# Machine Learning applied to femtolaser parameters inference

Applications are invited for an internship in Machine Learning/Data Mining at Université Jean Monnet Saint-Etienne, within the Data Intelligence team of the Hubert Curien la. The position is funded by the EUR Manutech Sleight.

**Location:** Hubert Curien Laboratory UMR 5516, Saint-Etienne

**Team:** Data Intelligence

**Level:** Master 2 - **Duration:** 6 months - **Gratuity:** $\simeq$ 550 euros/month

### Description

This internship is part of the COHYLA 2020 project funded by the EUR Manutech Sleight that is interested in the possibility of injecting a machine learning component for surface functionalization. The latter consists of adding a new surface characteristic to a material to improve its properties or give it new functions. Among the surface functionalization technologies, this project is more particularly interested in texturing by femtosecond laser. One of the difficulties of the laser surface treatment lies in determining the values of the parameters making it possible to obtain the desired property which may differ greatly depending on the type of substrate considered, a subject on which there is currently no consensus. For experts, the traditional approach is to linearly scan the values of the laser parameters while monitoring the output, until the desired property is achieved. This type of approach is obviously quite slow and can quickly become insoluble as the number of laser parameters involved is increasing.

The goal of this internship is threefold :

1. Provide a data analysis of the dataset built by Manutech USD engineers over the past year. This dataset gathered the results of several experiences on two type of materials, where the goal was to obtain the property of hydrophobia. In this context, an obervation consists of a set of variable regarding the material, the set of values used for the different laser parameter. As for the outputs, we have images (see Figure 1) as well as a variable indicating whether the surface is hydrophob or not after the laser treatment.

2. Develop a ML model to predict the set of laser values that engineers should use when looking for a particular property. This model will have to deal in particular with the issues of materials heterogeneity and two type of data output.

3. Study the possibility of generating characterization images and experiences with deep neural networks to compensate for the complexity (in time and material) of data collection.

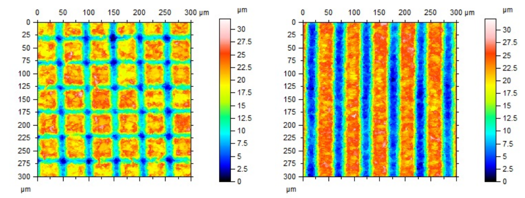

Figure 1: Example of characterization images - provided by L. Couge

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