Medical image texture analysis through ordinal pattern-based bi-dimensional empirical mode decomposition and entropy measures associated with artificial intelligence

1. PhD thesis work

Entropy-based measures developed in the 1990s to quantify the irregularity of time series have evolved to become a powerful tool for analysing medical-based data. Notable advancements in this research include the development of sample entropy (Richman and Moorman, 2000), permutation entropy (Bandt and Pompe, 2002), fuzzy entropy (Chen et al., 2007), distribution entropy (Li et al., 2015), dispersion entropy (Rostaghi et al., 2016). Some of these measures have also been extended to the bidimensional case or even tridimensional case to analyze the texture of images or volumes (Humeau-Heurtier, 2019, 2022). All these measures have their advantages (e.g., low computational time) and drawbacks (e.g., lead to undefined values for short data). Among the existing entropy measures, permutation entropy has the advantage of being computationally fast and simple. It is based on ordinal patterns (Amigo et al., 2023): each sequence of *n* successive values of a given data is mapped into a permutation pattern that represents the rank order of the samples within the sequence. Then, the Shannon entropy is estimated using the relative frequency (probability of occurrence) of each permutation pattern (Bandt and Pompe, 2002). Ordinal patterns have an implicit connection with many signal processing methods such as the empirical mode decomposition (EMD) (Huang et al., 1998).
EMD – a widely recognized data-driven iterative algorithm – has been designed for the recursive decomposition of a time series into intrinsic mode functions (IMFs). IMFs are zero-mean oscillatory waveforms contained within the data that can be modulated in both amplitude and frequency. However, as EMD has no real theoretical foundations, the question of how it achieves spectral band separation is still under study. One of the very recent works has revisited EMD from the ordinal patterns point of view (Jabloun, 2022): EMD for time series has been reformulated using the concept of ordinal patterns. Moreover, the integration of the ordinal pattern probability distribution into the EMD algorithm has been proposed to enhance its robustness. Nevertheless, to the best of our knowledge, the extension of ordinal pattern-based EMD to multidimensional data has not been performed yet. However, bidimensional EMD (BEMD) is now commonly used and has shown interesting results in many areas: economics and finance, geophysics, information sciences, target detection, biomedical applications… (Chen et al., 2013; Qin et al., 2018; Xudong et al., 2020 ; Zhu et al., 2020; Riahi et al., 2022) to cite only a few. **The first research step** of the PhD thesis work will therefore be to extend this unidimensional ordinal pattern-based EMD to the bidimensional case.

The second step of the PhD thesis work will be based on texture analysis. Indeed, entropy methods can be considered as meaningful feature extraction techniques, based on the repeatability of samples (for time series) or pixels (for images). In the same way, improved versions of BEMD and bidimensional variational mode decomposition have shown good results for the analysis of texture, among others (Guanlei et al., 2009; An et al., 2015; Li et al., 2022). Moreover, BEMD with classification tools based on machine learning (ML) or associated with deep learning (DL) have led to interesting findings in the biomedical field: automatic mass classification of mammogram images (Nagarajan et al., 2019), skin melanoma detection (Cheong et al., 2021), infrared small target detection (Chen et al., 2014) or other applications (Acharya et al., 2018; Riahi et al., 2022; Sonti et al., 2022; Hasan et al., 2023). The research for the second step of the PhD will involve analysing biomedical images texture with the ordinal-pattern based BEMD and with the bidimensional entropy-based measures that we already developed. Comparisons will be performed, in terms of

classification results (healthy *vs.* pathological subjects). For the classification step, ML will be used. Moreover, our results will be compared with DL classification results obtained from the same datasets. For the biomedical images, we will used some of the many biomedical publicly available databases (Rai et al., 2024).

The PhD thesis work will be conducted both in Angers (France), in SETU and ATU (Ireland). The PhD student will spend his first and third years in Angers and his second year in Ireland.

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