Master in Photonics – "PHOTONICS BCN"
Master ERASMUS Mundus "EuroPhotonics"

MASTER THESIS PROPOSAL

Dates: April 2023 – July or September 2023

Laboratory: Department of Electronic Engineering and Biomedicine
Institution: University of Barcelona
City, Country: Barcelona, España

Title of the master thesis: Machine learning strategies to automatically identify surface plasmons in electron energy loss spectra.

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Keywords: Surface Plasmons, Machine Learning, Electron Energy Loss Spectroscopy, Scanning Transmission Electron Microscopy.

Summary of the subject (maximum 1 page):

Understanding the behavior of plasmonic nanostructures with complex geometries or nanoparticles assemblies is crucial for a wide range of fields, including sensing, catalysis or nanotherapies. In this proposal, we focus on isolated and clustered gold and gold-cobalt nanodomes covering polystyrene nanospheres which are structures showing low symmetry, sharp irregular rims and metal thickness gradients.

The plasmonic response of nanostructures of almost any possible shape has been vastly studied because of their superior light confinement capacity 1–4. The outstanding optoelectronic properties of plasmonic nanostructures make them suitable for a wide range of applications, especially for life sciences, e. g., cancer treatment, drug delivery, improvement of optoelectronic devices 5–9, among others. Interestingly, nanoplasmonics has led to a major change in the biosensing field 10–12 owing to the possibility of merging size reduction, high sensitivity and spectral tunability by simply controlling the size and shape of the sensing structure. To achieve optimized plasmonic structures for each application through the tailored interaction with the electromagnetic fields, a huge number of simple and complex shapes have been investigated. However, for complex nanostructures the understanding and the prediction

of their interaction with the incident light can be difficult. This often hinders the development of optimized structures or leads to lengthy trial-and-error processes.

In this work, we want to study the surface plasmons of gold and cobalt-gold nanodomes through the Electron Energy Loss Spectroscopy (EELS), which is a spectroscopic technique carry out in Scanning Transmission Electron Microscopes. In EEL spectra, the surface plasmonic responses are located at the low-loss region of them, i.e., the part of the spectrum where the electrons have small energy-losses in the range up to ~50 eV. In particular, these isolated gold and cobalt-gold nanodomes, exhibit a plasmonic resonances at 1.5 eV and 2.4 eV.

Electron Energy Loss Spectroscopy offers high spatial and energy resolutions; thus, it is a convenient and suitable technique to characterize surface plasmons in nanostructures, as these nanodomes. However, dealing with the large amount of data acquired by each observation (i.e., spectrum image from a single nanodome) and the presences of an intense Zero Loss Peak near the plasmon peaks are still challenges to characterized plasmons. For that reason, in this work we propose to apply machine learning strategies to identify plasmonic peaks in a straightforward and automated way. Recently, the EELS community has deeply explored these strategies for analyzing the core-loss region of EEL spectra, the spectrum region corresponding to higher energy losses. In this sense, they have successfully applied Support Vector Machines, Neural Networks, clustering, and dimensional reduction techniques for analyzing core-loss features 13–16.

Objectives:

The main objective of this work is to find machine learning strategies to simplify and speed up the analysis of plasmon peaks in EEL spectra; and the final objective is to find a recipe to automatically characterize plasmonic resonances in EEL spectrum images.

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