Weighted Average of Human Motion Sequences for Improving Rehabilitation Assessment

9th Workshop on Advanced Analytics and Learning on Temporal Data (AALTD), ECML/PKDD 2024

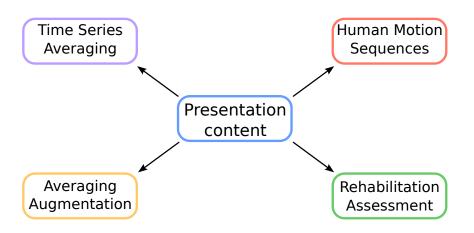
Ali Ismail-Fawaz¹, Maxime Devanne¹, Stefano Berretti², Jonathan Weber¹ and Germain Forestier^{1,3}

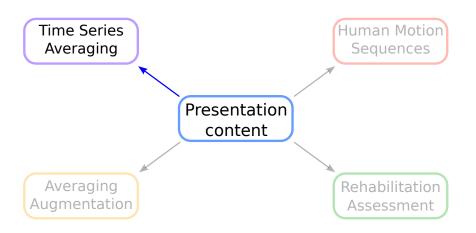
> ¹IRIMAS, Université Haute-Alsace, Mulhouse, France ²MICC, University of Florence, Florence, Italy ³DSAI, Monash University, Melbourne Australia

> > November 10, 2024



Presentation Content

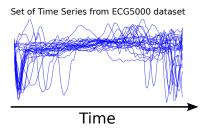




Time Series Averaging is a popular domain in machine learning, it can be used for: Time Series Clustering [1], Data Augmentation [2,3], Improving Nearest Neighbour classifier [4], etc.

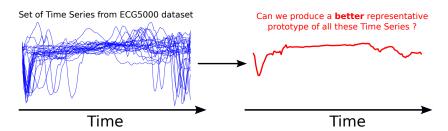
- [1] Petitjean, François et al. "A global averaging method for dynamic time warping, with applications to clustering."
 Pattern recognition 2011.
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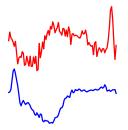
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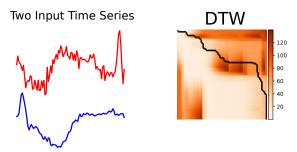


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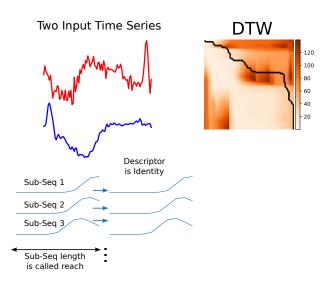
Two Input Time Series



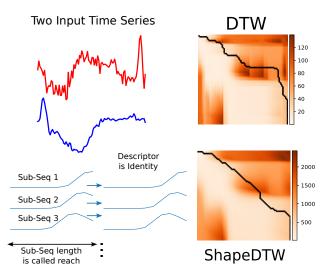
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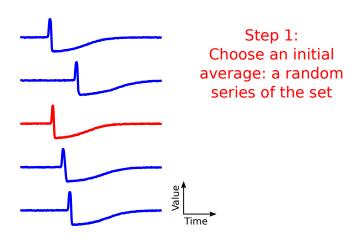
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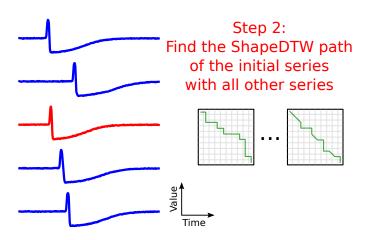
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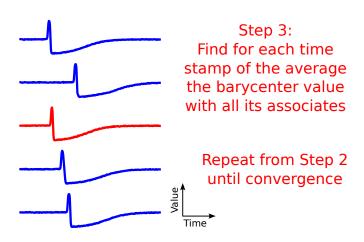
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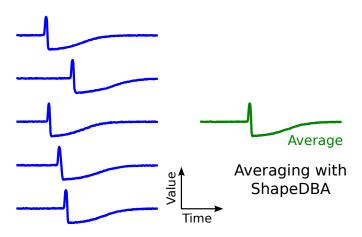
Sample taken from the Trace dataset.



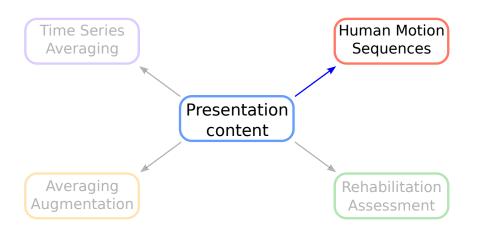
Sample taken from the Trace dataset.

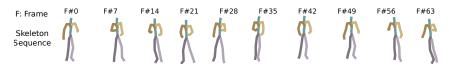


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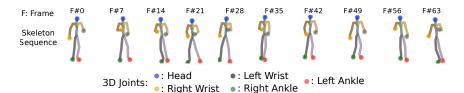


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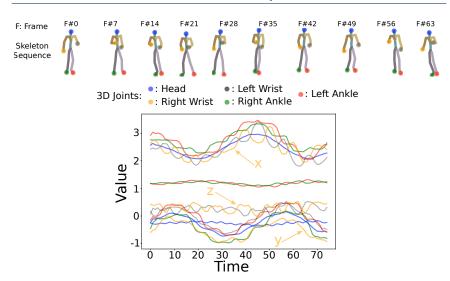


Sample taken from the HumanAct12 dataset



Sample taken from the HumanAct12 dataset

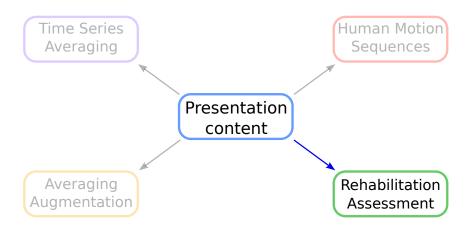
Guo, Chuan, et al. "Action2motion: Conditioned generation of 3d human motions." Proceedings of the 28th ACM International Conference on Multimedia 2020.



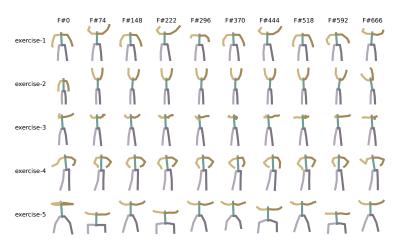
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Rehabilitation Assessment



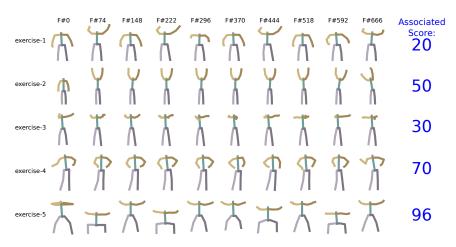
Patient's Recorded Exercises



Samples taken from the Kimore daataset

Capecci, Marianna, et al. "The kimore dataset: Kinematic assessment of movement and clinical scores for remote monitoring of physical rehabilitation." IEEE Transactions on Neural Systems and Rehabilitation Engineering 2019.

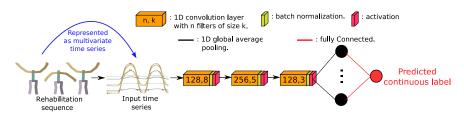
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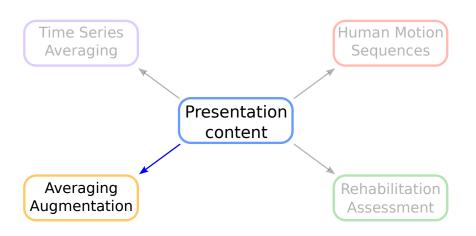
Deep Learning for Human Rehabilitation: An Extrinsic Regression Task



Used Architecture: Fully Convolutional Network.

Wang, Zhiguang, Weizhong Yan, and Tim Oates. "Time series classification from scratch with deep neural networks: A strong baseline." International joint conference on neural networks (IJCNN) 2017.

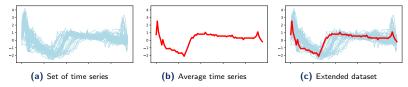
Averaging Augmentation



Averaging Augmentation to Create Synthetic Time Series

How to create synthetic time series?

- We averaged a set of time series and took the average as a new synthetic object
- We used weighted averages to generate multiple synthetic objects

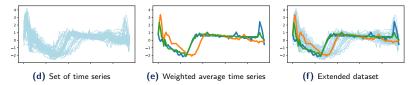


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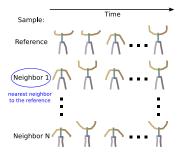
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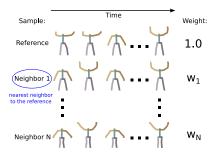


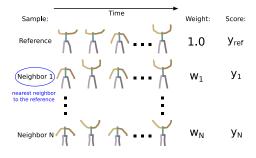
Samples taken from the ECG200 dataset.

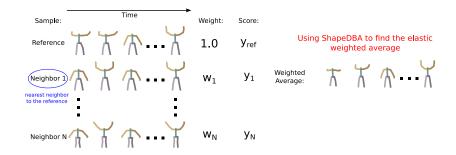
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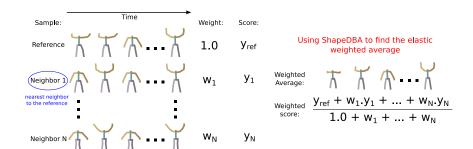




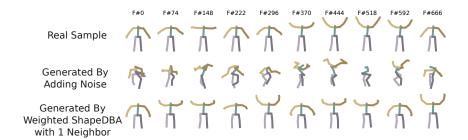




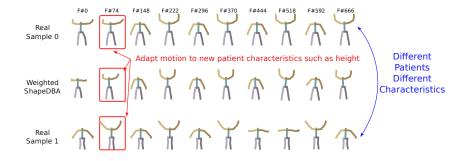




Qualitative Evaluation of Generation



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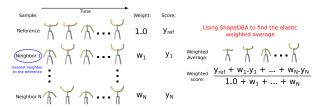


Quantitative Evaluation: Data Extension

- 1. We define five different train/test splits per exercise, using a cross subject setup
- 2. ShapeDBA augmentation: For each training sample, we generate one new sample using the reference sample and its N nearest neighbors ($N \in [1,5]$)
- 3. Noisy augmentation: For each training sample, we add a Gaussian white noise
- We perform six experiments training and evaluation is done over the same test set

Training Set	Exercise 1	Exercise 2	Exercise 3	Exercise 4	Exercise 5
MAE					
Ref.	0.206 ± 0.069	0.202 ± 0.037	0.204 ± 0.055	0.184 ± 0.068	0.224 ± 0.058
Ref. + Noise	0.186 ± 0.065	0.172 ± 0.040	0.203 ± 0.045	0.185 ± 0.073	0.229 ± 0.069
Ref. + ShapeDBA NN1	0.167 ± 0.070	0.175 ± 0.030	0.182 ± 0.051	0.141 ± 0.062	0.208 ± 0.079
Ref. + ShapeDBA NN2	0.169 ± 0.057	0.177 ± 0.041	0.194 ± 0.041	0.168 ± 0.056	0.226 ± 0.066
Ref. + ShapeDBA NN3	0.173 ± 0.063	0.183 ± 0.047	0.199 ± 0.058	0.168 ± 0.083	0.225 ± 0.055
Ref. + ShapeDBA NN4	0.168 ± 0.059	0.179 ± 0.043	0.199 ± 0.043	0.180 ± 0.080	0.231 ± 0.060
Ref. + ShapeDBA NN5	0.166 ± 0.067	0.185 ± 0.043	0.201 ± 0.050	0.182 ± 0.089	0.226 ± 0.061
RMSE					
Ref.	0.251 ± 0.083	0.247 ± 0.045	0.248 ± 0.065	0.230 ± 0.083	0.267 ± 0.073
Ref. + Noise	0.203 ± 0.078	0.226 ± 0.043	0.238 ± 0.046	0.227 ± 0.090	0.274 ± 0.092
Ref. + ShapeDBA NN1	0.199 ± 0.087	0.226 ± 0.036	0.214 ± 0.054	0.178 ± 0.074	0.251 ± 0.094
Ref. + ShapeDBA NN2	0.203 ± 0.075	0.232 ± 0.052	0.226 ± 0.044	0.210 ± 0.074	0.268 ± 0.083
Ref. + ShapeDBA NN3	0.205 ± 0.082	0.235 ± 0.050	0.240 ± 0.062	0.214 ± 0.105	0.268 ± 0.066
Ref. + ShapeDBA NN4	0.198 ± 0.071	0.235 ± 0.050	0.234 ± 0.048	0.230 ± 0.105	0.279 ± 0.070
Ref. + ShapeDBA NN5	0.202 ± 0.079	0.230 ± 0.049	0.244 ± 0.057	0.231 ± 0.109	0.280 ± 0.080
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Take Away Message



- Paper titled "Weighted Average of Human Motion Sequences for Improving Rehabilitation Assessment"
- Data augmentation / Generation of synthetic temporal data is still an evolving domain, and it should depend on the application such as the case of human motion rehabilitation
- Weighted ShapeDBA allows the association of a contribution value for each sample when producing the average sequence
- We believe in reproducibility https://github.com/MSD-IRIMAS/Weighted-ShapeDBA-4-Rehab
- Contact: ali-el-hadi.ismail-fawaz@uha.fr
- Website: https://hadifawaz1999.github.io/