DynImp: Dynamic Imputation for Wearable Sensing Data Through Sensory and Temporal Relatedness

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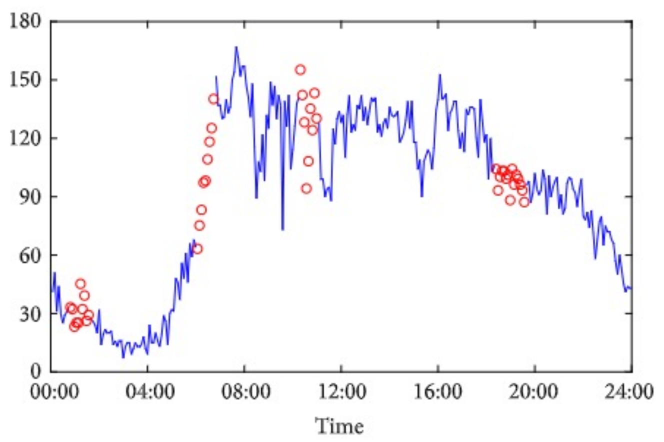
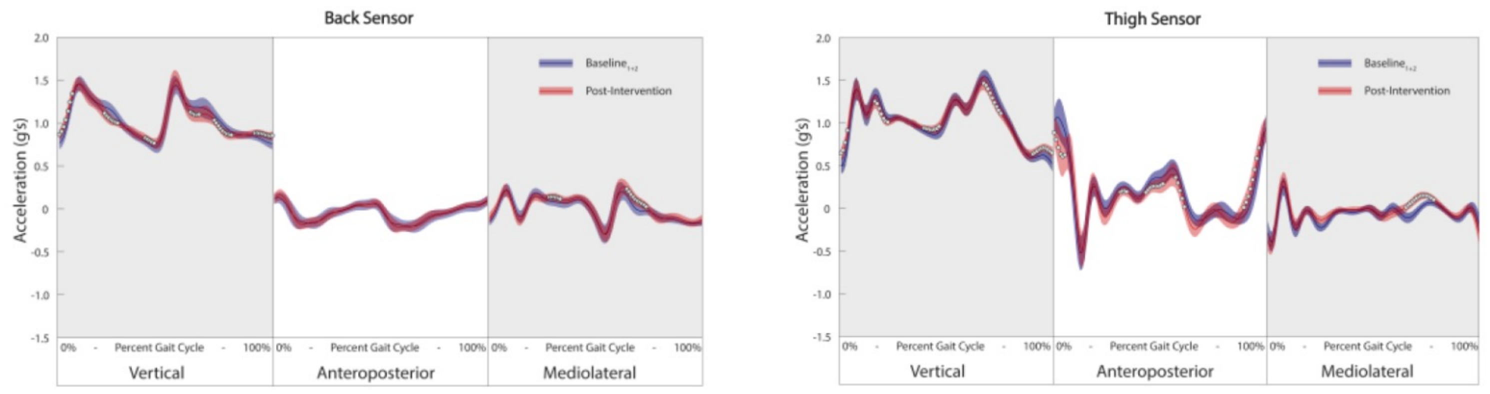
Introduction

In wearable sensing applications, data is inevitable to be irregularly sampled or partially missing, which pose challenges for any downstream application.



An unique aspect of wearable data is that it is time-series data and each channel can be correlated to another one, such as x, y, z axis of accelerometer.



We argue that traditional methods have rarely made use of both times-series dynamics of the data as well as the relatedness of the features from different sensors. We propose a model, termed as **DynImp**, to handle different time point's missingness with nearest neighbors along feature axis and then feeding the data into a LSTM-based denoising autoencoder which can reconstruct missingness along the time axis.

Methodology

- Denoising LSTM-based Autoencoder has two parts, where first it will encode the input to an encoded space and the decoder will reconstruct it back to the original signal.

$$\theta^*, \theta'^* = \mathrm{argmin}_{\theta^*, \theta'^*} \frac{1}{n} \Sigma\, L\left(x^{(i)}, z^{(i)}\right)$$
$$= \mathrm{argmin}_{\theta^*, \theta'^*} \frac{1}{n} \Sigma\, L\left(x^{(i)}, g_{\theta'}\left(f_\theta\left(x^{(i)}\right)\right)\right)$$

- where θ^* and θ'^* are the encoder and decoder's parameters
- Padding in a KNN format can help to recover the nearest neighbors' feature space, where we have the hidden layer's function:

$$h\left(x^{(i)}\right) = g\left[W' \cdot \left(\left(M^t \odot x^{(i)}\right) + P\right) + b\right]$$

- where the M^t is our masking matrix that and P is our padding matrix

$$M^t = 1_{(m,l)} \begin{cases} 0 & if\ i = m, t = l \\ 1 & otherwise \end{cases}$$

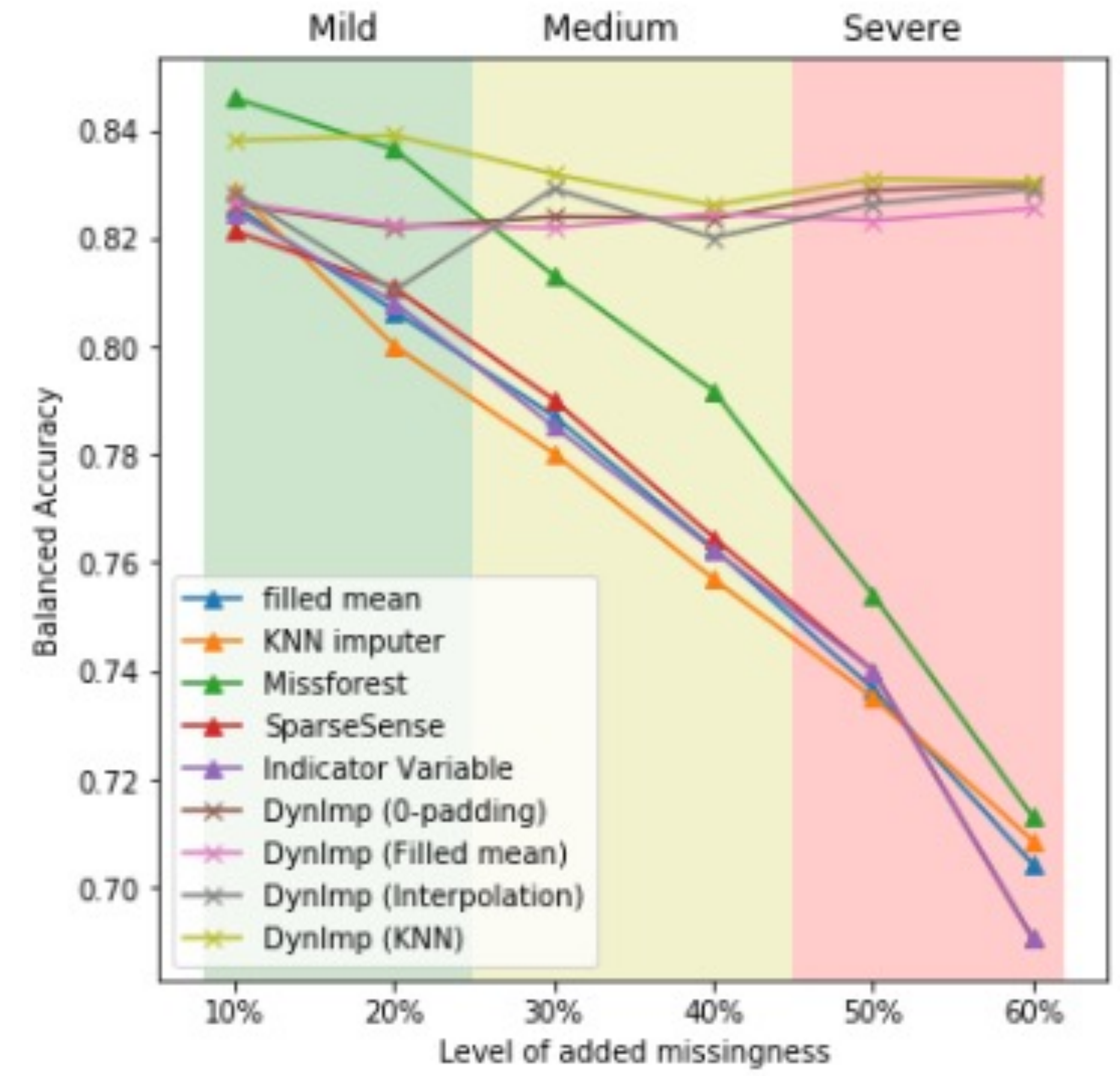
- where m and l are the indicator indices of the masking matrix at i-th data entry at t-th time point

$$P^t = \begin{cases} \frac{\Sigma_j x^{(j)}}{k} & if\ j\ in\ top\ k\ neighbors\ of\ i, \\ 0 & otherwise \end{cases}$$

- where i is index of interest and j is selected if it's in top k neighbors of i

Prediction Results

- We experiment the model on the extreme missingness scenario (> 50% missing rate) which has not been widely tested in wearable data.
- We incorporated strong baselines that include both traditional methods as well as deep model
- Our experiments on activity recognition (UCSD ExtraSensory dataset) show that the method can exploit the multi-modality features from related sensors and also learn from history time-series dynamics to reconstruct the data under extreme missingness, and thus outperforms the baselines



Model pipeline

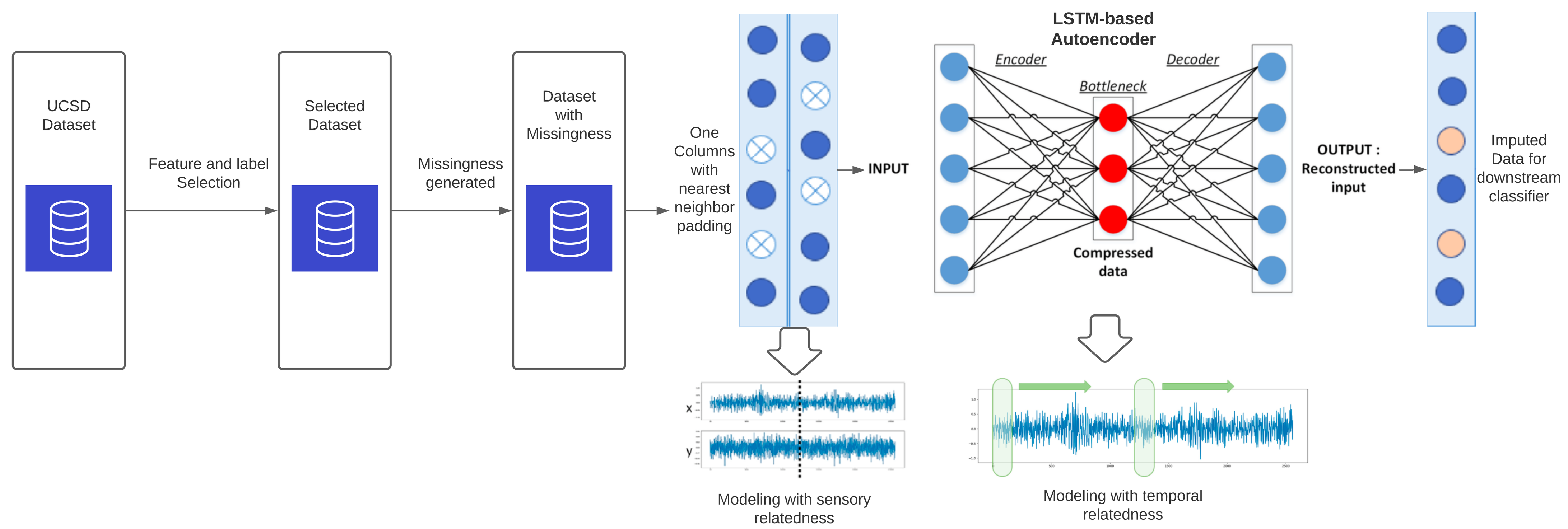


Fig. 1. The model pipeline is shown to the left, which is to use feature axis and time axis relatedness for modeling. The KNN-padding will find the close the features in the Euclidean space and LSTM-based Autoencoder will model the temporal relatedness to reconstruct the missingness.

Conclusion

we proposed a dynamic imputation technique for remote sensing data. The method is through a trainable mechanism by the use of deep learning model to learn the missing dynamics along the time axis to impute the missing data. The model shows strong performance compared to baselines.

Acknowledgement

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