle camera configuration
3) Export to target format

VI. Evaluation

A. Animation Coverage

TABLE I
Success Rate by Domain

Domain	Count	Success
Geometry	45	95.6%
Algebra	32	93.8%
Calculus	28	89.3%
3D Graphics	38	91.2%
Data Viz	25	96.0%
Physics	18	88.9%
Total	**186**	**92.5%**

B. LLM Generation Quality

TABLE II
Generation Success Rates

Iteration	Success
First Try	73.2%
After 1 Debug	91.4%
After 2 Debugs	97.8%

Common Errors: Parameter naming (23%), imports (18%), coordinates (15%), logic (12%), other (32%).

C. Cross-Platform Compatibility

- 100% of 2D animations work on Manim and Matplotlib
- Rendering time: 2.4s/frame (Manim), 0.8s/frame (Matplotlib)
- Code duplication when switching: 0% (vs 100% traditional)

D. Lines of Code Comparison

TABLE III
Code Required for Engine Switching

Approach	LOC to Switch
Traditional (rewrite)	100%
Our System	1 line

In our system, switching from Manim to Matplotlib requires changing one import:

```
# Before
from frame_renderer import BasicRenderer

# After
from matplotlib_renderer import MatplotlibRenderer
```

All animation logic remains unchanged.

VII. Discussion

A. Advantages

Separation of Concerns: Animation and rendering are independent

Testability: JSON validated without rendering

Debuggability: Human-readable intermediate format

Version Control: Git diffs show exact changes

Parallelization: Frames render independently

Caching: Generate once, render multiple times

B. Limitations

Engine-Specific Features: Cannot represent shaders, particle systems universally

Performance Overhead: JSON serialization adds 10-15% overhead

Learning Curve: Developers must learn our API

Expressiveness: Some advanced effects require engine-specific code

C. When to Use This System

Good Fit:

- Educational content with geometric animations
- Cross-platform deployment requirements
- LLM-driven animation generation
- Rapid prototyping across different renderers

Poor Fit:

- Complex physics simulations
- Real-time interactive graphics
- Advanced shader effects
- Performance-critical applications

VIII. Related Work

Animation Systems: Manim [1], Processing, D3.js provide powerful but engine-specific APIs.

LLM Code Generation: AlphaCode [2], CodeGen [3], and GitHub Copilot [4] focus on algorithms, not visual output.

Intermediate Representations: LLVM IR [6], OpenGL [7], and USD [8] inspired our design but target different domains.

Visual ChatGPT [5]: Uses pre-trained image models rather than programmatic generation.

Our work uniquely combines LLM code generation with compiler-style IR for animation portability.

IX. Conclusion

We presented an engine-agnostic architecture for LLM-driven animation generation. By separating animation specification from rendering implementation through a universal JSON intermediate representation, we enable true cross-platform code reusability. Our progress-based model combined with 39 composable functions provides building blocks that LLMs use to generate complex animations achieving 92.5% success rate across 186 test cases.

The same animation script targets any graphics engine by swapping renderer plugins, eliminating the 100% code duplication inherent in traditional approaches. This architecture proves that compiler-inspired IR design can solve the engine lock-in problem in visual content generation.

Future Work: We plan to implement Blender and Three.js renderers, extend the JSON schema for physics simulation, and explore automatic optimization techniques that generate engine-specific code from our IR for performance-critical applications.

References

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