From Human Cognitive Expertise to Ontological Formalization: Bridging the Knowledge Gap for Nanophotonic Calculator Design and Simulation*

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Abstract

In response to the escalating limitations of traditional electronic computing, the potential of nanophotonic calculators, which utilize light instead of electricity to enhance computing performance, appears promising. Nonetheless, the development of nanophotonic calculators presents significant challenges for physicists, primarily due to the complexity of design and the absence of established guidance to optimize the operation conditions from a vast parameter landscape, as well as the need for a collaborative framework to manage knowledge and support decision-making. This paper introduces an innovative approach that combines cognitive psychology and ontological formalization to capture and structure expert knowledge and domain-specific constraints. This interdisciplinary strategy enables the formalization of knowledge into structured, machine-readable ontologies, optimizing simulation and fabrication processes for nanophotonic calculators. By integrating expert insights with artificial reasoning, our approach aims to improve the efficiency and reliability of simulations, thereby reducing the time and cost associated with experimental methods. The developed ontology has been successfully applied in multiple simulation scenarios, demonstrating its effectiveness in guiding the development of all-optical nanophotonic devices.

Keywords

Cognitive knowledge elicitation, Ontology formalization, Artificial reasoning, Nanophotonic calculator

1. Introduction

The demand for faster and more efficient computing systems has driven technological advancements in recent decades. Traditional electronic computing devices, which rely on silicon-based transistors, have experienced remarkable progress in speed and miniaturization [1]. However, as the limitations of these devices become increasingly apparent [2, 3], the quest for alternative computing paradigms has intensified. A promising direction lies within the field of nanophotonics, where light is used instead of electricity to transmit and process information [4]. By exploiting the natural properties of photons, such as their high-speed transmission and low energy consumption, nanophotonics can transform computing architectures and propel us into

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a new era of computing capabilities. Therefore, developing nanophotonic calculators offers a potent alternative to traditional electronic processors.

Conventional devices operate within the confines of electrical circuits and semiconductor materials and obey the laws of solid-state physics applied to electrons in materials. In contrast, the development of nanophotonic calculators must adhere to the constraints and fundamental laws of optics and light propagation. Thus, research into nanophotonic calculators requires technical expertise and a profound understanding of light-matter interaction principles. This poses a significant challenge for physicists and engineers in this field, mainly because this understanding often relies on experimental results and evolving expertise. Depending on the operator to be developed, physicists must determine the optimal structure and excitation parameters to fabricate the nanophotonic calculator. In addition to the constraints of physics, the solution must consider additional parameters such as material properties, simulation environment, and fabrication constraints according to technical limitations and available fabrication processes.

The first successful experimental results were obtained using a double hexagonal structure (DH) for a set of logic gates [5, 6]. However, the discovery of more complex calculator configurations may be limited by the choice of structure and simulation parameters, often defined from intuitive assumptions of domain experts, through experimental and/or numerical tests, which can be time-consuming and costly. To address this issue, we propose employing artificial reasoning to verify the validity of optical simulation parameters before proceeding to real experimentation. This approach aims to enhance efficiency by using computational models to systematically evaluate shapes and excitation parameters, thereby eliminating configurations that do not adhere to expert knowledge and domain constraints. This strategy not only reduces the time and cost associated with experimentation but also facilitates the exploration of more complex calculator configurations beyond those previously considered feasible.

To do that, collecting, comprehending, and formalizing the expert knowledge and the domain constraints is essential. In this paper, we propose an innovative approach that combines cognitive psychology techniques inspired by work psychology [7, 8] and ontological formalization, commonly used in artificial intelligence [9]. Our approach aims to collect and structure expert knowledge and domain-specific constraints using knowledge elicitation techniques and formalize it into a shared and formal model using ontology engineering to facilitate the reasoning process.

Integrating perspectives from cognitive psychology into our approach enhances the acquisition and comprehension of experts' knowledge and domain constraints. Employing ontology modeling and reasoning allows for the formalization of collected knowledge in a well-defined and structured manner that is machine-readable. The objective is twofold: first, to describe and consolidate nanophotonic knowledge and constraints into a unified and formal model, and second, to mitigate fabrication errors by ensuring the validity of simulation parameters according to defined constraints. This approach enables experts to easily explore solutions involving new shapes and excitation parameters, while providing the validity of optical simulation before advancing to real experimentation. This synergistic combination leverages both human expertise and machine reasoning capabilities, resulting in a robust framework for knowledge management and decision support in the development of nanophotonic calculators.

2. From Cognitive Knowledge Elicitation to Ontology Engineering

Developing a reasoning model requires the acquisition of explicit and tacit knowledge from experts who have a deep understanding of domain constraints. Explicit knowledge refers to information readily articulated by individuals, whereas tacit knowledge involves expertise gained through experience, which might be complex to verbalize. These two knowledge forms are crucial to creating a formal model with a deep understanding of the domain, thus ensuring that the reasoning process aligns with the limitations and constraints of the real world.

Knowledge acquisition is an essential step in the development of knowledge-based reasoning systems. However, in practice, collecting expert knowledge is a complex social interaction process that faces several difficulties impacting the quality and the completeness of the resulting model [10]. To avoid comprehension errors and omission of necessary knowledge, it is essential to employ adapted elicitation techniques to ensure the reliability, accuracy, and relevance of the collected knowledge and then facilitate the formalization process. To do that, we propose a collaborative approach that integrates expertise from cognitive psychology with ontological engineering to facilitate the transition from expert knowledge to a formal model.

Figure 1 illustrates the main phases of our methodology, which combines cognitive knowledge elicitation with ontology engineering. The initial step concerns knowledge acquisition using a cognitive knowledge elicitation technique developed in collaboration with researchers in human and social sciences [11]. Rooted in the psychology of work and development domains, this technique integrates conversational, observational, and analytical methods of elicitation [12]. It is designed to be flexible, allowing for adaptation to the specific needs of the application domain and the constraints inherent in reasoning processes. A cognitive analyst possessing

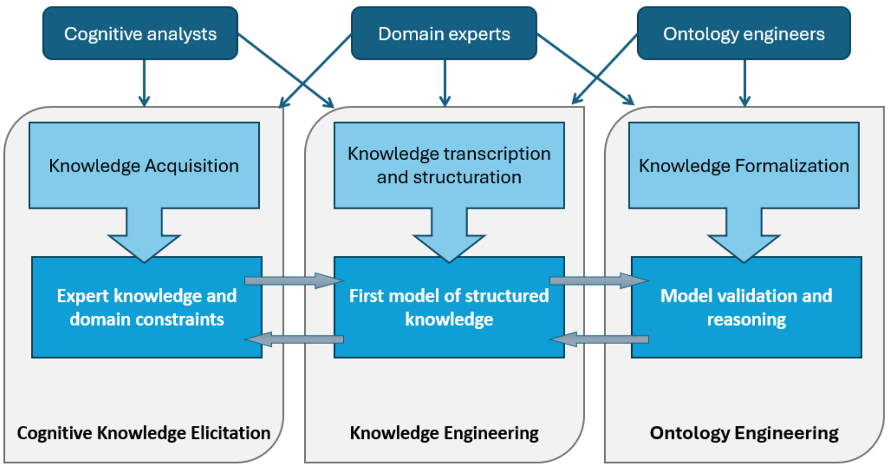

Figure 1: Combining Cognitive Knowledge Elicitation and Ontology Engineering.

the necessary skills to conduct and facilitate knowledge acquisition sessions with domain experts performs the knowledge acquisition process. This phase focuses on understanding and capturing experts' explicit and tacit knowledge and the domain's constraints.

After the acquisition phase, the collected knowledge will be organized and structured into a semi-formal model using mind maps and UML diagrams [11]. At this stage, domain concepts with their properties and relationships are defined, allowing the development of a preliminary model of structured knowledge. This initial model serves as an intermediary result of the process, presenting the collected information in an organized manner and preparing it for further refinement. During this phase, the combined efforts of cognitive analysts, ontological engineers, and domain experts are essential to ensure a precise interpretation of knowledge and the development of coherent models aligned with expert descriptions. Through iterative discussions and feedback loops, this collaborative approach facilitates a deeper understanding of the knowledge. It also aids in identifying inconsistencies and gaps in knowledge, potentially prompting revisions in the acquisition phase to enhance the model's accuracy and comprehensiveness.

The final phase involves transforming structured knowledge into a formal representation, such as an ontology, for reasoning purposes and the development of artificial intelligence solutions. During this phase, the formalized knowledge model is collaboratively tested and refined with domain experts to ensure that the formal model is aligned with both the expert knowledge and the domain's specific descriptions and constraints. It is an iterative process in which feedback and adjustments are consistently integrated to refine the model and enhance the accuracy and precision of the reasoning system according to domain-specific knowledge.

3. Application for the design and simulation of a nanophotonic calculator

The conception of a holistic nanophotonic calculator, i.e. that performs the calculation in itself rather than as part of a cascaded network of devices, requires the determination of the specific shape of the device and excitation parameters, including the laser position, polarization, and phase, according to the intended logic gates. These parameters are defined by domain experts who thoroughly understand the constraints imposed by physical laws, practical conditions, and limitations of fabrication processes, optical drive, and read-out. Thus, a deep understanding of both theoretical aspects of the field and practical production and operation challenges is crucial for the formalization process. This ensures that the developed reasoning model conforms to the domain's constraints and aligns with the objectives defined by the physics experts.

A knowledge acquisition process is necessary to identify the expert knowledge and domain constraints that must be formalized for nanophotonic calculators. This process aims to extract domain-specific terminology, systematically defining concepts and their interrelations. Performed in collaboration with cognitive analysts, this process uses our approach's cooperative knowledge elicitation technique to ensure a thorough understanding of the domain [11].

After the acquisition process, the collected expert knowledge and domain constraints are structured and modeled using a UML (Unified Modeling Language) class diagram [13]. This graphical and standardized representation, known for its clarity and ease of understanding, is an essential tool for validating the accuracy and completeness of the captured knowledge. Figure 2 presents a simplified overview of the UML model related to the simulation of a nanophotonic calculator. This class diagram visually outlines the domain concepts, their properties, and their interrelations, fostering a shared understanding among physics experts and computer engineers.

It guarantees that the modeled knowledge aligns with the insights of the physics experts and accurately reflects the predefined domain constraints. This step is essential to ensure that the foundational knowledge for the nanophotonic calculator is correctly interpreted, laying a solid basis for the subsequent formalization process.

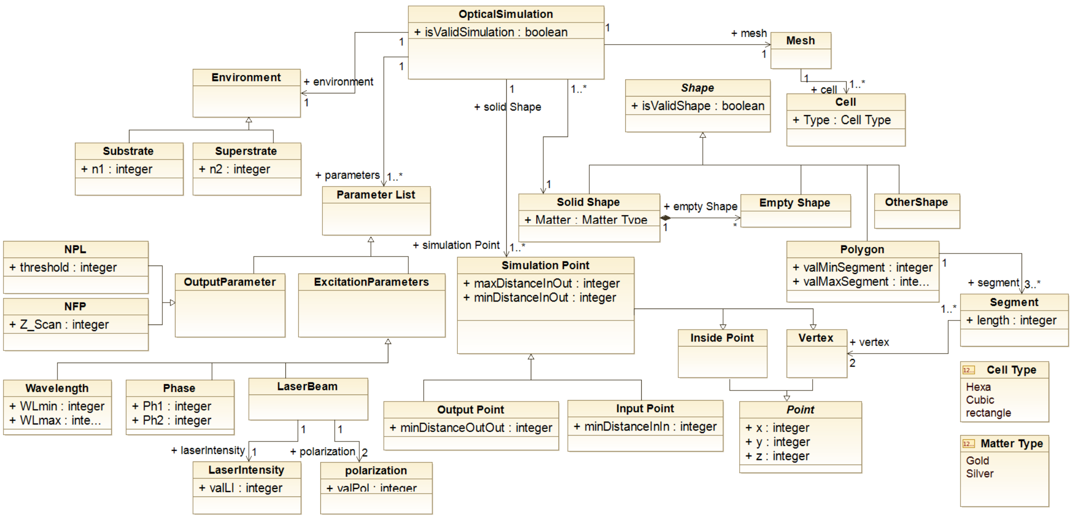

Figure 2: Simplified view of the UML model related to the studied nanophotonic calculator application.

The validated UML model is then used in the formalization process, during which a formal model is constructed as an ontology for reasoning purposes. In this phase, concepts represent classes, while attributes and relationships transform into data and object properties. Complex constraints are formalized using the SWRL rules (Semantic Web Rule Language)[1], which are used during the reasoning process. The resulting ontology is rigorously tested across diverse use cases and validated by physics experts to confirm its robustness and practical applicability. The reasoning process is used not just to infer new knowledge, but also to explain the reasons behind the invalidity or infeasibility of a simulation. To do that, the ontology incorporates concepts and parameters relevant to the validity of each parameter during the experimentation phase. For instance, an optical simulation is considered valid if its specified shape and excitation parameters adhere to constraints set by experts, such as the permissible minimum or maximum size of a segment within the defined polygonal shape or the minimal distance between two excitation points for the laser beam. This method guarantees that simulations are theoretically verifiable, aiding experts in selecting suitable parameters in alignment with the physical law and fabrication constraints.

Figure 3 describes a simplified view of the developed ontology. The complete version is available via this link[2]. This ontology formalizes the knowledge collected to model an optical simulation, as well as the information needed to generate a numerical simulation of the laser field using the PyGDM tool[3] [14]. The developed ontology provides a formal way to describe the

[1]https://www.w3.org/submissions/SWRL/
[2]https://ontology.dalhai.webapp.ciad-lab.fr/
[3]https://homepages.laas.fr/pwiecha/pygdm_doc/

parameters of each optical simulation. It encompasses the geometry of the polygonal shape in terms of line segments and their point coordinates, the parameters for laser excitation, the input excitation points, and the output parameters necessary for defining the aimed logical gates. Each concept within the ontology is enriched with a set of data properties, object properties, and SWRL rules describing collected knowledge and domain constraints. This ontology can be populated with data related to a given simulation, and an inference engine is used to verify the coherence and validity of this simulation.

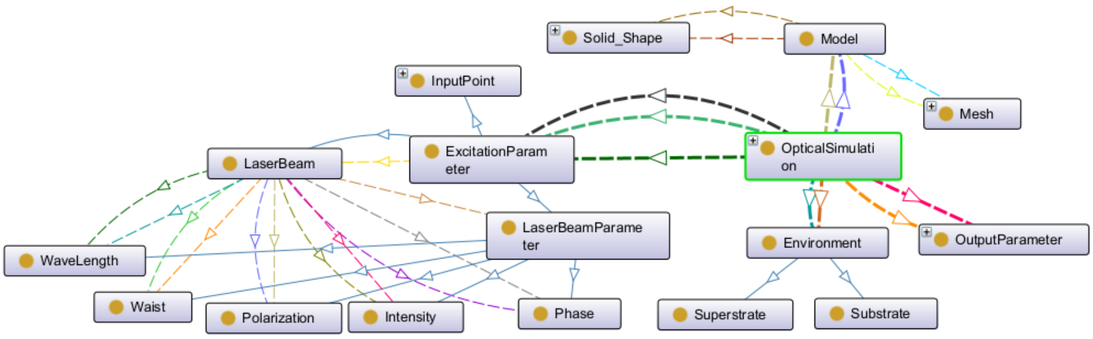

Figure 3: Simplified view of the ontology related to the studied nanophotonic calculator application.

We have conducted various optical simulation tests on different shapes and parameters to validate our approach and the ontology developed. These simulation tests are provided by either expert physicists or automatically generated by a machine learning algorithm. For each simulation, the ontology is automatically populated with data related to the description of a shape and its excitation parameters. This includes a detailed set of segments and their coordinate, input excitation points, laser beam characteristics, etc.

A reasoning process will then be applied to the populated ontology to ensure the validity of the optical simulation regarding the physical and real fabrication constraints defined in the ontology. Expert physicists will use the result of the reasoning process to validate the simulation or adjust its parameters before advancing to the fabrication and optical experimentation stages. To simplify the interpretation of the reasoning results, we introduced a Boolean data property for each concept, indicating the validity of each related element in the simulation. As shown by the example presented in figure 4, the value of this data property is inferred by the reasoner based on the ontology's stored knowledge and predefined rules. This enables experts to easily identify elements that do not meet the specified constraints, facilitating adjustments or corrections to enhance the reliability of the simulation. This approach improves the precision of experiments and ensures that the transition from theoretical models to practical applications is efficient and effective.

4. Conclusion and Future Work

This paper presents a methodological approach to transforming expert knowledge into ontologies and illustrates its application through the simulation of nanophotonic calculators. Our

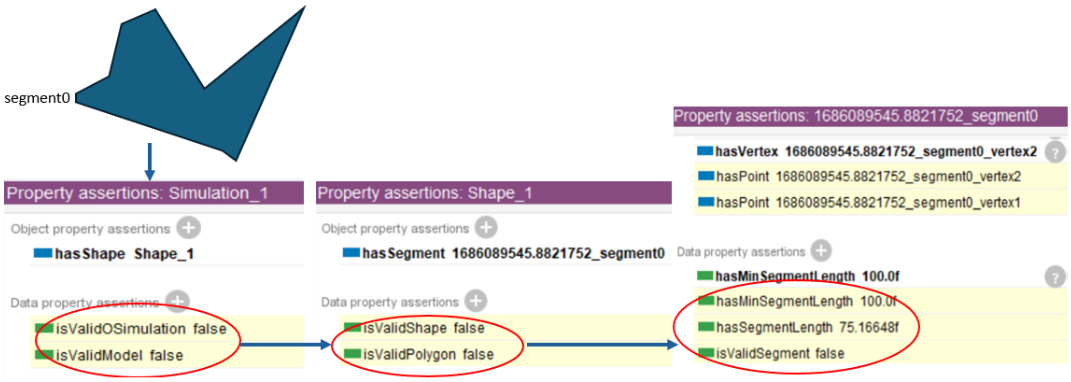

Figure 4: Example of reasoning process: In this example, the optical simulation is not valid because the reasoning process identified that the shape used for the simulation is not valid. The shape contains a segment whose length, calculated according to a rule defined in the ontology, is less than the minimum segment length defined by the domain expert.

approach integrates techniques from cognitive sciences to ensure a comprehensive capture and deep understanding of domain-specific expertise, thus enabling the transformation of informal expert knowledge into a formalized, structured ontology. This method highlights the critical role of expert insights for precise ontological development and showcases the synergy between cognitive science methodologies and ontological formalization. Such an integration enhances the creation and application of reasoning systems, improving their applicability and reliability in the addressing of complex challenges. Transitioning from a nuanced understanding of human experts to a formalized ontological model, our approach offers a streamlined path for developing cognitive-informed artificial reasoning systems.

We have applied this methodology to formalize expert knowledge in the context of simulating nanophotonic calculators. Based on cognitive knowledge elicitation, the developed ontology has been tested across multiple simulation scenarios, demonstrating its effectiveness in aiding physicists to select simulations for fabrication and experimental validation. This harmonization of human expertise with formal modeling demonstrates the importance of interdisciplinary collaboration and the advantages of integrating cognitive sciences with artificial intelligence. It illustrates how a deep understanding of human cognition and expert knowledge can be effectively converted into computational and former models, facilitating the development of more precise and reliable artificial reasoning systems.

For future work, we aim to integrate the developed ontology with a machine learning algorithm automatically. This integration will enable us to evaluate a vast array of machine learning simulations while also using ontological knowledge to guide and refine the learning process. This future direction seeks to enhance the precision and efficacy of simulations, thereby advancing the development of nanophotonic calculators.

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References

[1] C. Auth, A. Shankar, Evolution of transistors: Humble beginnings to the ubiquitous present, IEEE Solid-State Circuits Magazine 15 (2023) 20–28.

[2] R. W. Keyes, Physical limits of silicon transistors and circuits, Reports on Progress in Physics 68 (2005) 2701.

[3] E. O. Johnson, Physical limitations on frequency and power parameters of transistors, in: Semiconductor Devices: Pioneering Papers, World Scientific, 1991, pp. 295–302.

[4] P. L. McMahon, The physics of optical computing, Nature Reviews Physics 5 (2023) 717–734.

[5] U. Kumar, A. Cuche, C. Girard, S. Viarbitskaya, F. Dell'Ova, R. Al Rafrafin, G. Colas des Francs, S. Bolisetty, R. Mezzenga, A. Bouhelier, et al., Interconnect-free multibit arithmetic and logic unit in a single reconfigurable 3 μm2 plasmonic cavity, ACS nano 15 (2021) 13351–13359.

[6] F. Dell'Ova, Y. Brûlé, N. Gros, J. Bizouard, D. Shakirova, A. Bertaux, A. Leray, O. Labbani Narsis, C. Nicolle, G. Colas des Francs, et al., Compact implementation of a 1-bit adder by coherent 2-beam excitation of a single plasmonic cavity, ACS Photonics 11 (2024) 752–761.

[7] J. Arnold, R. Randall, F. Patterson, J. Silvester, I. Robertson, C. Cooper, B. Burnes, D. Harris, C. Axtell, D. Hartog, Work psychology, Pearson Education Canada, 2010.

[8] J. E. Burge, Knowledge elicitation tool classification, Artificial Intelligence Research Group, Worcester Polytechnic Institute (2001).

[9] T. R. Gruber, Toward principles for the design of ontologies used for knowledge sharing?, International journal of human-computer studies 43 (1995) 907–928.

[10] S. Sharma, S. K. Pandey, Requirements elicitation: Issues and challenges, in: 2014 international conference on computing for sustainable global development (indiacom), IEEE, 2014, pp. 151–155.

[11] O. L. Narsis, C. Nicolle, Cooperative knowledge elicitation for formal ontology design: An exploratory study applied in industry for knowledge management, in: 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, 2023, pp. 3744–3749.

[12] T. Iqbal, M. Suaib, Requirement elicitation technique:-a review paper, Int. J. Comput. Math. Sci 3 (2014) 1–6.

[13] O. A. Specification, Omg unified modeling language (omg uml), superstructure, v2. 1.2, Object Management Group 70 (2007) 16.

[14] P. R. Wiecha, pygdm—a python toolkit for full-field electro-dynamical simulations and evolutionary optimization of nanostructures, Computer Physics Communications 233 (2018) 167–192.