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Advanced Simulation Datasets for Deep Learning-Based Photonic and Electromagnetic Research using FDTD Methods

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Abstract: *We have provided finite numerical datasets using the FDTD technique, which describes the electromagnetic field distribution against the changes in material and structural characteristics in this paper. It holds information related to many numerical parameters and the field images of the corresponding shape and size for different configurations for Gold, MgF2, and glass. This dataset was created to enhance the study of photonics, optics, and electromagnetic waves and serve as an input for reinforcement learning models intended to make precise estimations of field behavior induced by material and/or geometrical inputs for photonics and optics. We also describe other datasets mentioned in the contextual literature and establish how our dataset is different by providing a more comprehensive, parameterized set of images and simulation data. Thus, describing the approach used to create the dataset, we discuss its possible use in various disciplines – from nanophotonic to machine learning where precise electromagnetic field modeling is needed.*

Keywords: finite-difference time-domain (FDTD), electromagnetic field distribution, parameterized dataset, photonics and plasmonics, deep learning

INTRODUCTION

New applications for photonics, nanotechnology, and material sciences depend on sophisticated simulation routines to accurately model light and electromagnetic fields in the medium. FDTD methods have now emerged as being one of the most accurate and popular numerical approaches to solving the time domain Maxwell equations and thereby enable researchers to study the interaction of launched electromagnetic waves with materials at the nanoscale.

Simulation datasets are therefore widely used in enhancing their efficiency by offering reusable information materials to both the experimental and machine learning communities. However, commonly available simulation-based datasets do not always contain a rich enough set of parameters that are required to be modeled to attempt to optimize the design and functionality of a structure for numerous and diverse applications. This paper presents a new dataset generated through FDTD simulations for various parameter settings, and their related electric field maps recorded in the form of images. This dataset is not only important for photonics and optical engineers but also essential as a dataset for training deep learning models to predict electromagnetic behavior based on the material structure input.

FDTD SOFTWARE AND ITS USES

The Finite-Difference Time-Domain (FDTD) technique is a widely aspired numerical modeling approach that solves the problem of electromagnetic field distribution in dispersed objects. FDTD spatially discretizes the simulation space, solving Maxwell's equations at each time point and it is thus very flexible in handling geometries and material types.
FDTD Solutions Software is a leading tool in this domain, providing powerful simulation capabilities for a wide range of key features and applications:

Key Features of FDTD Solutions

Electromagnetic Simulations: It simulates how electromagnetic fields transfer or respond to materials and can be applied for geometries, dispersive materials, and nonlinear responses.
Full 3D Simulations: It can do the simulations in free 3D – this is critical for studying nanostructures and other complex layouts that cannot be reduced to 2D or 1D.
Broad Spectrum Analysis: FDTD Solutions is capable of simulating over a wide range of wavelengths and it is therefore suitable for infrared to ultraviolet regimes.
Customizable Material Libraries: The tool comes with a predefined materials database and other physical parameters (metals, dielectrics, semiconductors), but one can also input individual material parameters with desired characteristics.
Design and Optimization: FDTD Solutions can built-in design and optimization design goals to determine the best structure. This is particularly useful to design waveguides, optical cavities, and photonic crystals, as said before.

Application Areas:

Nanophotonics: A two-temperature model for light interaction in nanoscale structures such as plasmonic devices.
Integrated Optics: Performing optics waveguide, cavity, and photonic integrated circuits design and modeling.
Metamaterials: Introducing new forms of wave materials and exploring methods of achieving a material that has a negative refractive index.
Solar Cells: A critical review methods and strategies for the simulation of light absorption and efficiency in thin Film Solar Cells.

Visualization: From the electric and magnetic field distributions, power flow, and other electromagnetic characteristics, users can virtually monitor how light interacts within their planar structure.

Interoperability: FDTD Solutions can be used together with other design tools and simulation software, mode Solutions by Lumerical Company (for waveguide design), and devices for semiconductor devices.

LITERATURE REVIEW

Based on our work, here are some discussions about datasets derived from FDTD simulations**,** electromagnetic fields, photonics, and machine learning applications**.**Specifically, Krasikov, Tranter, and Bogdanov, (2022) Sapient metaphotonics augmented with artificial intelligence. Opto-Electronic. This paper considers applying machine learning to metaphotonics, where electromagnetic field distributions are modeled by FDTD simulations. It calls for the need to acquire greater amounts of data to aid in refining the models and enhance the performance of the photonic devices [1].

Kuhn, L., Repán, T ., & Rockstuhl, C. (2023). Using graph neural works for the FD- TD optical simulations. APL Photonics. In this work, a dataset obtained from FDTD simulations of optical systems is provided as proof that graph neural networks can be used to predict the response of electromagnetic fields in photonic devices [2].

Ali, M., Haque, AKMN., Sadik, N., & Ahmed, T. Predicting strongly localized resonant modes of light in disordered arrays of dielectric scatterers: A machine learning approach. Optics Express. The authors employed FDTD simulations to compute resonance modes of disordered dielectric arrays, while addressing the impact of scatterers on the electromagnetic fields, as well as the potential of machine learning models when supplied with such datasets [3].

Ma, W., Liu, Z., Kudyshev, Z. A., & Cai, W. (2021). Neural networks in the design of photonic structures. Nature Photonics. In this work, they propose the utilization of machine learning to plan photonic structures. The dataset storage contains electromagnetic fields simulated using FDTD, which in turn are used to train models that improve photonic architecture design [4].

Zhelyuzhenkov, M. V., & Zhelyeznyakov, M. V. (2019) Brunton, S., & Majumdar, A. (2011) The accelerating the scatterer-to-field mapping using deep learning for the inverse design of dielectric metasurfaces. ACS Photonics. Thus, the dataset presented in this paper is critical to the fast iteratively trained deep learning models for the inverse design of dielectric metasurfaces based on FDTD simulations of electromagnetic scattering [5].

Kanmaz, T.B., Ozturk, E., & Demir, H.V. (2023). Several near-field electromagnetic identification and metasurfaces reverse designs are based on deep learning. Optica. In this work, the generation of FDTD datasets for the excitation of electromagnetic near-fields in metasurfaces is presented. The dataset allows deep learning models to determine metasurface geometries/parameters for arbitrary target field distributions can be determined [6].

The authors whose work is under consideration in this paper are Liu Z, Zhu D, and Raju L. Artist's impression of photonic inverse design using machine learning approaches challenging traditional optimization methods. Advanced Science. The paper shows how a dataset of FDTD-simulated electromagnetic fields can be utilized to train models for the purpose of inverse design of photonic systems thereby minimizing the time taken to design [7].

Singh, R., Agarwal, A., & Anthony, B.W. (2020). Design of light meta-structures in integrated photonics with implications to beams using deep learning. Scientific Reports. This paper includes a dataset obtained from the FDTD simulations for designing the beam in optical metastructures. The dataset is employed for developing deep learning algorithms for designing bespoke beam profiles [8]. Li, Y., Wang, Y., Qi, S., & Ren, Q. (2020). Using DNN for the prediction of scattering from complex nanostructures. IEEE. In the present work, the emphasis is made on the use of FDTD datasets for the prediction of electromagnetic scattering from complex nanostructures. The trained models behave as effectively as the original FDTD simulations in producing the same results with significant reductions in computation time [9].

Malkiel, I., Mrejen; M. & Wolf, L. (2017). Efficient classification of nano-photonic structures with deep learning for design and retrieval. arXiv. The paper presents a dataset derived from FDTD simulations to develop deep learning models for the conception and search of nanophotonic structures. The dataset covers field distributions for a range of nanostructure types [10].

HOW THE PROPOSED DATASET IS DIFFERENT THAN OTHERS DATASET?

Compared to the mentioned above datasets my dataset has more diverse values of parameters and more types of material interactions, Gold, MgF_2, and glass. In contrast, many of the reviewed studies target certain applications including beam engineering, and designing photonic structures, or metasurfaces while my gathered dataset refers to multiple field types, including electric, magnetic, power, etc., and time-evolution data for various cases. This versatility makes it applicable in a wider field of study from photonics ànd nanophotonics to deep learning.

Furthermore, it means that in our dataset, researchers can adjust boundary conditions, position source, and other aspects and test numerous settings that differ only slightly and compare results seen in a wider research setting. Unfortunately, this extent of granularity is not always present in other application-oriented data. Moreover, the machine-executable format of the data set combined with the possibility of using it in machine learning for field predictions or inverse design makes it suitable for AI –centered scientific studies and optimization in photonics, metamaterials, and sensors.

METHODOLOGY

In this section, the general method used to generate the dataset is described but about this specific material and simulation setup, the following subsections will detail the FDTD simulation setup and the variation of the parameters as well as the images output by each simulation run. It has to represent a wide spectrum of behavior of electromagnetic fields as depends on the type and amount of material used, as well as the positions of the monitoring points.

These simulations were completed with Finite-Difference Time-Domain (FDTD) Solutions software. It was programmed to observe electromagnetic wave behaviors inside structures that have materials such as Gold, MgF_2 (Magnesium Fluoride,) and glasses. Different geometries of the body, different types of layers of material, different positions of source, and different boundary conditions were modified in each run of the simulation.

Description of the Used Material

Gold (Au)

Type: Metal

Electromagnetic Properties: Gold-based protective clothing materials are highly reflective and display strong plasmonic characteristics because of the negative part of the permittivity at visible and near-infrared frequencies. This makes it a preferred material for plasmonic devices, sensors as well as waveguides.

Simulation: Gold is normally fitted with a Drude-Lorentz model or by employing measured data from either the Palik material database or a similar source. The software needs to record the frequency-dependent permittivity of gold because gold has different optical behavior at different frequencies. In all kinds of plasmonic simulations, FDTD can simulate Surface Plasmon Polaritons (SPPs), which are electromagnetic waves that can be guided along the gold surface.

Magnesium Fluoride (MgF_2)

Type: Dielectric

Electromagnetic Properties: MgF_2 is a transparent, colorless dielectric material with relatively low r.i. $\approx$ 1.37 in the visible wavelengths; is used for the production of anti-reflective or optical spacers.

Simulation: In the simulation, MgF_2 is typically assumed to be a non-dissipative media, which makes its simulation easy. Due to its low refractive index, it can be applied for instance in multicoated elements in operations that involve lenses or mirrors where there is a need for minimal reflection. In FDTD, Magnesium fluoride can be used in the formation of multilayered photonic structures, or in the design of optical waveguides or the cladding structure to direct the wave through lower indices regions.

Glass (SiO_2)

Type: Dielectric (amorphous)

Electromagnetic Properties: Glass is characteristically a dielectric, commonly SiO_2, and has a transmittance of more than 90 percent with a refractive index of about 1.45 in the visible range of the spectrum. It is generally applied in the practice of optical fibers, waveguides, and lenses.

Simulation: Unlike MgF_2 however glass, is modeled as lossless dielectric although it can be added with the purpose of dispersion if the application is multicolor. In FDTD simulations, glass is used as substrate material or for cladding material otherwise known as optical waveguides.
As a result, the refractive index of glass may slightly vary depending on the simulated wavelength range (visible light or infrared and it can be easily adjusted with the aid of the Sellmeier equation or other dispersion models in the material properties settings).

Example Use Cases for These Materials in Simulations

Plasmonic Devices: It act as a plasmonic sensor, which can support surface plasmons. This simulation could include a gold nanoparticle or thin film surrounded by MgF_2 or glass or embedded in a glass substrate. It may be employed to improve the light-matter coupling near the nanoscale, which may be of interest to sensing or field enhancing in near-field optics.
Anti-Reflection Coatings: MgF_2 is widely employed in combinatorial coating on glass or other base materials in order to suppress reflection by achieving destructive interference at a specified wavelength. MgF_2 thin films deposited on the glass substrate can be modeled to verify the reflection reduction.
Optical Waveguides: Glass and MgF_2 may be employed in a waveguide structure where light is confined in the high refractive index medium (such as glass) surrounded by a low refractive index medium (such as MgF_2). FDTD would aid in the process of modeling the path of the light through the waveguide, low loss, and minimum reflection on the interfaces.

Practical Considerations in FDTD Solutions:

Meshing: Due to the large change in fields near the surface of metals such as gold, it is necessary to have a fine mesh surrounding gold structures in order to capture plasmonic effects effectively.
Material Dispersion: Anisotropy is also present in both glass and MgF_2 in terms of material dispersion which is the wavelength dependency of the refractive index – be sure to select the correct dispersion model in FDTD.
Boundary Conditions: When modeling structures with these materials, select such boundary conditions as Perfectly Matched Layers (PML) to minimize reflection at the edges of the simulation domain.
The following parameters, as detailed in the CSV file, were varied systematically:
Image Path: A direction of the folder where each set of images produced by the simulation is contained.
Circle_x_min, Circle_x_max, Circle_radius: These parameters specify the range of the x-axis and the radius of a circular area which probably represents a material or a source region in the simulation domain. These circles may depict structures in which the fields come into contact with other materials or interfaces.
Boundary_layer_min, Boundary_layer_mix: These give the thickness and profile of the boundary layers through which electromagnetic waves pass and the manner they are either reflected or absorbed at the outer periphery of a simulated space.
Source_x_min, Source_x_max, Source_y_min, Source_y_max: These parameters set the geographical area associated with the source for the conceived simulation space to emit the electromagnetic waves.

Monitor_x_min, Monitor_x_max, Monitor_y_min, Monitor_y_max: These parameters show the location of the monitors in the simulation, which measures electromagnetic field at certain locations at different stages of the simulation area.

Mesh_x_min, Mesh_x_max, Mesh_y_min, Mesh_y_max: These specify the simulation planning in the x as well as y direction, which is used for discretizing the simulation area. The higher the mesh density the refined geometry of the simulation and at the same time with higher the computational overhead.

Gold_x_min, Gold_x_max, Gold_y_min, Gold_y_max, Gold_z_min, Gold_z_max: The values quantify the spatial location and the thickness of the Gold layer for use within the simulation section. Gold is used for desired plasmonic characteristics that may alter the field strength to a large extent.

MgF2_x_min, MgF2_x_max, MgF2_y_min, MgF2_y_max, MgF2_z_min, MgF2_z_max: These parameters explained the position and size of the MgF_2 layer in the context of studying in the simulation. MgF_2 has full use in optical devices that work as a dielectric material.

Source_z_min, Source_z_max: Adds the direction in which the source lies in a three-dimensional space along the z-axis that completes the six degrees-of-freedom control of where the electromagnetic waves are generated.

Monitor_z_min, Monitor_z_max: These define the monitoring planes in the z-direction through which field data can be recorded in various z slices across the vertical planes.

Mesh_z_min, Mesh_z_max: These control the discretization of the mesh normal to the plane of the paper, and make a modest contribution to the overall spatial resolution of the simulation in three dimensions.

Monitor_point: This parameter specifies the point location at which the fields are observed during the simulation of the model.

Mesh_step: This determines the distance between nodes, that is, the spacing in all directions that determines the faceted area and the level of detail of the simulation.

For each set of parameters, 10 images were produced for each of the simulation run categories that are described below to yield a total of 100 images per run. Such images give a very clear picture of electromagnetic fields and their effects on the material.

e: The dashed and solid lines correspond to the electric field (E-field) configuration inside the simulation. These images represent the strengths and directions of the electric field vectors at various points in the simulation space.

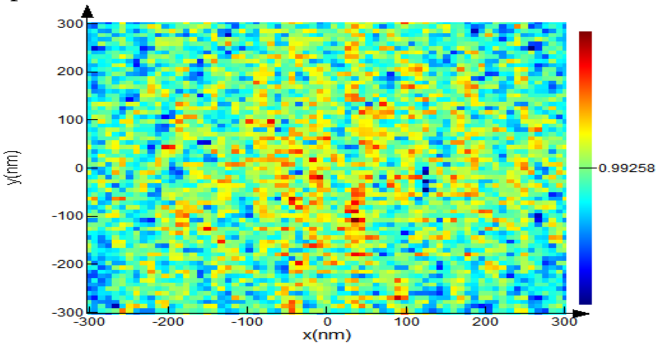

Figure 1. e field

e1: A distinct modification or perhaps some section of the electrical field (for example, the E-field in a certain direction).

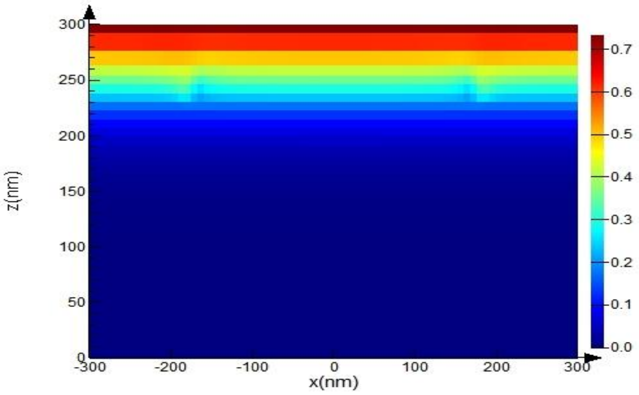

Figure 2. e field in a certain direction

field: Refers to a total electromagnetic field that incorporates the electric as well as the magnetic part.

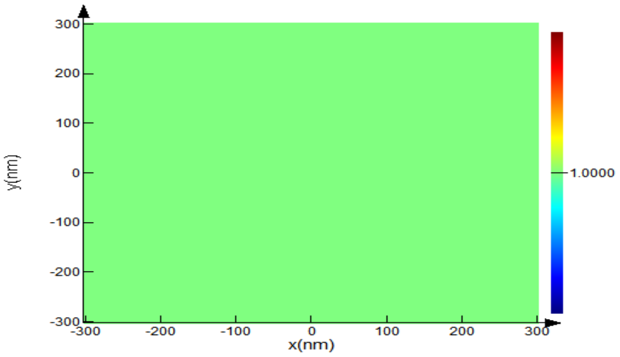

Figure 3. field

h1: Matches the magnetic field (H-field), used to analyze the response of magnetic field components within the simulation domain.

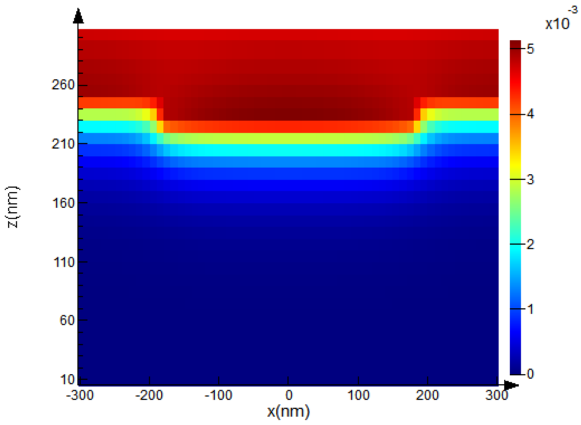

Figure 4. h field

p: P-field or energy field indicating the strength or distribution of power over the simulation domain.

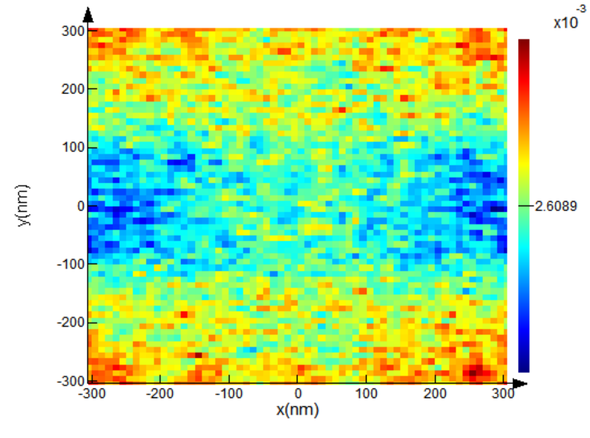

Figure 5. P-field or energy field

p1: A subclass or member of the power density, which is developed to address certain directions or field quantities.

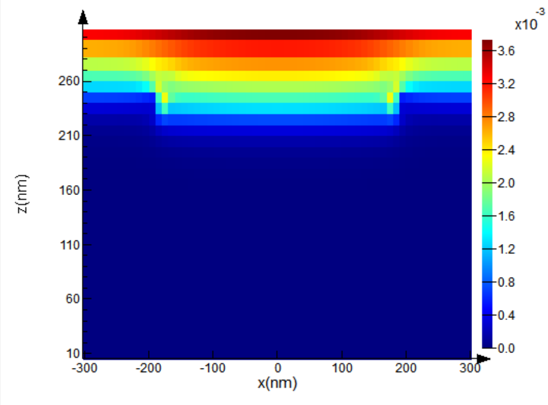

Figure 6. P-field or energy field in a certain direction

spectrum: These are images of the spectral response of the system in which one views the transmission and reflection coefficients of electromagnetic waves through the materials.

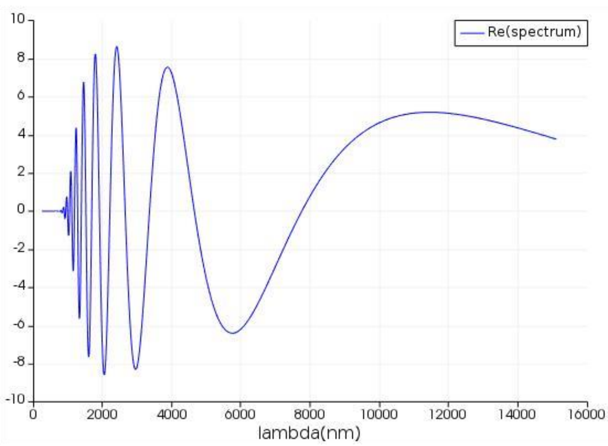

Figure 7. Spectral response

t: Explains how the electromagnetic fields of the simulation change in the progress of time during the evaluation of the fields.

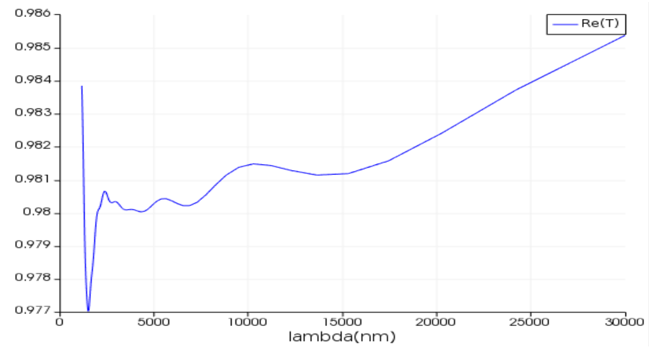

Figure 8. The progress of time during the evaluation of the fields

t1: Some variation of the domain results in the time domain, which provides information about one aspect of the field behavior over time.

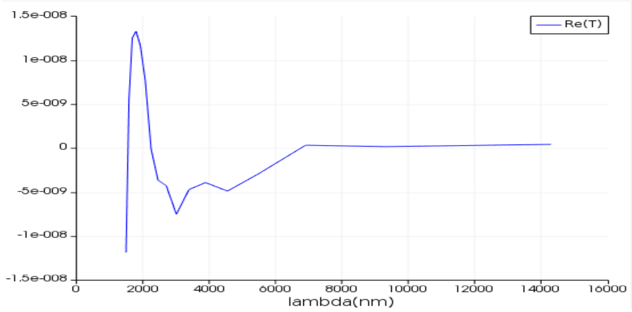

Figure 9. One aspect of the field behavior over time

time: Records the general temporal development of the electromagnetic fields or rather the time-varying nature of the fields right from the system as a whole.

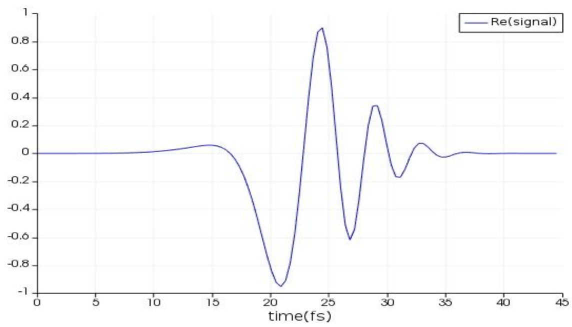

Figure 10. time-varying nature of the fields

Simulation, Workflow, and Data Generation

This dataset was obtained by carrying out multiple simulation runs with different parameter values of the above-mentioned variables. For each simulation, the electrical material properties of gold, MgF_2, and glass used in the design were introduced as well as the source configurations and geometry of the system into the FDTD software to create the electromagnetic fields. Observations in the field took place at distinct points and levels in the simulation domain of the fields. The obtained data (such as electric fields, magnetic fields, power distribution, and so on) were stored in image formats in the categories listed above. Another file was created in CSV format and served to associate each parameter with the ImageSet in which it had been produced.

The composition of the dataset and the descriptions of the parameters

Numerous CSV rows present the dataset, where each of the rows contains information on a particular simulation setup. For each row in the CSV file: The Image Path column monotonically maps to the directory of the set of images produced for that specific simulation. The variable columns which include Circle_x_min, Gold_x_min, Source_z_min, and so on describe the specifics of the simulation performed for each image of the field. The images are identified by their sort (e, e1, field, and so on) and help visualize the electromagnetic nature in those instances. This systematic approach guarantees that each row in the obtained dataset contains all the parameter values and additional field images.

Simulation Structure

2D Views of Simulation Domain – Field Distribution (Top-view in the x-y plane). The map displayed above is a two-dimensional top view of the simulation domain, which, as is sometimes the case, portrays the strength of electric or magnetic fields in a cross-sectional plane. The grey squares and the lines dividing the image into these squares represent the discretization of the simulation space used in the FDTD method; each small square represents the position in space where the solution of Maxwell's equations is calculated. The central circular shape (in blue or cyan) might be a nanoparticle, a dielectric material (MgF_2), or a void in which the fields are different from those of the rest of the system. The color distribution might be the field intensity and the color change can be related to the changes in the field strength. The three areas colored in blue and cyan details may propagate areas with low field intensity and the magenta or pink area outside them depict areas of higher field or boundary layers.

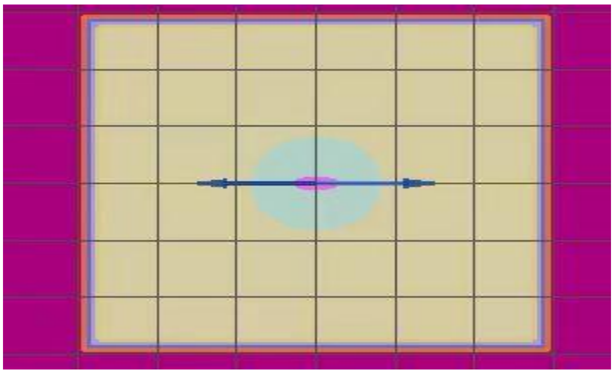

Figure 11. 2D Views of the Simulation Domain

Obviously, before discussing the evaluation of the results, it is essential to look at the 3D perspective view of the simulation domain. This is the simulated perspective view of the simulation geometry and gives information about the layers, sources, and boundary conditions of the material. The box-shaped object noted in the figure is perhaps the simulation domain surrounded by PML or ABC which are used to eliminate reflections from the boundaries of the domain. The purple and orange boxes mean different material layers or boundaries: and in general, may indicate the metallic layers (as for Gold) or dielectric regions (MgF_2 or glass). In illustrating the construction of the headquarters, the horizontal transparent plane in the middle resembles a monitoring plane on which the fields detected are recorded or mapped. This could be things like field intensity at this particular height for instance. This image also gives an easy way to visualize the position of the materials, field sources, as well as boundaries that are important for the analysis of the interaction of electromagnetic waves.
Left elevated view of the simulation domain with field source.

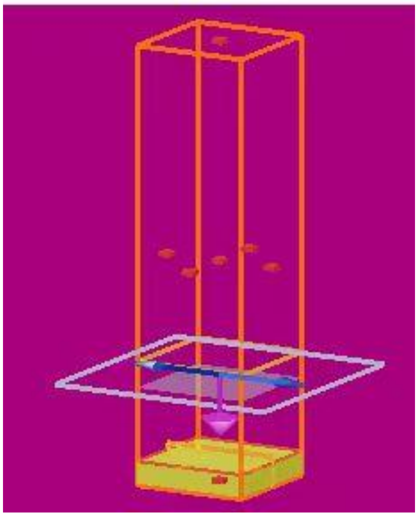

Figure 12. 3D view of the simulation

This represents the side view of an inner organization of the simulation zone and is labeled as 2D. The orange and yellow objects lying horizontally could depict different materials and the pigeon depicts a view of electromagnetic waves going through or getting through the layer of materials used in the simulations like Gold, MgF_2, or glass. The arrows in the middle may indicate the direction of wave propagation or current produced by the source which is always located at the center of the domain or at least on the border of it. The grey grid pattern together with colors represents the mesh used for FDTD discretization which grouped the small cells in the area where larger detail is needed like near the material interfaces and the large cells where little detail is needed.

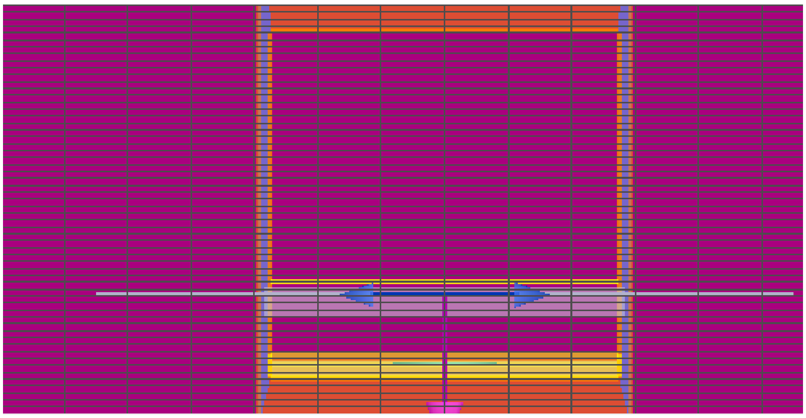

Figure 13. Inner organization of the simulation zone (2D)

Distribution of Vertical Cross-Section with Field Source and Monitoring Points. It is quite like the third picture but offers another side view of the simulation domain and comes with more information with key parts being labeled; the field source in purple and a potential monitor point in blue. The arrow originating from the source (purple region at the bottom representing the Z direction) is aimed at indicating the initial field direction or the position of the source of the electromagnetic wave in the domain. The blue sphere and the dashed line can be an interpretation of the monitoring point or sensor location where certain field quantities like electric or magnetic field strength might be measured at that point. Vertical orange lines represent either simulation space where the field interaction is well localized or boundary conditions that help propriety the field without interference by reflections at the edges of the simulation space.

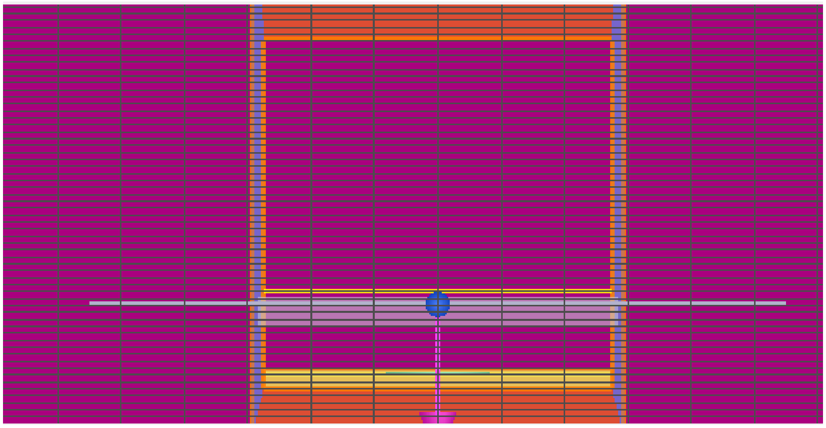

Figure 14. Distribution of Vertical Cross-Section with Field Source and Monitoring Points

CONTRIBUTION OF THE DATASET TO THE RESEARCH FIELD

Data-Driven Simulation Analysis: Prospective researchers and practitioners are enabled to understand how various parameters affect some characteristics of the electromagnetic fields, or others, in our dataset. By providing not only the raw parameter values but also visual data (the simulation images), we're enabling other researchers too. Identify general trends of tendencies between parameters and outcomes that had not been clear from the parameters or data from the simulation process that were done directly.

Potential for Machine Learning Applications: Training Data for Predictive Models: Consequently, the 4matrix tools can be used to store and analyze crucial data for creating training data sets for machine learning. Researchers could apply it to construct models of electromagnetic field behaviors which would ease and enhance simulation and optimization processes in tasks that involve designs (photonic devices, antennas, sensors).

Optimization Studies: Scholars might use our dataset to calculate losses or seek optimized options in AI using our project for shapes or optical designs where parameters, such as boundary layers, mesh sizes, or source positions can be adjusted.

Valuable for Experimentalists: Photonics, metamaterials, or nanophotonics experimental researchers may find our dataset useful as a roadmap of how such experiments can be conducted. This means that simulation data is generally the most essential starting point since performing actual experiments physically can prove to be impractical or financially draining. By comparing experimental results and simulation pictures, experimenters can either modify parameters or redesign the better setups.

Enabling the Study of Complex Electromagnetic Phenomena: Simulation brings out complex electromagnetic phenomena. Plasmonics and nano-optics are among the most appropriate fields in which our work, with materials like Gold and MgF_2, in particular, will play an important role. Simulation is the most important way in this field to study light-matter interaction at a nanoscale. The subject matter belongs to that area where heavy use-to-accurate simulation data is concentrated for modeling devices such as waveguides, photonic crystals, and sensors. The applications are myriad, from the variety in our dataset to image types, parameters, and material properties. This may span engineering optical devices to the design of metamaterials and the study of the propagation of light in different media.

Allows Interdisciplinary Research: This kind of dataset cuts across a wide domain spectrum. Examples include:

Physics and Photonics: These scientists find direct utility in the simulations we have parameterized.

Machine Learning and Data Science: Data scientists might use such models to make predictions or classify simulation outcomes; this would also bring new insight into the ways in which machine learning may contribute to scientific discovery.

Material Science: With materials like Gold, MgF_2, and glass featured in our study, our work may turn out to be of great interest to people in the field of studying the optical properties of materials, coatings, and thin films.

Novelty in combining parameterized data with visual results: Numerical parameter data combined with corresponding simulation images are a unique dataset unto themselves. It is also likely to inspire new means of analyzing or optimizing such simulations. Most research projects look at results from final processed data as device efficiency the dataset provides conditions leading to such an outcome. These conditions go way deeper, and they are there for the detection of what drives a given outcome.

Potential to Influence Design Automation: Most of today's research fields, starting from photonics down to electronics, go on automating the design process and optimization. Our data set could be interesting for studying how variations in parameters will affect a design in a completely automated workflow, which can make designing complex devices easier.

APPLICATIONS OF THE DATASET

Photonics and Nanotechnology: This dataset is the fundamental building block on which research related to the interaction of light with nanostructured surfaces should be based. Researchers in fields like plasmonics and metamaterials will be able to utilize, for the purpose of optimizing their device designs, the parameterized variations contained within this dataset, such as increased light absorption in solar cells or enhanced signal transmission in optical waveguides.

Deep Learning: Therefore, this makes the dataset suited to the application of several deep learning approaches. This can be used as the deep learning normal application and to design many electronics design [11, 12]. Some of the potential areas could be:

> **Field Prediction Models:** Training models on the dataset to predict the distribution of electromagnetic fields contingent on given parameters for quicker design iterations.
> **Inverse Design:** These deep learning models can get the optimal configuration of material and geometries for a particular field behavior; this helps in enhancing efficiency during the fabrication process.

Design Automation

This dataset would help to automate the design of complicated optical systems, enabling machine learning algorithms to investigate how changes in physical parameters alter the behavior of the field. This significantly reduces the time taken for waveguide design optimization, sensors, and other photonic components.

CONCLUSION

This dataset offers a versatile, complete resource for researchers from the fields of photonics, electromagnetics, and deep learning. In addition, by offering a wide range of parameters and corresponding images of electromagnetic field distributions, the possibility is opened for performing optimization studies, accelerating design procedures, and revealing new opportunities for machine learning applications in optical simulations. Given the breadth of applications it has, this dataset is sure to be integrated into many potential contributions within academic research and industrial development with AI-driven workflows.

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