Influencing Factors Mining and Modeling of Energy Expenditure in Running Based on Wearable Sensors

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Introduction

Background:

- Running is one of the most popular and widely participated sports worldwide.
- Researching real-time and accurate Energy Expenditure (EE) assessment methods plays a crucial role for athletes.
- Deep learning models struggle to explain feature usage.

Data Collection:

- Indirect calorimetry: EE.
- Motion data: multi-IMU.
- Physiological data: ECG.

Table 1: Demographic information.

Statistical characteristic	Value
Number of subjects	34 (22 M / 12 F)
Age (years)	29.32 ± 7.20
Height (cm)	170.53 ± 9.17
Weight (kg)	64.59 ± 12.11
BMI (kg/m^2)	22.04 ± 2.49
Waistline (cm)	77.75 ± 9.02
BMR (kcal/day)	1570.61 ± 239.25

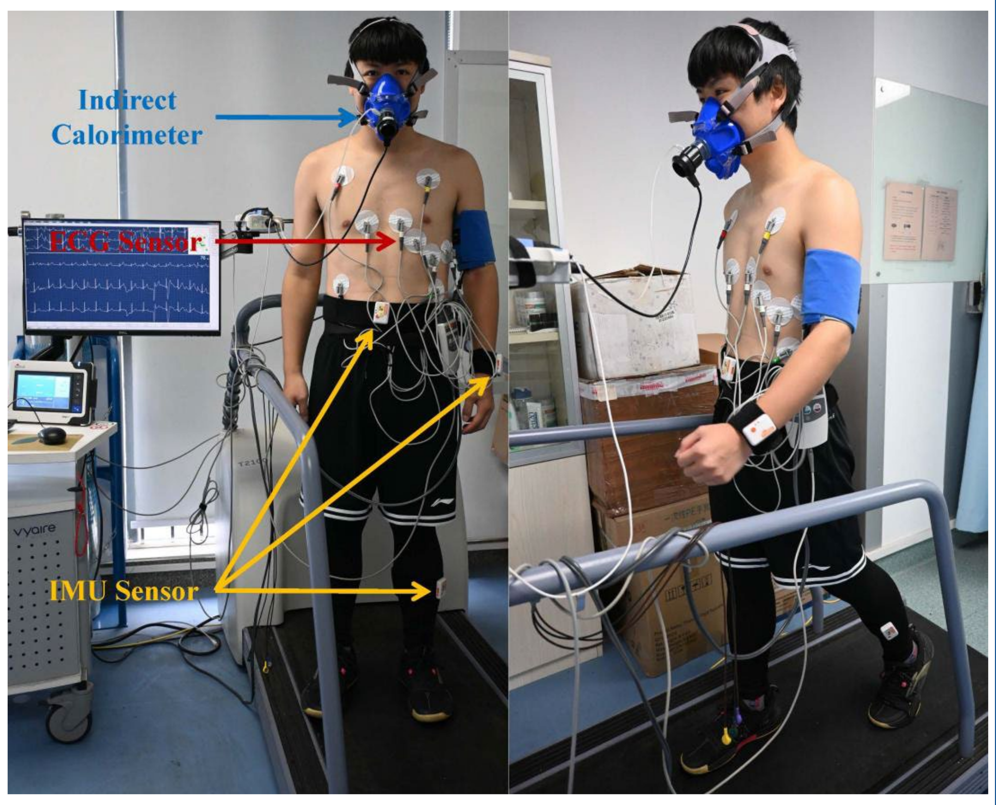

Figure 1: Experimental data collection scenarios.

EE-related Factors Analysis

Framework:

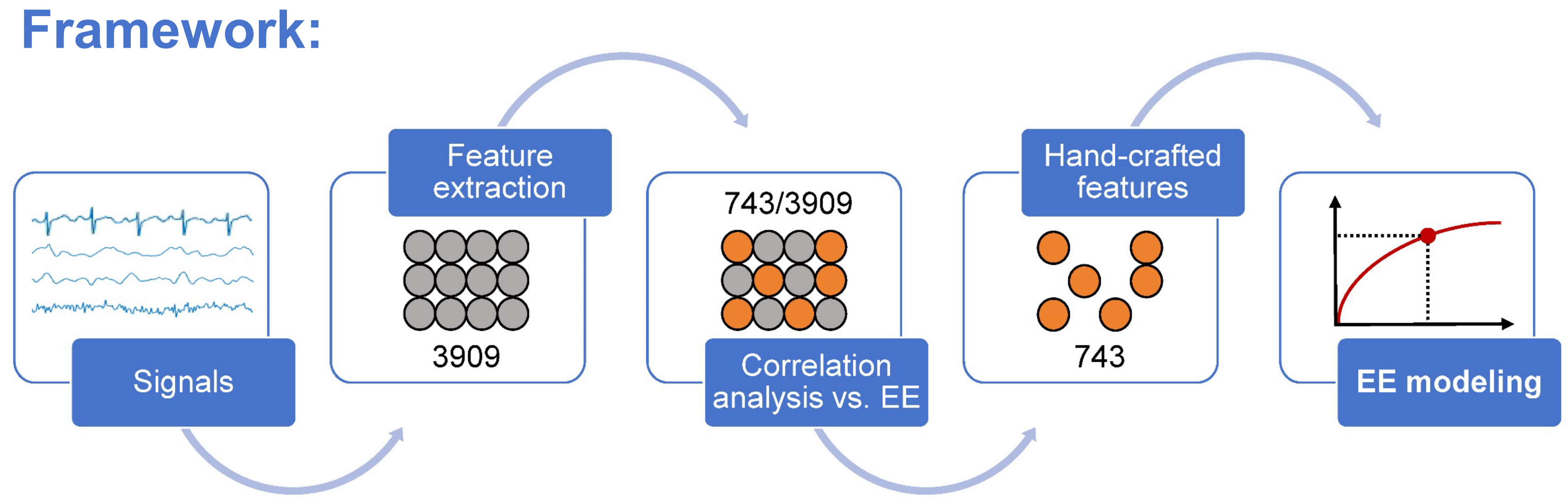

Figure 2: The framework of our work.

Pearson's correlation Analysis:

- Except for age, the remaining six demographic metrics were significantly correlated with EE.
- Use TSFEL library to extract 3909 features (7 demographic features + 156 motion features × 8 channels × 3 IMUs + 158 physiological features).
- Use Pearson's correlation analysis to select 743 features significantly correlated with EE (6 demographic features + 708 motion features + 29 physiological features).

Energy Expenditure Modeling

Experimental Results:

Table 2: Experimental results of energy expenditure regression.

Year	Method	Data	CC	RMSE	MAE
2015	MC-DCNN [20]	DI+IMU+HR	0.899 ± 0.040	3.370 ± 0.369	2.859 ± 0.334
2021	DenseNet-GRU [21]	IMU	0.673 ± 0.088	8.071 ± 0.578	6.935 ± 0.528
2022	DMTRN [22]	DI+IMU+ECG	0.909 ± 0.356	3.165 ± 1.125	2.382 ± 0.916
2022	LightGBM [23]	HRV	0.812 ± 0.047	2.519 ± 0.190	1.890 ± 0.142
Our	LR	Hand-crafted	0.814 ± 0.098	2.723 ± 0.594	1.920 ± 0.350
Our	DT	Hand-crafted	0.928 ± 0.026	1.575 ± 0.245	1.163 ± 0.178
Our	KNN	Hand-crafted	0.880 ± 0.038	2.219 ± 0.321	1.646 ± 0.283
Our	RF	Hand-crafted	0.957 ± 0.024	1.207 ± 0.265	0.869 ± 0.206
Our	SVR	Hand-crafted	0.893 ± 0.044	2.012 ± 0.374	1.524 ± 0.325
Our	GBR	Hand-crafted	**0.970 ± 0.017**	**1.004 ± 0.240**	**0.729 ± 0.179**

EE Prediction :

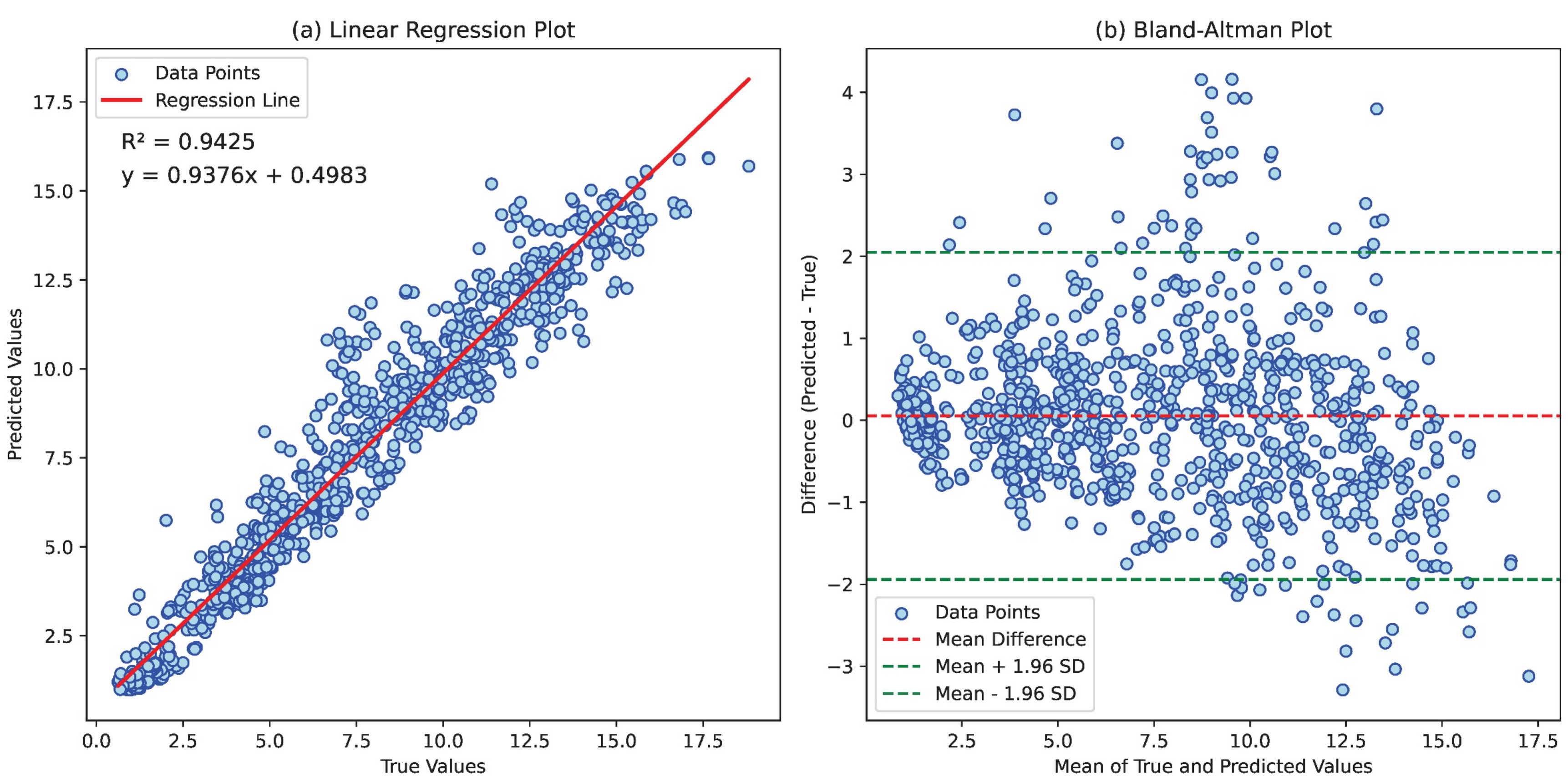

Figure 3: EE prediction performance: (a) linear regression plot, (b) Bland-Altman plot.

Individual Tracking:

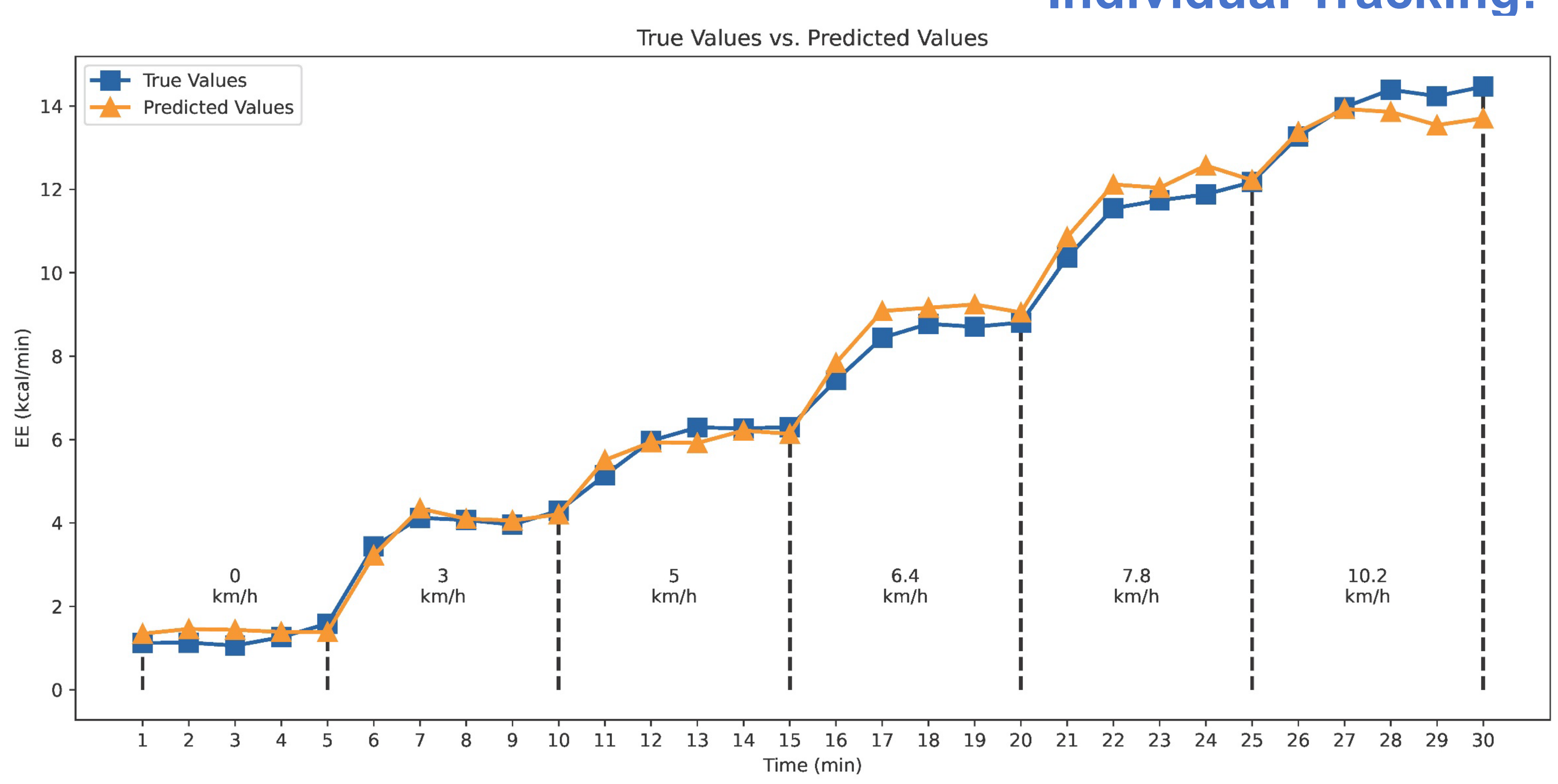

Figure 4: Tracking performance of hand-crafted features in EE regression.

Conclusion

- We analyzed the correlation of multi-dimensional features, including demographics, motion, and physiological metrics, with EE in running sports.
- We proposed a hand-crafted feature selection method and selected 743 relevant features for modeling the EE of running.
- We found that motion metrics make a greater contribution to the EE computational model than physiological metrics.

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