Title: Reverse Engineering Intelligence: Building an AI Model from Mechanical Wristwatch Systems

Abstract:
Mechanical wristwatches are marvels of engineering, embodying precision, elegance, and compact complexity. This paper explores the potential for building an AI model that learns the structure, function, and design space of mechanical watches through video-based reverse engineering. By leveraging narrated repair videos, computer vision techniques, and graph-based representations, we aim to generate 3D digital models, simulate kinematics, and explore generative design. This framework not only provides a benchmark for mechanical understanding but also lays the foundation for similar work in other intricate mechanical systems.

1. Introduction
The mechanical wristwatch represents a dense, miniaturized ecosystem of interacting components. While modern digital design and simulation tools flourish in large-scale manufacturing, few systems offer such a constrained yet expressive domain for studying the boundaries of digital-mechanical understanding. This project proposes to develop a learning framework—an AI model—that can derive mechanical knowledge from annotated visual media, particularly detailed watch repair videos. The goal: a digital twin of a watch's internal workings, not just in form, but in function.

2. Why Mechanical Watches?

- **Inherent Constraints:** Watches are closed systems. Their parts—gears, levers, springs, escapements—are highly interdependent and exist within tight spatial tolerances.
- **Rich Yet Bounded Design Space:** The mechanical vocabulary is expressive but limited. This makes it ideal for structured learning (e.g., via graph grammars).
- **Simplified Kinematics:** Reduced dynamical models are easy to formulate.

- **Legacy of Narrated Documentation:** Watch repair videos (e.g., *Wristwatch Revival*, *Watch Repair Channel*) provide hours of semantically rich, well-lit, narrated footage—essentially paired vision-language datasets.

3. Learning from Repair Videos

- **Narrated Supervision:** Since these videos include commentary like “now we remove the barrel bridge,” the audio can serve as weak supervision for image-label alignment.
- **Frame-by-Frame Decomposition:** Applying object tracking, image segmentation, and speech-to-text models allows automated generation of time-aligned training data. See Samurai.
- **CAD Reconstruction via Segmentation + Scaling:** Using reference parts (e.g., screw sizes) to scale components and reconstruct them into CAD-like representations.
- **Tool Interactions:** By tracking tools (tweezers, screwdrivers), we can infer forces, manipulation dynamics, and possibly mechanical constraints.

4. Building the Mechanical Grammar

- **Graph Grammar Approach:** Define components as nodes (wheels, bridges, screws), and relationships (contact, motion transfer, fastened-by) as edges.
- **Simulation-Friendly:** Given most mechanisms are 2D planar kinematics, simulations can be computationally tractable.
- **Material Constraints:** Incorporate how friction, tolerances, and material deformation affect motion—critical in springs and escapement design.

5. Generative Design Potential

- **New Watch Architectures:** Once trained, the model could explore novel designs within learned constraints.
- **Failure Modes as Data:** Learning from damaged or malfunctioning watches could help define design limits.
- **Integration with Additive Manufacturing:** Print prototypes of AI-generated designs for real-world testing. This requires careful consideration of nondimensionalization of relevant parameters.

6. Robotics and Dexterity Benchmark

- **Assembly as a Challenge:** Can robots build these watches? This poses a high-dexterity task ideal for testing fine motor control and manipulation.
- **Feedback Loops:** Watching robotic assembly errors could offer new insights into what features are truly critical for functionality.

7. Beyond Watches: A Mechanical Intelligence Framework

This approach generalizes to other mechanical devices that share key features:

- Typewriters
- Curta calculators
- Analog cameras (using optics simulation)
- Mechanical computers

Each system offers new challenges: typewriters have sequence and feedback, cameras deal with optics and timing. But all of them are finite, analog computational devices—perfect testbeds for a new kind of mechanical AI.

8. Discussion: A Graph-Based Mechanical Understanding of the World

Ultimately, this project isn’t just about watches. It’s about developing a representation language for mechanical reasoning—a way to encode how parts fit, interact, and move. Similar to grammar-based approaches in furniture design and modular robotics, this system explores mechanical abstraction at its most fundamental level.

9. Conclusion

This white paper proposes a comprehensive framework for modeling and learning mechanical systems, starting with wristwatches. With advances in computer vision, natural language processing, and simulation, we have the tools to begin building a mechanical intelligence—one that can learn, simulate, and eventually design complex machines from raw, annotated video data.