Classification of Spike Domains in Grain-Oriented Electrical Steel Using Neural Networks

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In soft magnetic materials, such as grain-oriented electrical steel (GOES), iron losses can be explained by changes in the magnetic domain structure. Here, the movement of 180° magnetic domain walls (180° DW) is an essential physical phenomenon, influencing the magnetic characteristics. Thus, quantifying the spacing between 180° DW is an important research objective of computerized analysis. The paper is focused on the problem to quantify corresponding numerical results of 2D Fourier analyses for distinction of Bloch walls of main domains and spike domains, respectively. We show that an automatic distinction is attained by applying artificial neural networks (ANN), as a representative deep learning technique.

Keywords: magnetic domains, grain-oriented electrical steel, deep learning

1. Introduction

In grain-oriented electrical steel (GOES), the domain structure is a critical physical feature influencing iron losses [1]. In particular, the spacing between 180° magnetic domain walls (180° DW) is closely related to iron losses, especially the eddy current loss, in GOES [1]. In previous studies [2,3], we attempted to quantitatively analyze the domain structures of GOES, using a 2D Fourier transform (2DFT). The method enabled quantitative evaluation of the spacing between 180° DW, which had traditionally been assessed visually. Generally, domain images of experimental Kerr effect or Faraday effect are of 2D type, represented as black or white strips, respectively. However, domain structures inherently possess 3D characteristics along the thickness of the steel. In fact, the previous 2DFT approach [2,3] could not distinguish clearly between distances between 180° DW and spike domains.

Taking advantage of artificial neural networks (ANN), as a deep learning technique, the present paper reports the development of a “Spike-identification ANN”. The program design was initially assisted by ChatGPT (OpenAI). The authors reviewed and modified the outputs to ensure correctness and suitability.

2. Methodology and result

For a 9 mm x 9 mm sample of GOES, Fig. 1 depicts two grains, that are separated by a grain boundary. We based the identification of wall types on a 2 mm x 2 mm large “moving window”. The upper window represents the case “mere main walls”, the lower one the case “existence of spike walls”. As a third type, “small supplementary domains” was defined, such as sub-structures of lancets.

For classification, we applied ANN as we have reported already in 1996 for the prediction of performance parameters of transformer cores [4]. Crossing point positions as pixels within a window were fed in, in order to by classified as one of the three mentioned types, including supplementary structures that cannot be processed so far.

Fig.2 depicts a result of classification for a total of about ten grains of GOES. Sub-regions that include spikes were identified after training of the ANN by more than 20,000 manually classified windows. The accuracy rate exceeded 80 %. However, the final aim of work is to identify spikes for both surfaces of the given sample of steel.

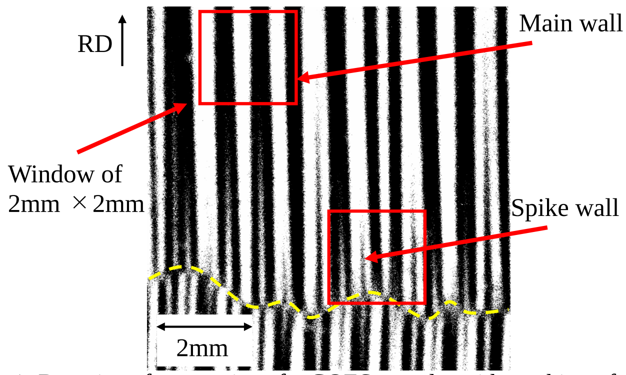

Fig.1 Domains of two grains of a GOES sample, with marking of two crossings with (not shown) detection grid of moving windows.

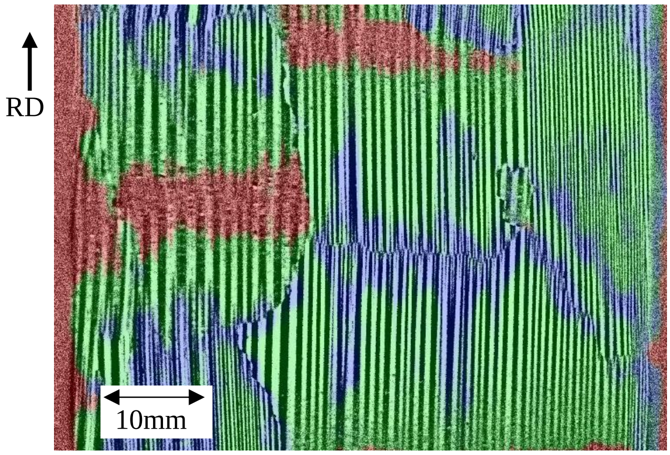

Fig.2 Result for about 10 grains, with marking of spike regions in blue.

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