Supplementary Study Between E2USD and FLOSS

1 Introduction

The objectives of this study are threefold. First, we aim to clarify the task differences between E2USD [Lai et al.(2024)] and FLOSS [Gharghabi et al.(2019)]. Second, we present the augmentation process for FLOSS to achieve Unsupervised State Detection (USD) for MTS, an implementation from [Wang et al.(2023a)]. Finally, we compare the performance of E2USD, augmented FLOSS, and the SOTA model TIME2STATE [Wang et al.(2023b)] on the USD datasets previously utilized in [Wang et al.(2023b), Lai et al.(2024)].

2 Task differences

Understanding the distinct tasks that E2USD and FLOSS are designed for is crucial. FLOSS primarily focuses on time series segmentation, identifying semantic segments within a time series by detecting boundary points [Gharghabi et al.(2019)]. However, it does not assign state indexes to these segments [Wang et al.(2023a)]. Conversely, E2USD extends beyond segmentation by automatically clustering segments and assigning state indexes. This fundamental difference indicates that while E2USD and FLOSS are engaged in related tasks, they are not entirely the same. To bridge this gap and enhance FLOSS with capabilities akin to those of E2USD, an augmentation has been developed to enable FLOSS to automatically assign state indexes to segments, as presented in [Wang et al.(2023a)].

Notably, in E2USD, we meticulously adhere to the experimental settings established by the SOTA USD model, TIME2STATE [Wang et al.(2023b)], to ensure fair comparisons. Additionally, as TIME2STATE has supplied supplementary materials for comparing TIME2STATE and FLOSS [Wang et al.(2023a)], we adhere to their established conventions to conduct our comparison between E2USD and FLOSS. We borrow the implementation codebase of the augmented FLOSS under the TIME2STATE's experimental settings from [Wang et al.(2023a)].

3 Augmentation of FLOSS

As detailed in the study comparing Time2State with FLOSS [Wang et al.(2023a)], the augmentation of FLOSS incorporates a clustering component, specifically the Time Series KMeans (TSKMeans) [Tavenard et al.(2020)], to allocate state indexes to each segment identified by FLOSS. Both Euclidean and Dynamic Time Warping (DTW) distance measures are employed within TSKMeans. Further experimental details, please refer to the supplementary materials of Time2State [Wang et al.(2023a)].

4 Performance Comparison

We evaluate the performance of E2Usd, augmented FLOSS, and Time2State using datasets used in [Wang et al.(2023b), Wang et al.(2023a), Lai et al.(2024)]. The performance results for Time2State are directly sourced from its original paper [Wang et al.(2023b)], while the results for augmented FLOSS are derived from the supplementary materials of Time2State [Wang et al.(2023a)]. Our comparison utilizes metrics such as the Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI), as shown in Figs. 1 and 2.

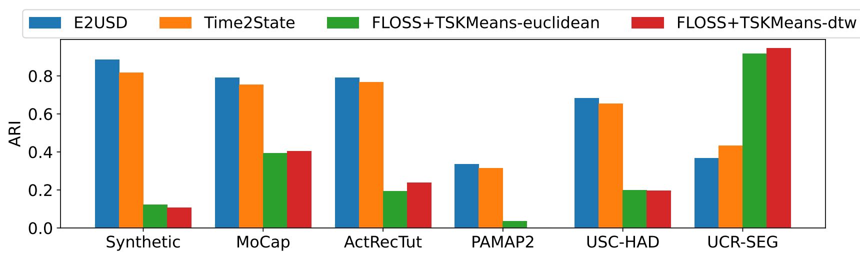

Fig. 1: Adjusted Rand Index Comparison

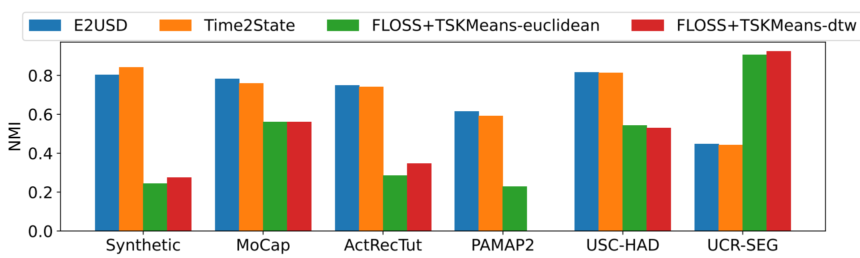

Fig. 2: Normalized Mutual Information Comparison

The results show that, E2Usd achieves the SOTA performance on five datasets: Synthetic[Wang et al.(2023b)], MoCap[Matsubara et al.(2014)], ActRecTut[Bulling et al.(2014)], PAMAP2[Reiss(2012)], and UscHad[Zhang et al.(2012)], outperforming both Time2State and the augmented FLOSS. However, on the UcrSeg dataset [Gharghabi et al.(2017)], the augmented FLOSS demonstrates superior performance, with Time2State and E2Usd ranking behind.

The authors of TIME2STATE, as elucidated in [Wang et al.(2023a)], attribute the augmented FLOSS's superior performance on the UcrSeg dataset to the dataset's distinctive characteristics. Specifically, the dataset is characterized by almost unique states, meaning that each state appears only once, without repetition within the time series. This uniqueness transforms the task of MTS state detection into one closely resembling MTS segmentation. Given that FLOSS was originally designed for MTS segmentation, it naturally excelled in this context, surpassing both TIME2STATE and E2USD.

5 Conclusion

This study clarifies the task differences between E2USD and FLOSS, presents the augmentation for FLOSS to achieve Unsupervised State Detection (USD) for MTS, and compares their performances on various USD datasets. Besides, we present the potential factors behind the enhanced performance of the augmented FLOSS on the UcrSeg dataset, as identified by the authors of TIME2STATE [Wang et al.(2023a)].

6 Acknowledgments

We extend our sincerest gratitude to the authors of TIME2STATE [Wang et al.(2023b)] and FLOSS [Gharghabi et al.(2019)] for making their codebases publicly available at [Wang et al.(2023a)], which served as an essential foundation for our comparative analysis. Additionally, we wish to express our appreciation to the authors of TIME2STATE for providing supplementary materials [Wang et al.(2023a)] that enabled a comprehensive comparison of time series state detection methods with time series segmentation approaches such as FLOSS.

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