Machine-learning enabled automatic classification of KSTAR ECE images

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A significant amount of data generated by high temperature plasma diagnostics is never analyzed in depth. While reasons for this fact are manifold, easier access to relevant measurements is a key enabler for better scientific study of fusion plasmas. The current state of identifying measurements relevant to a particular study requires human knowledge of the measurement corpus as well as human interpretation of measurements. That is, humans have to know where to look and how to identify relevant parts of the measurements. Being able to automatically query a database, only providing a semantic description of the required data could dramatically accelerate this workflow. In particular, measurements from fusion experiments need to be added continuously to this database. The sheer amount of this data is overwhelming makes manual labelling of new data unfeasible.

To start solving this problem, this work explores how unsupervised machine learning models can be used to classify a corpus of electron cyclotron emission imaging (ECEI) data from the KSTAR tokamak. A dataset consisting of prominent phenomena such as magnetic islands and sawtooth instabilities is collected and a set of unsupervised learning algorithms, various clustering algorithms as well as deep learning based methods [1] [2] [3], are used to cluster the data. The performance of the various algorithms on the dataset at hand is presented, highlighting particular issues of the various algorithms when applied to ECEI data

This work was supported by the R&D Programs of "KSTAR Experimental Collaboration and Fusion Plasma Research (EN2201-13)").

References

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