Preliminary Experiments of Qualitative Reasoning Model Construction Using Large Language Model

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Abstract. Qualitative Reasoning (QR) is a reasoning framework for simulating physical behavior based on naive knowledge of the physical system. However, it is not easy to build a model of the physical system based on physical laws and principles. Therefore, example-based model libraries are used to support the creation of a model. This approach requires extensive knowledge to represent a variety of physical systems. If suitable components are not prepared for a problem, new components must be added to the library.

Therefore, the main focus of this work was on developing a method to utilize Large Language Model (LLM) to solve this problem. Although LLM alone doesn't have the architecture necessary to perform QR, it performs well at discovering information such as physical phenomena and objects related to the problem if a sophisticated prompt can be prepared. To this end, we proposed a new model construction method using LLM as a tool to extract the fragmentary information. This information is used as a key to access the previously prepared database to get the physical parameter relations based on physical laws and principles. We introduce and validate this framework using a simple motion example that considers both spring motion and friction.

1 Introduction

Qualitative Reasoning (QR) is a reasoning framework for simulating physical behavior based on naive knowledge about the physical system. Qualitative Process Theory (QPT) [2] is one of the methods that uses knowledge about qualitative relationships between physical parameters. This method is good at representing the physical system using generalized concepts such as physical phenomena [4] and anchor concepts [3]. This framework can simulate the physical system well if the user succeeds in creating an appropriate model for the system. However, although the system provides a basic vocabulary to construct a model of the physical system, it is not easy to construct a model using these vocabularies. Therefore, the utilization of example-based model libraries such as physical feature(PF) [4] and subclass of anchor concepts [3] has been proposed in the literature. This approach requires a good amount of knowledge to represent varieties of physical systems.

Recently, Large Language Models (LLMs) such as ChatGPT[2] are used in various tasks. LLMs are trained on a large variety of documents and can predict physical behavior based on the trained knowledge. However, the quality of the result of this prediction is not good enough because LLMs are trained only on the textual contexts and generate statistically plausible text, not correct reasoning [3]. However, based on the preliminary analysis of LLM and considering that they are trained on a large number of texts containing descriptions of a variety of physical systems, they can be used as a retriever to make a list of the related physical laws and principles for the given situations. Therefore, a new framework for qualitative reasoning model construction using LLM was proposed here. In this framework, the description of the physical system is provided as text, and LLM helps to collect general model fragments and relationships among them to support the model construction process. By using this framework, we assumed that the size of the knowledge for describing varieties of physical systems used in the previous methods can be reduced. We introduce and validate this framework using a simple motion example that considers spring motion and friction.

2 Model Construction for Qualitative Reasoning

Although the knowledge used for qualitative reasoning is general and reusable, it is necessary to construct a model for behavioral simulation. Therefore, Kiriyama et al. [4] proposed to use physical features(PFs) that represent typical physical systems with related physical phenomena. The Knowledge Intensive Engineering Framework [7] supports the construction of a model for qualitative reasoning by combining these building blocks. Nonetheless, it is necessary to create example-based libraries to represent the variety of components used in the physical system. Anchor concepts [3] also have a similar problem for model construction. For example, the "motion" has 355 subclasses to represent different situations. It is desirable to have a general framework for constructing a model based on an understanding of the physical system configuration.

Recently, it has been demonstrated that LLMs can perform well in various tasks. So LLMs' ability for QR has been experienced (e.g. for design [5] and spatial reasoning [1]). As Forbus says [3], their success criterion is the generation of statistically plausible text, not correct reasoning. On the other hand, LLM can entail possible physical phenomena that occur on the given physical system configuration (e.g., sliding entails the possibility of friction). This feature was used here to support the QR model construction.

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1 Equal contribution.
2 https://www.openai.com/chatgpt (Last accessed on June 19, 2024.)

Table1 summurize the comparison of Kiriyama, Forbus, and our method. Primitive concepts are atomic representation of physical behavior.

3 A New Model Construction Method

LLMs perform well at gathering information about cases that are similar to a given physical system configuration. However, their ability to combine this information varies. For example, they excel at tasks such as gathering and then comparing information about two subjects, namely A and B, a process that can be expressed using a chain of thought (CoT) [6]. However, they are not necessarily good at solving problems that require synthesizing multiple pieces of knowledge based on first principles, such as estimating behavior based on physical knowledge. To address this issue, this study exploits the LLM's ability to skillfully gather case-related information by collecting data related to objects, processes, and physical parameters. This information is then used in a framework that employs a QR model to infer behavior. The output of the LLM can also be viewed as information that solves the problem of creating case-specific PFs needed to describe when certain physical phenomena occur.

This method exploits the strengths and compensates for the weaknesses of LLMs. In this research, we used ChatGPT (GPT-4) to solve a problem involving the motion of a single particle on a frictional constraint surface, without dealing with specific numerical values.

To construct the proposed method, we created a database for QR with physical laws and principles (Figure 1). This database stores the physical laws and principles corresponding to each process, and further contains physical parameters related to these laws and principles, along with their qualitative temporal changes and constraints. By extracting the process names from the output of LLM, the associated physical laws and principles are compiled with their corresponding physical parameters and relationships, instantiated on a per-object basis. In this step, due to the variations of description about physical laws and principles generated by LLM, we manually rewrite the description for finding out the data stored in the database.

This instantiation details the relationships between the generic physical parameters defined in the process for the specific object, thereby creating a physical parameter network used to construct the model.

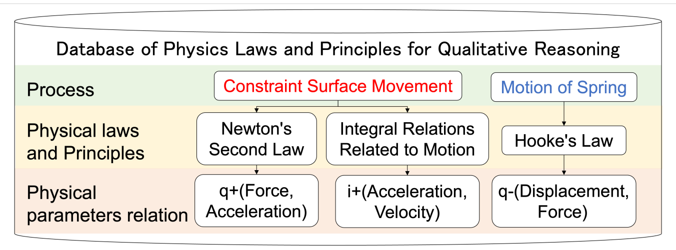

Figure 1. Database of Physics Laws and Principles for Qualitative Reasoning

The proposed method suggests a three-step approach for building the model and inferring behavior (Figure 2).

(1) Analysis of Physical Problems Using LLM to extract necessary information such as objects, processes, and missing physical parameters from the text of physical problems.

(2) Construction of a Physical Parameter Network Using the process names as keys to access corresponding physical laws and principles from a database of physical laws and principles for QR, instantiate the qualitative time-varying relationships between the associated physical parameters for each object, and construct a physical parameter network.

(3) Calculation of System State Transitions Obtain the initial values of the physical parameters from the LLM. And based on these initial values and the qualitative time-varying relationships between the physical parameters, calculate the possible state transitions.

The following sections explain this method with a practical example. The problem addressed is "The spring attached to the wall was pulled sufficiently in the opposite direction of the wall and then released along the rough floor". See Appendix A for details on the prompt and output used for ChatGPT. Information for the next step are manually extracted from the output.

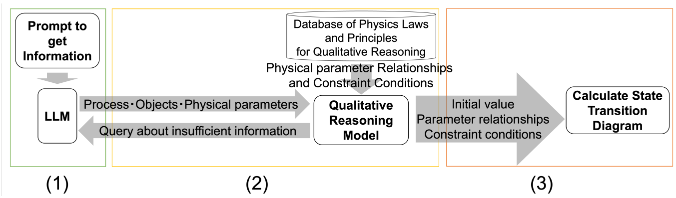

Figure 2. Proposed framework of Qualitative Reasoning

3.1 Analysis of a Physical Problem

We enter the text about a physical problem with an instruction prompt to LLM for identification of physical system configuration (objects and their contact states) and a list of physical phenomena that occurred in the system. This instruction prompt is designed for extracting such information based on the flow described in Figure 3.

The details of the procedure are as follows. First, the objects appearing in the problem are recognized and it is determined whether their motion conforms to a constraint surface, such as a floor. If the motion is along a constraint surface, the axis and slope are determined by checking whether the constraint surface is a slope, for example. Next, it detects how the objects are in contact with the constraint surface, whether vertically or horizontally. Then it extracts the information corresponding to the process. With these steps, a prompt template for analyzing the basic information of the problem is created and entered into ChatGPT along with the problem being handled. From the example input, the output was able to extract objects such as a spring and a wall, and a horizontal floor as a constraint surface. However, the wall is considered immobile and is not treated as an object. Similarly, processes such as Constraint surface movement, Friction movement, and Spring movement were applicable as inferred from the content obtained.

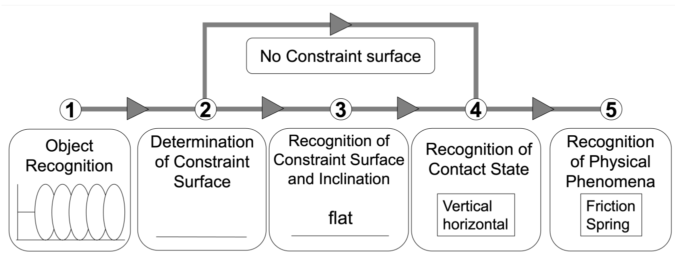

Figure 3. Procedure of analyzing problem

Table 1. Comparison of the Physical feature, Anchor concepts, and the Proposed method

	Kiriyama et. al., 1992 [4]	Forbus 2023 [3]	proposed method(Ours)
Primitive Concepts	Physical Phenomena	Anchor concepts	Physical Phenomena
Example Based Components	Physical feature	Subclass of Anchor concepts	
Difficulty of Model Construction	Easy	Easy	Supported by LLM
Size of Knowledge Base	Large	Large	Small

3.2 *Construction of the Physical Parameter Network*

A physical parameter network is constructed from the information obtained.

3.2.1 *Generation of Relationships Between the Physical Parameters*

Using the process names obtained from the analysis of the physics problem as keys, access is made to a pre-created database of physical laws and principles for QR (Figure 1). Based on the physical laws and principles associated with the processes, the qualitative time-varying relationships of the physical parameters are instantiated for each object.

In addition, forces are automatically aggregated by component along each axis. If information is missing, such as the conditions under which static friction occurs, ChatGPT is queried, and from the output, the action of static friction is defined. In this case, it corresponds to the restoring force of the spring.

Thus, for the example problem, a physical parameter network has been created concerning the qualitative time-varying relationships of instantiated physical parameters (Figure 4). However, due to the complexity, the constraints are omitted.

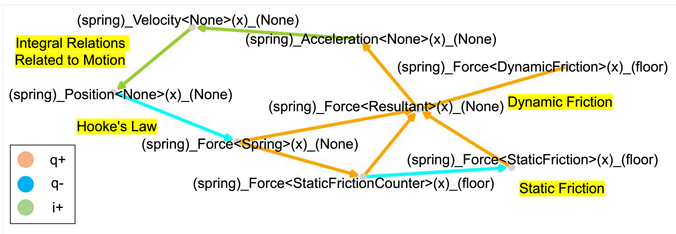

Figure 4. Physical parameter network

3.3 *Calculation of System State Transitions*

This section explains the method used to determine the system's state transitions by setting the initial values of the physical parameters in addition to the information from the physical parameter network created through the above processes. In this study, the values of the physical parameters are qualitative and indicate one of three directions: +, 0, or -.

3.3.1 *Obtaining Initial Value Information*

To get the initial value information of the physical parameters, we design CoT prompt for extracting initial value. In this prompt, we ask LLM to provide the information about the axis of motion, the origin, and the definition of positive and negative directions, first. Then, using CoT, we re-identify the problem, identify the axis and origin, positive and negative directions, and list the initial values for position and velocity. Next, we can list the acting forces. If friction is present, distinguish between static and dynamic friction and select the appropriate one, then re-list the acting forces, and list the resultant force and acceleration. A prompt containing these instructions is typed into ChatGPT to obtain initial values, and the output was obtained. From this output, the initial values of the physical parameters for the example problem were set.

For this example text "The spring attached to the wall was pulled sufficiently in the opposite direction of the wall and then released along the rough floor", the system extract the initial values as follows; Position (+), Velocity (0), Acceleration (-), Resultant Force(-), Dynamic Friction (0), Static Friction (+), Reaction of Static Friction (-), Spring Force (-).

3.3.2 *Envisioning*

çlabelsec:envisionning Based on the obtained physical parameters, their qualitative temporal changes and initial values, an envisioning simulation of state transitions through QR is performed by a QPT-based simulator.

In the simulation results (Figure 5), each node in the diagram represents the state of the system at each point in time (Detail of the initial state and each states are shown in Appendix B). The orange node on the right represents a positive position, the yellow-green node in the middle represents the origin (the natural length of the spring), and the light blue node on the left represents a negative position. The edges represent the direction of the state transitions, and the state represented by the central red label indicates the final state. The resulting state transitions are mainly counterclockwise including periodic behavior of simple harmonic motion and transitions to a rest state due to friction.

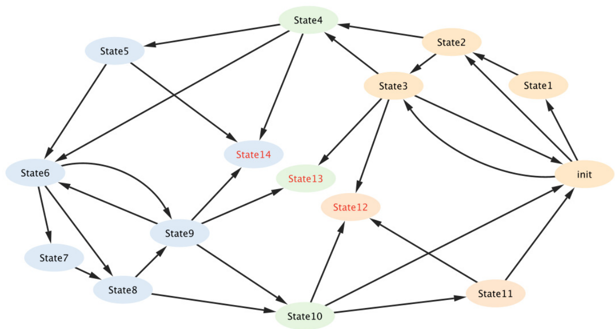

Figure 5. State Transition Diagram

4 Conclusion

In this research, we proposed a framework for the construction of a QR model using physical phenomena and relationships between the objects collected from text provided by the LLM. This model integrates first principles such as physical laws and principles to simulate the behavior. The operation of the framework was demonstrated using simple harmonic motion on a friction plane as an example. In the future, various challenges should be addressed including extending the knowledge of the physical laws and principles and applying the system to problems involving other physical phenomena. In addition, there is a need to build an end-to-end framework and provide feedback information on the state transitions of the inference results to the LLM, which could extend the range of potential applications to generating explanations.

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A Prompt and output of the system

A.1 Prompt1

System message
Please consider the following "movement" within the scope of high school physics.
Please identify the following materials related to the movement of the following "movement".
Please answer in the form of an itemized list for each of the following materials.
Please consider the Earth's gravity.
Please do not output any text other than the requested materials. **System message end**
Movement
The spring attached to the wall, stretched sufficiently, is about to start moving along the rough floor in the opposite direction of the wall, having been released.
Movement end
Materials

- **objects**: List all objects featured in the movement.
- **is constraint surface movement**: Please determine whether it is a motion along the constraint surface.
- **constraint surface**: List names and angles (flat, slope upward, slope downward, vertical etc..) of the constraint surface, if it exists.
- **constraint surface objects**: Extract objects from "constraint surface" that are not part of objects in "objects".
- **objects and constraint surface objects**: Combine "objects" and "constraint surface objects" into a bullet-point list.

Materials end

A.2 Output1

Materials

- **objects**:
  - Spring
  - Wall
- **is constraint surface movement**: Yes
- **constraint surface**:
  - Floor (flat)
- **constraint surface objects**:
  - Floor
- **objects and constraint surface objects**:
  - Spring
  - Wall
  - Floor

Materials end

A.3 Prompt2

Explain concisely what kind of motion will occur based on physical laws and principles for each object.
Let's think step by step about this logically.

A.4 Output2

When the spring, attached to the wall and stretched on a rough floor, is released, the following motion occurs based on physical laws and principles:

- **Elastic Potential Energy to Kinetic Energy**: The stretched spring holds elastic potential energy. Upon release, this energy converts into kinetic energy, causing the spring to move.
- **Motion Against Friction**: The spring moves on a rough floor, indicating the presence of friction. This friction opposes the motion of the spring, gradually reducing its kinetic energy.
- **Oscillatory Motion**: The spring will likely undergo oscillatory motion (back and forth) due to its elastic nature, until all its kinetic energy is dissipated through friction and internal damping within the spring.
- **Effect of Gravity**: Earth's gravity acts vertically downwards, but since the motion is horizontal on a flat surface, gravity primarily affects the normal force between the spring and the floor, which in turn influences the frictional force.

Overall, the motion involves a conversion of elastic potential energy to kinetic energy, oscillatory movement, and energy dissipation due to friction and internal damping, within the constraints of gravitational and frictional forces.

A.5 Create Physical parameter Network

The following can be interpreted from these outputs.

- **objects**:
  - Spring
- **constraint surface**:

- Floor (flat)

- **Physical phenomena**:
  - Constraint surface movement
  - Spring movement
  - Friction

Then, access the database and create a physical parameter network (Figure: 4). However, since the restoring force of the spring is insufficient this time, inquire with the LLM.

A.5.1 Prompt

What force acts as the reaction to static friction?

A.5.2 Output

The reaction to static friction is the force exerted by an object against the surface it is in contact with. In the context of the spring attached to the wall and moving on a rough floor, when static friction is acting to prevent the spring from starting its motion, the reaction to this static friction is the elastic force (restoring force) exerted by the stretched spring in the direction away from the wall. This force is trying to move the spring across the floor, and the static friction is what resists this motion. According to Newton's third law of motion, for every action, there is an equal and opposite reaction. Thus, the force the spring exerts against the floor to move forward is matched by an equal and opposite force from the static friction preventing that motion.

A.5.3 Add information

Therefore, set the static friction force as the restoring force of the spring.

A.6 Prompt3

Direction

- **origin**: Point at the natural length of the spring
- **positive direction**: Away from the wall from the origin.
- **negative direction**: Toward the wall from the origin.

Direction end

List the initial signs of the physical parameters based on the "Direction".

1. **Step 1**: Check the "Movement".
2. **Step 2**: Check the "Direction".
3. **Step 3**: List the initial values of Position, Velocity.
4. **Step 4**: List all added forces for each object.
5. **Step 5**: If friction is applied, distinguish static friction and dynamic friction, and reconsider which is applied.
6. **Step 6**: List the initial values of all added Forces.
7. **Step 7**: List the initial values of resultant forces and Acceleration.

A.7 Output3

Based on the "Movement" and the defined "Direction", let's list the initial signs of the physical parameters:

- **Step 1: Movement** - A spring attached to a wall, stretched sufficiently, and about to start moving along the rough floor in the opposite direction of the wall, having been released.
- **Step 2: Direction** -
  - Positive Direction: Away from the wall.
  - Negative Direction: Toward the wall.
- **Step 3: Initial Values of Position and Velocity** -
  - Position: Positive (since the spring is stretched away from the wall).
  - Velocity: Zero initially (at the moment of release, the spring is momentarily stationary).
- **Step 4: Added Forces for Each Object** -
  - Spring: Elastic force (restoring force), frictional force (due to the rough floor), and gravitational force.
  - Wall: Reaction force exerted by the spring.
  - Floor: Normal force exerted by the spring.
- **Step 5: Friction** - Initially, static friction applies (as the spring is just about to move). Upon movement, it transitions to dynamic (kinetic) friction.
- **Step 6: Initial Values of all Added Forces** -
  - Elastic force: Negative (restoring force towards the wall).
  - Static friction: Zero initially (since the spring is not yet moving), but it will be positive (opposing the motion away from the wall).
  - Gravitational force: Neutral in terms of direction (acts downwards, perpendicular to the direction of spring's motion).
  - Normal force: Neutral in terms of direction (acts perpendicular to the motion).
- **Step 7: Initial Values of Resultant Forces and Acceleration** -
  - Resultant force on the spring: Initially negative (due to the restoring elastic force).
  - Acceleration: Initially negative (the spring accelerates towards the wall due to the restoring force).

B States generated by the envisioning system

Followings are description of the states generated by the envisioning system.

Init The length of the spring is longer than the normal length and it starts accelerating towards the wall (acceleration = -, velocity = 0, position = +).

State1 The length of the spring is longer than the normal length and it starts accelerating towards the wall and it starts moving towards the wall (acceleration = -, velocity = -, position = +).

State2 The acceleration is 0 because the force of the spring and the dynamic friction force are balanced (acceleration = 0, velocity = -, position = +).

State3 The acceleration direction changes because the dynamic friction force is greater than the spring force (acceleration = +, velocity = -, position = +).

State4 The length of the spring becomes the normal length (acceleration = +, velocity = -, position = 0).

State5 The length of the spring is shorter than the normal length and moves towards the wall (acceleration = +, velocity = -, position = -).

State6 The length of the spring is shorter than normal and stops (acceleration = +, velocity = 0, position = -).

State7 The length of the spring is shorter than normal and is moving away from the wall (acceleration = +, velocity = +, position = -).

State8 The acceleration is 0 because the spring force and the dynamic friction force are balanced (acceleration = 0, velocity = +, position = -).

State9 The acceleration direction changes because the dynamic friction force is greater than the spring force (acceleration = -, velocity = +, position = -).

State10 The length of the spring becomes the normal length (acceleration = -, velocity = +, position = 0).

State11 The length of the spring is longer than the normal length and moves away from the wall (acceleration = -, velocity = +, position = +).

State12 Length of spring is longer than normal length and stops (spring force and static friction force are balanced)

State13 Length of spring is normal length and stops (spring force and static friction force are balanced)

State14 Length of spring is shorter than normal length and stops (spring force and static friction force are balanced)