# Surface characterisation with light scattering and machine learning

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**Abstract** Light scattering technology has been intensively investigated for surface measurement [1, 2]. However, most of developments have focused on the estimation of roughness indicators via area integrating methods, while, due to the high nonlinearity of the scattering process, few have addressed the challenge of reconstructing the actual topography, which implies solving a more complex inverse problem. In this study, rather than attempting to obtain a full reconstruction of surface topography from light scattering data, a novel approach is proposed to use light scattering information combined with machine learning to discriminate amongst different topographies. This is useful not only to compare surfaces, but also to automatically detect any type of undesired variation in manufacturing, e.g. the appearance of defects, or any other type of drift. The preliminary solution presented here operates on 2D geometry (topography profiles) and 2D light scattering far fields, investigating performance and behaviour purely via simulation. First, virtual models of different classes of surface topographies are artificially generated and labelled. Then, the far field scattering signals are obtained by simulation under different conditions of incident light through a boundary element method (BEM) [3, 4]. The scattering signals are used as the training datasets for a machine learning system, based on neural networks (NNs) [5], to implement an automated multi-class classifier. With the trained classifier, new observed surfaces can be classified with high accuracy using the associated far field scattering result. Preliminary experiments have been conducted to characterise three types of grating surfaces (blaze, sinusoidal and square gratings). The NN was designed as a three-layer densely connected network. In the experiment, 3300 datasets (3000 for training, 300 for testing) were used, consisting of gratings with different spacings. For the case studies, the accuracy of classification (number of correct predictions over number of total predictions) was higher than 99%. The results demonstrate that the proposed method is effective for discrimination of surfaces classes. For future work, the proposed method will be verified with scattering measurements of real surfaces. The method will also be implemented for defect detection in different kinds of surfaces and a 3D version of BEM model will be developed and utilised for characterisation of 3D surfaces.

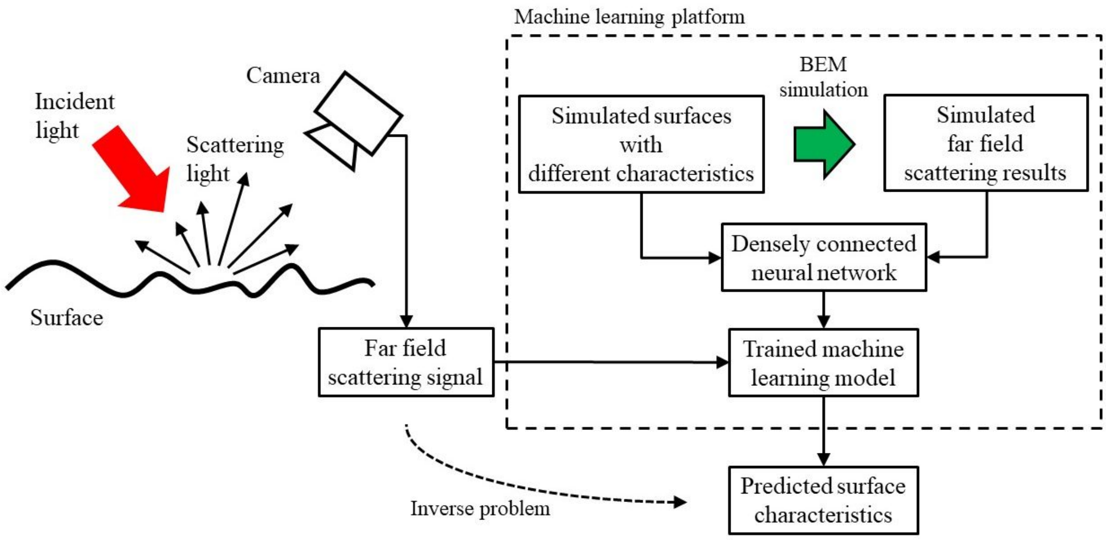


**Figure 1**. Schema of the proposed method.

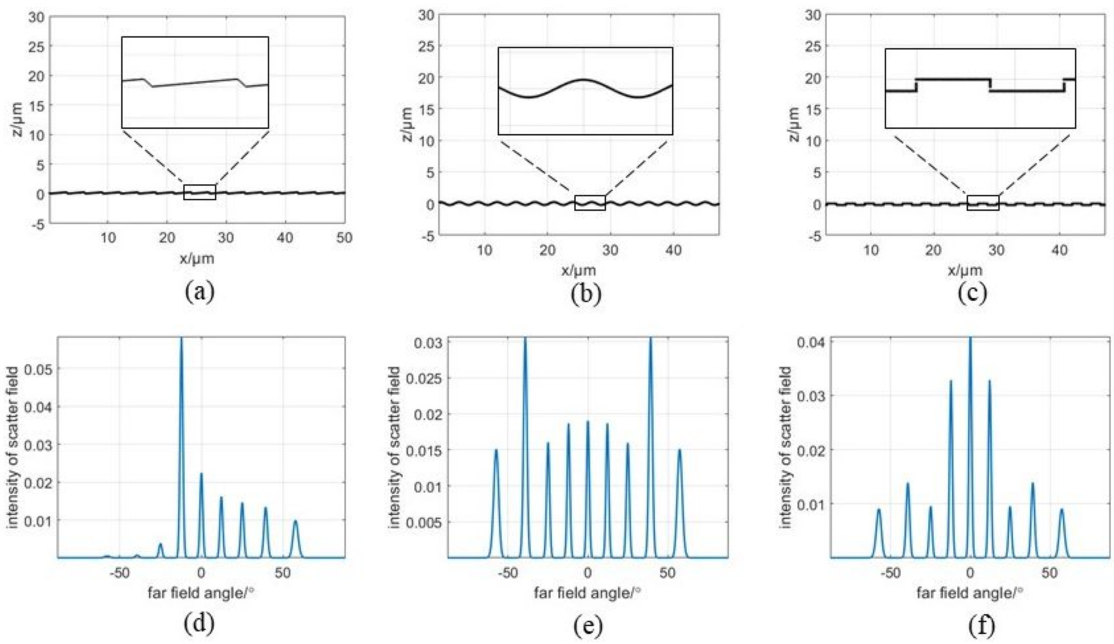


**Figure 2**. Typical profiles for (a) blaze grating, (b) sinusoidal grating, and (c) square grating, and simulated far field results for (d) blaze grating, (e) sinusoidal grating, and (f) square grating.

**Main References**


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