Immersive interaction (AR, VR & MR) and machine learning methods to optimize and control 3D trajectories simulation

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Abstract

Today's physics presents a number of hurdles in terms of visualizing and interacting with abstract data, as well as significant usability limits on the tools that attempt to address them. This PhD aims at overcoming those limitations by studying the use of immersive visualization and machine learning methods to optimize, control and analyze 3D trajectory simulations. This thesis will be carried out by relying on the context of electron microscopy as a field of study and more specifically on electron trajectories simulations developed at the CEMES [1, 5].

Context

The CEMES is a CNRS laboratory dealing with the study of matter's properties at the nanometric and even atomic scale. Transmission Electron Microscopy (TEM) is one of its preferred methods for obtaining data at this scale. A powerful stream of electrons is focused on a sample by a first set of electromagnetic lenses, after which a second set of post-sample lenses allows a much larger image of the observed object to be formed. Although this type of microscope allows for very advanced experiments, it is challenging due to the number of components that affect the course of the beam in a sequential manner.

Main Objectives

1. Apply and create machine learning methods to facilitate the interaction with the microscope configuration and data.
2. Production of an immersive interactive 3D trajectories control system for demonstration purposes communicating with the existing simulations and the microscope.
3. Develop a new training approach based on the developed system and machine learning methods for transmission electron microscopy.

Machine Learning for TEM

Interacting with the TEM configuration is not trivial and requires a deep understanding of the underlying physics to be proficient. Machine learning can empower users by converting abstract commands such as "shift the focus point to this position" to actual configuration's modification such as "set the objective lens current to 2.0V and the first diaphragm to position 1".

Data Collection

The first step in this process is to collect data from the microscope, we are using a camera inside the microscope column to get a video feed of the images produced by the electron beam on a phosphorous screen corresponding to the current configuration of the microscope components.
This video is then processed to extract the relevant parameters from the frames forming with the configuration a dataset usable for machine learning applications (figure 1).

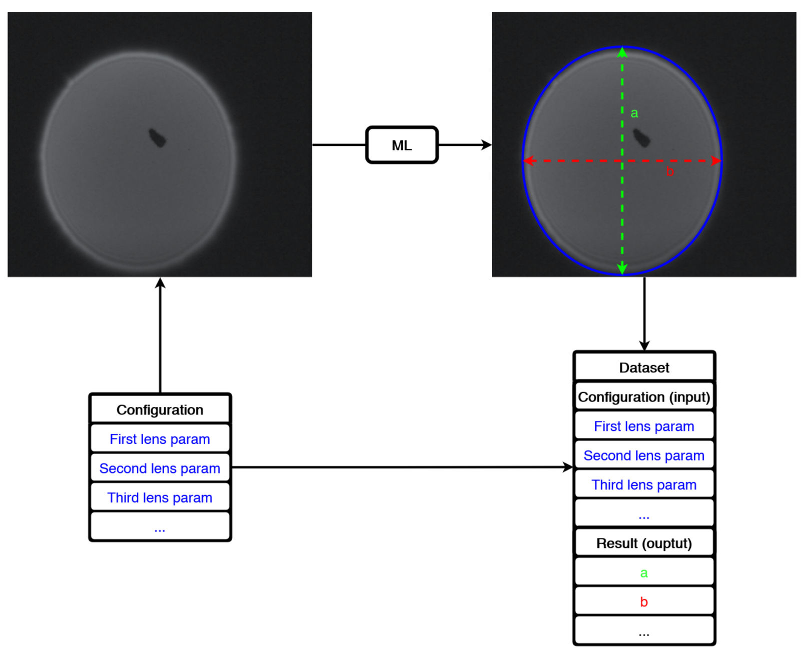

Figure 1: Data Collection process

Simulation Correction and Meta-Parameters Configuration

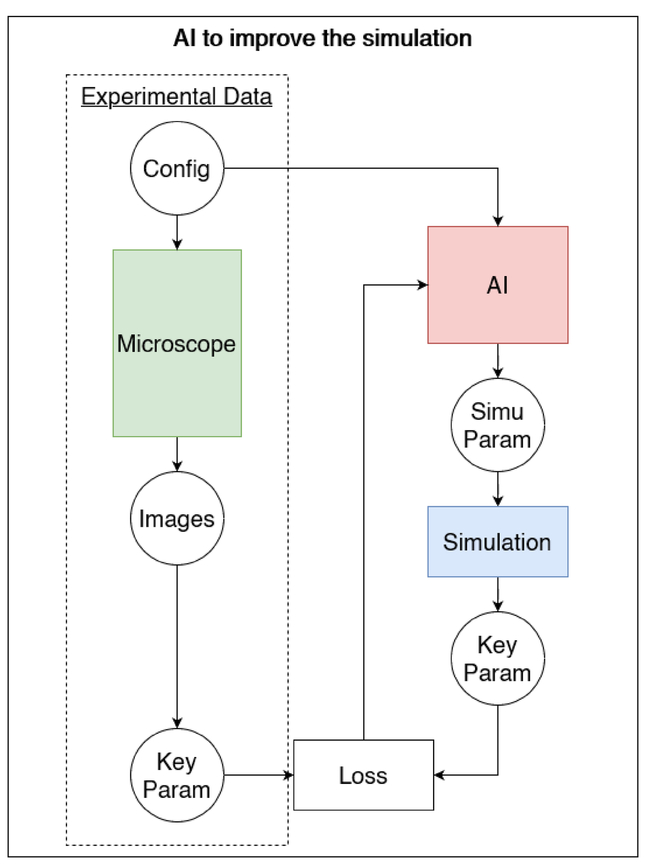

Figure 2: ML training process

Using the data accumulated, the first objective is to correct some parameters of the simulation to make it closer to reality by using the process described in the diagram 2.
Once this is done, the next goal will be to identify key parameters of the beam (meta-parameters) a TEM user wants to manipulate and train supervised learning algorithms to translate this in configuration modifications.

Reinforcement Learning

Once the training pipeline is correctly set up, we might try implement a real time version, feeding microscope's data continuously to a reinforcement learning algorithm. This could be used to let the model learn how the microscope behave on its own. It is also possible to add inputs to control the behavior of such models, give it training sessions linked to a specific task, or do real-time corrections.

Demonstrator: Twin4TEM

The second objective of this PhD is the production of a digital twin prototype [4] of the microscope in an immersive environment. The electron trajectories inside the microscope are hard to understand especially for a neophyte due to multiple rotations, deviations and splitting of the beam. Therefore spatializing the data in a 3D space with the tools to interact with this representation is crucial.

From a Configuration Interface...

This study is based on previous work [1, 5] which lead to the development of two simulations of the electron trajectories inside the microscope as well as a software to interact with these simulations presented figure 3. The interface presented already allows the user to configure most of the components from the simulations or the microscope in an efficient way. However, it lacks the immersion needed for a beginner to understand what is happening inside the microscope at a glance and modifying the configuration isn't intuitive.

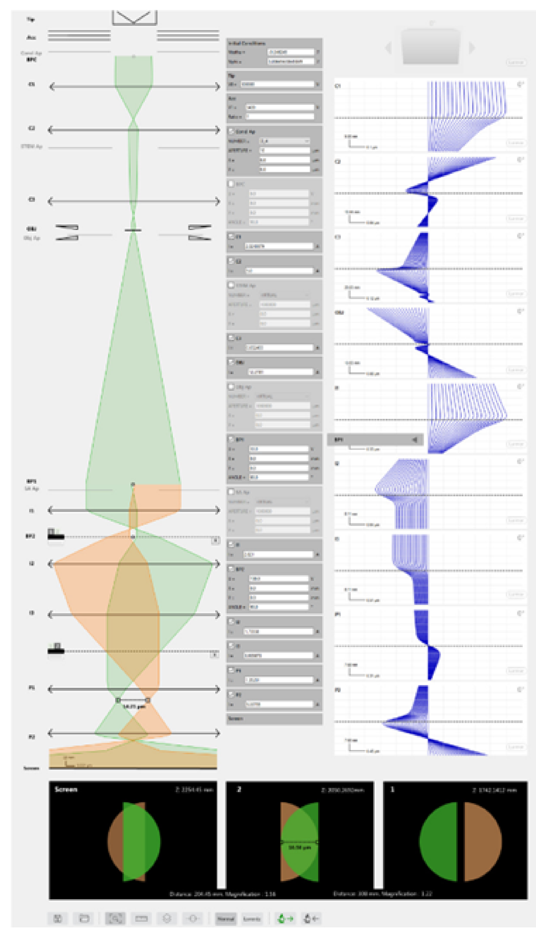

Figure 3: Screenshot of the configuration interface

...To an Immersive Digital Twin

To resolve those hurdles, we propose to use mixed reality and other types of immersive environments to create an interactive digital representation of the microscope which will use new interactions methods based on the previously presented machine learning algorithm to enhance user experience.
A first prototype with basic configuration tools is already running on *Hololens 2* (figure 4) and will be further improved upon when the machine learning tools are ready.

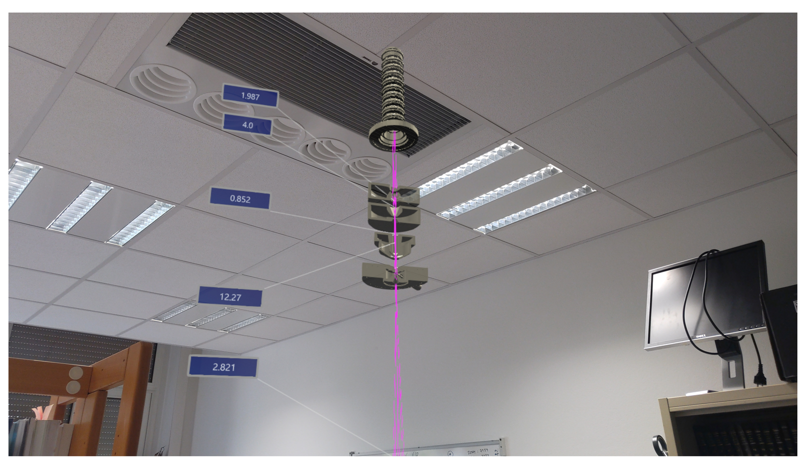

Figure 4: Screenshot of the digital microscope interface prototype

Enhanced TEM Training

Upon completion of the demonstrator, our third objective will be to study new ways of training transmission electron microscopists using the immersive environment to make trainees visualize the real 3D trajectories of the electrons inside the column as well as the effects caused by the modification of the microscope configuration (figure 5). This direct representation lessen the burden of having to make one in his mind for the trainee or to infer it from approximate drawings made by the lecturer and could reduce the learning curve to master TEM.

Figure 5: TEM training illustration

References

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