

Sweat Loss Estimation Solution for Smartwatch

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Abstract— This study aimed to develop the new fitness function for wearable devices, namely – Sweat loss estimation during running activity. Machine learning model (polynomial Kernel Ridge Regression) was trained and validated with large and diverse dataset. Totally 568 human subjects participated in 748 running tests. Sweat loss contributing factors such as users' anthropometric parameters, distance, ambient temperature and humidity were distributed in the wide range of values. The performance of fully automatic sweat loss estimation algorithm provides average root mean square error (RMSE) = 236 ml; more important health-related parameter body weight percentage RMSE (RMSEBWP) = 0.33% and coefficient of determination (R^2) = 0.79. To the authors' knowledge the algorithm provides the highest performance among existing solutions or ever described in literature.

Keywords—sweat loss estimation, running, fitness, wearables, wrist-wearable device, smartwatch, sensors, IMU, PPG, skin temperature.

I. INTRODUCTION

Maintaining a proper body hydration is an important aspect of healthy lifestyle. Knowing personal physiological requirement of water intake amount for sweat losses replacement could be critical for instances of intensive physical exercises (such as long-distance running). Dehydration (lack of drinking) poses a risk of impaired thermoregulation and thus could lead to heat exhaustion or heat stroke [1]. Overhydration (excessive drinking) in rare cases can lead to hyponatremia [1]. Thirst is not an accurate indicator and stimulus for proper fluid consumption, the most of guidelines include detailed recommendations for ideal fluid intake practices based on approximate estimates of sweat losses that will be incurred [1].

So sweat loss estimation may be essential for individuals interested in maintaining optimal physical performance and minimizing the health risks associated with sports and fitness activities (at professional and amateur level). Individual armed with information about sweat losses during physical exercise can effectively plan water intake before (prehydration), during and after the physical activity (rehydration).

The most straightforward method to measure sweat losses is calculating difference between baseline individual's body weight (BW) before and after some physical activity (nude weight with carefully towed off sweat) [2]. Although BW method is commonly used as a reference for research studies, it is impractical for individuals in real life at sports and fitness activities.

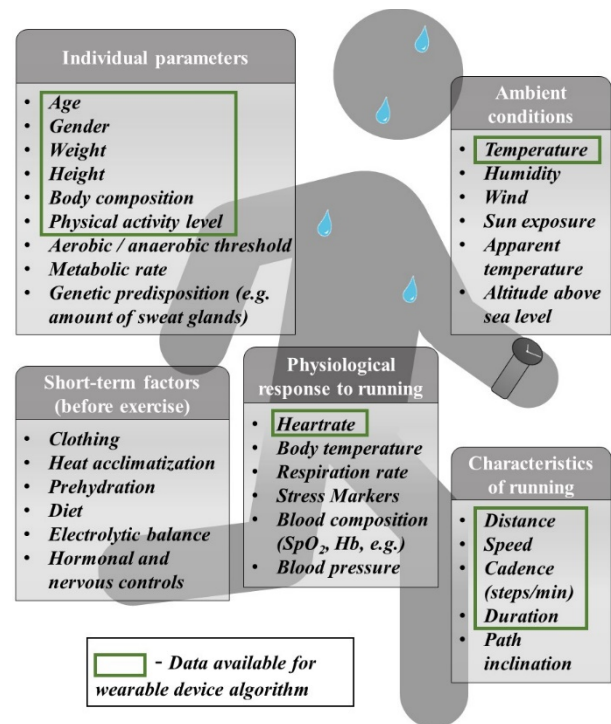


Figure 1. Factors influencing on runner's sweat loss amount conditionally grouped by the origin. Rectangles mark the factors currently available for analysis with wearable devices (a part of them are used by the reported algorithm).

A number of studies are devoted to adopting direct sweat loss measurement sensors for wearable devices in the form of: absorbent patches, filter paper, glass capillaries and microfluidic collectors [3]. These methods involve disposable parts or require periodic maintenance by qualified researcher and thus inapplicable for wearables mass product. For the

same reason urine specific gravity and other medical tests are out of our research scope.

Our study was aimed to develop a method of indirect sweat loss estimation during running activity by using of data available from existing wearable sensors and general user information.

Multiple factors influencing sweating during the running exercise are specified in Fig. 1. It is shown that only a part of factors (marked with rectangles) can be used for wearable health services (without manual input from user at every exercise).

Although a detailed information about ambient conditions could be available for wearables at outdoor running case (e.g. from local online weather forecast), we've intentionally excluded the most of ambient factors in order to describe unified solution for all the cases (outdoor and indoor, with or without internet connection).

Obviously, an uncertainty about all the ambient conditions, user's clothes, physical and functional status before and during running leads to the limited performance of indirect method under inquiry. The following key components of the study were carried out in order to reduce the sweat loss estimation error:

- 1) *Collecting a dataset with a variety of external conditions and user parameters*
- 2) *Data augmentation for dataset expansion*
- 3) *ML algorithm for sweat loss estimation*

These components are described below in separate sections II and III. The results (section IV) confirms high prediction performance of the algorithm suitable for wearable devices to provide valuable information for the users. Conclusions and further research directions are presented in the section V.

II. COLLECTING A DATASET

A total of 568 human subjects (age 18-53 years) participated in a total of 748 running trials (distances 2-20 km, both indoor and outdoor). A special test rooms with treadmills and controlled environmental conditions (ambient temperature range 10-40 °C and relative humidity range 25-75 %) were prepared for indoor running trials. More information about subjects' characteristics and ambient conditions can be found in Table I. All subjects were capable of running distances under the specific environmental conditions (preliminary agreed). Subjects admission to the tests and control of subject's condition during running was supervised by a medical doctor.

Two remote testing sites were chosen for dataset collection. The most part of data (549 running trials) was collected with Eastern Asian subjects (South Korea, Kookmin University). The smaller part of data (199 running trials) was collected with Eastern European subjects (Russian Federation, Institute of Biomedical Problems). The purpose of testing sites diversification was validation of methods with inter-ethnic data collected with different conditions, equipment and researchers in order to minimize risk of bias between algorithm performance for train data and any other data (including real-life conditions).

The data collection protocol was reviewed and approved by the Commission on Biomedical Ethics at the Institute of Biomedical Problems of the Russian Academy of Sciences

TABLE I. MAIN VALUES CHARACTERIZING POPULATION SAMPLING AND CONDITIONS USED FOR ALGORITHM TRAINING AND VALIDATION

Parameter	Weight, kg			
	42-59	60-72	73-84	85-123
<i>Men</i>				
<i>N subjects</i>	22	103	61	101
<i>N running trials</i>	29	103	83	160
<i>Age, yr</i>	30±6	28±6	30±7	30±6
<i>Height, cm</i>	167±4	173±4	179±5	182±6
<i>Steps, min⁻¹</i>	172±14	160±12	159±12	146±16
<i>Heartrate, min⁻¹</i>	157±11	153±15	149±14	148±15
<i>Amb. temp., °C</i>	25±3	24±8	25±7	23±8
<i>Amb. r.h., %</i>	46±10	44±17	44±15	44±16
<i>Women</i>				
<i>N subjects</i>	175	89	16	1
<i>N trails</i>	189	135	38	11
<i>Age, yr</i>	29±8	31±10	32±7	36±0
<i>Height, cm</i>	162±5	169±6	174±4	169±0
<i>Steps, min⁻¹</i>	157±15	144±18	149±16	151±3
<i>Heartrate, min⁻¹</i>	153±16	153±12	157±10	166±4
<i>Amb. temp., °C</i>	24±6	23±7	22±7	21±9
<i>Amb. r.h., %</i>	38±14	40±15	42±6	25±0

(Protocol No 0251 of March 1, 2020) and by the Institutional Review Board (IRB) of Kookmin University (IRB registration number KMU-202101-HR-253 of February 15, 2021). Before the participation, all subjects received detailed explanation of the clinical tests and signed the informed consents. The data was kept anonymized and it was used only for the intended research purpose.



Figure 2. Subject's sequence of actions during data collection with running distances < 10 km; for longer distances (≥ 10 km) subject stops running at the middle of distance for additional body weighing, so the sequence is 1-2-3-4-5-3-4-5.

According to the protocol each subject was examined by the medical staff to measure anthropometric parameters (including height) and to survey about general information (age, gender, medical history, exercise habits and current medication). After the screening, subjects were asked to put on the smartwatch device on the left wrist and do the following actions (see Fig. 2): rest (seating) for 20 minutes in a room with normal temperature (about 23°C); perform the 1st nude body weighing with precise CAS-HB-150 (South Korea) scales; run a distance with predefined conditions.

If the trial distance is shorter than 10 km, then the subject runs the whole distance at one go; carefully towels off sweat; performs the 2nd nude body weighing and completes the test. In this case, sweat loss reference is defined as the difference between the 1st and the 2nd body weights, excluding water intake. If the trial distance is equal or longer than 10 km, then the subject stops running in the middle of the distance; performs the 2nd nude body weighing; changes into dry clothes; runs the second half of the distance; carefully towels off sweat; performs the 3rd nude body weighing and completes the test. In this case, there are two sweat loss references: for the half of distance (difference between the 1st and the 2nd body weights, excluding water intake) and for the

whole distance (difference between the 1st and the 3rd body weights, excluding water intake). In the second case, half-distance and whole-distance trials were considered as two samples in the dataset.

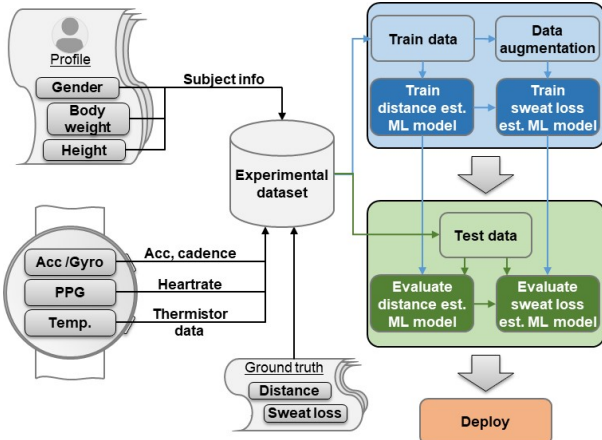


Figure 3. Data processing pipeline of sweat loss algorithm training and testing. Sweat loss ML model requires general subject's information, IMU, PPG and temperature data.

A smartwatch Galaxy Watch Active 2 (Samsung, South Korea) model was used for data collection. This smartwatch includes a set of sensors commonly used in modern wearable devices: photoplethysmography (PPG used for heartrate measurement), inertial measurement unit (IMU including three-axis accelerometer and three-axis gyroscope) and internal thermistors (commonly used for monitoring of components temperature). Smartwatch devices were sufficiently tightly fixed on the wrist (not too tight, not too loose) during the running, providing convenient wearing for a subject and correct operation of sensors to obtain a high signals quality.

Besides the raw sensors signals the dataset contains processed values of heartrate from PPG and running cadence (steps/min) from IMU. The whole data processing pipeline is presented in Fig. 3.

III. DATA AUGMENTATION FOR DATASET EXPANSION

Data augmentation procedure was implemented in order to expand the dataset and make it more diverse in distances. The protocol of clinical tests was limited to obtain only one reference value (targets) of sweat loss in the end (or in the middle) of running trial. A technique described in this section allows to obtain reference values of sweat loss for any segment of running trial, thus increasing a number of samples to train the sweat loss estimation ML model.

Augmentation procedure consists of two steps: first – training a model for aggregated output regression, second – augmentation of training dataset with reference target normalization. Aggregated output regression is a task, where label associated with a set of observation in a region. Suppose we have some covariate space X and a response space R . The aggregated output regression model [4] is defined as (1):

$$\int_X f(x) d\Pi_i(x) + \xi_i, \quad (1)$$

where $X_i \subseteq X$ is an observation region with distribution Π_i with Lebesgue density π_i and ξ_i is an independently distributed Gaussian noise with $\sigma > 0$. Multilayer perceptron (MLP) is used for aggregated output regression (see Fig. 4). We use batch normalization right after input, ReLU is used as dense layer activation function. This model approximates target conditional distribution $P(y|f)$ – where f is our set of features. This vector contains the same statistical values as in sweat loss estimation model, calculated for small segments of a trial (1-minute-long). Estimation of a sweat loss for each segment is calculated after forward pass through the neural network. The sum of estimations for all segments of a workout gives the estimation of total sweat loss. Differences between these aggregated estimations and ground truth targets for workouts were used to calculate MSE loss function for error backpropagation.

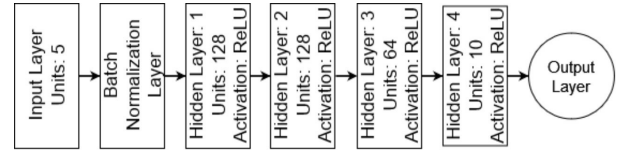


Figure 4. Multilayer perceptron used for aggregated output regression. It allows to estimate sweat loss targets for short (1 km) running segments for further training of ML model.

After MLP is trained, the dataset is augmented by splitting the whole running trials into segments of approximately 1 kilometer-long. We've also experimented with other length of segments (2, 3, 4 km), however we've found that 1 km augmentation gives the best performance. MLP estimations are normalized for each running trial as follows:

$$y_{new} = \frac{\hat{y} * y}{\sum_{i=0}^n \hat{y}_i}, \quad (2)$$

where \hat{y}_i – vector of estimated sweat loss targets for each of 1 km segments.

Data augmentation allowed to expand dataset from 748 to 6296 running samples (including whole running trials and their segments). The technique described in this section helped us to improve sweat loss estimation algorithm performance (especially at short running distances < 5 km) for both train and test data.

IV. ML ALGORITHM FOR SWEAT LOSS ESTIMATION

The amount of data (even with augmentation) has appeared to be insufficient for deep learning architectures implementations. The best estimation performance was achieved with feature-based kernel ridge regression model [5] with polynomial kernel:

$$k(x_i, y_j) = (1 + \sum_{k=1}^d x_{i,k} y_{j,k})^m, \quad (3)$$

where d is a size of feature vector.

The solution of Kernel ridge regression model has the following form:

$$f(x) = \sum_{n=1}^N \alpha_i k(x, x_i), \quad (4)$$

where N - is a size of training set.

Input feature vector contains a set of features, calculated from each running sample (whole trials and segments): *maximum heartrate, average cadence (steps/min), average thermistor temperature, user's gender, distance run * user's weight * average thermistor temperature.*

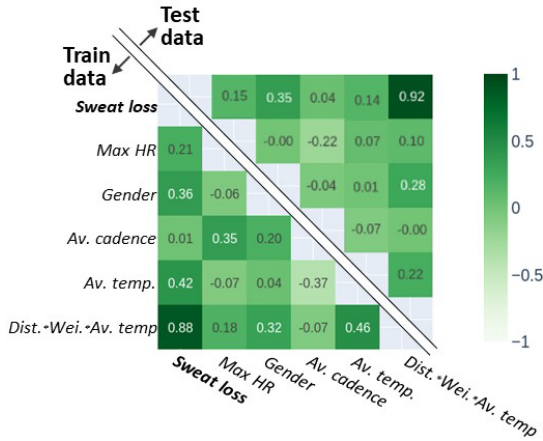


Figure 5. Correlation analysis between features and target of the Sweat loss estimation ML model. High correlation between target ‘Sweat loss’ and multiplicative feature ‘Dist.*Wei.*Av. temp’ can be observed.

The last multiplicative feature was found through a deep data analysis (it can be associated with work done by runner under the certain temperature conditions). Correlation plot between those features and target is shown in Figure 5. We have found that multiplicative feature has the best correlation with target. Each feature is linearly transformed to range from 0 to 1.

Regularization parameter and parameters of kernel (3) were selected by optimization of RMSE error calculated using cross-validation with the training part of dataset. Implementation, provided by Optuna framework [6], was used to perform hyper parameters tuning. Tree parzen estimator model was selected as surrogate model.

Performance of the ML model trained with and without data augmentation technique is presented in Table II. Ridge regression model with polynomial kernel was trained on a training data split and evaluated on both train (cross-validation) and test data splits. Model that was trained using augmentation technique outperforms model with no augmentation at all performance metrics.

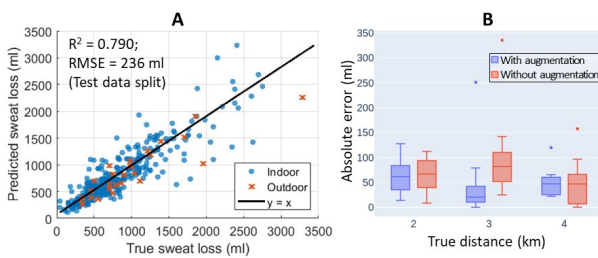


Figure 6. (A) – Scatter plot of predicted versus true sweat loss for the model trained with augmentation. (B) – Comparative boxplot of absolute sweat error for models trained with and without augmentation.

An important health-related parameter is body weight percentage of sweat loss. A number of sport medicine publications [1, 2] states that 2% of body mass water loss with sweat can be harmful for a human with some changes on mental performance and endurance. Our ML model provides low RMSEBWP error (<0.4%), thus it can reliably inform user about upcoming dehydration threat.

TABLE II. PERFORMANCE OF SWEAT LOSS ESTIMATION ML MODEL

Data splits (number of trials)	Parameters of regression performance			
	MAE, ml	RMSE, ml	RMSEBWP, %	R ²
Model trained only with whole running trials				
Cross-val (332)	198	289	0.377	0.744
Test (416)	156	237	0.330	0.788
Model trained with augmented running samples (trials and segments)				
Cross-val (332)	193	286	0.374	0.750
Test (416)	152	236	0.330	0.790

MAE – mean absolute error

RMSE – root mean square error

R² – coefficient of determination

RMSEBWP – body weight percentage RMSE

$RMSEBWP = 100 \cdot \sqrt{\frac{1}{N} \cdot \sum_{i=1}^N \left(\frac{y_i - \hat{y}_i}{BW_i} \right)^2}$, where N – number of trials in a data split, y_i – predicted sweat loss (ml), \hat{y}_i – true sweat loss (ml), BW_i – body weight (g).

Figure 6A shows concordance between sweat loss predicted by the ML model and ground truth values (from changes of body weighting). Only a few data samples have high sweat loss error (up to 1000 ml), for the most of cases predictions are well correlated with true sweat loss. Figure 6B illustrates that augmentation is especially beneficial at short running distances, e.g. at 3 and 4 km.

V. CONCLUSIONS

The described method of sweat loss estimation is based on sensors that are currently available in the most smartwatches and fitness trackers. Although we used indirect estimation (no direct measurements of sweat amount) the approach showed a high performance.

It was shown that multiple factors influence sweating during the running exercise and only a part of factors can be used for smartwatch algorithm. A set of measures to overcome an uncertainty of unknown factors were implemented: dataset with a variety of external conditions and user parameters, improved running distance estimation, data augmentation technique and sweat loss ML model optimization.

The essence of the proposed algorithm is the top performance among existing solutions or ever described in literature in the area of smartwatch-based fully automatic sweat loss estimation (to the authors' knowledge).

REFERENCES

- [1] M. N. Sawka, L. M. Burke, E. R. Eichner, R. J. Maughan, S. J. Montain, N. S. Stachenfeld, Exercise and fluid replacement. *Med Sci Sports Exerc* 39, 377-390 (2007)
- [2] K. J. Sollanek, M. Liu, A. Carballo, A. R. Caldwell, S. N. Cheuvront, The accurate prediction of sweat rate from energy expenditure and air temperature: a proof-of-concept study. *Appl Physiol Nutr Metab* 45(11), 1299-1305 (2020)
- [3] K. Van Hoovels, X. Xuan, M. Cuartero, M. Gijssels, M. Swarén, G. A. Crespo, Can Wearable Sweat Lactate Sensors Contribute to Sports Physiology?. *ACS Sens.* 6(10), 3496-3508 (2021)
- [4] Y. Tanaka, T. Tanaka, T. Iwata, T. Kurashima, M. Okawa, Y. Akagi, H. Toda, Spatially aggregated gaussian processes with multivariate areal outputs. *Advances in Neural Information Processing Systems* 32, 3000–3010 (2019)
- [5] K. P. Murphy, *Machine Learning: A Probabilistic Perspective* (MIT press, 2012)
- [6] D. Passe, M. Horn, J. Stofan, C. Horswill, R. Murray, Voluntary Dehydration in Runners Despite Favorable Conditions for Fluid Intake. *International Journal of Sport Nutrition and Exercise Metabolism* 17, 284-295 (2007)