Estimation of Fluid Intake Volume from Surface Electromyography Signals: A Comparative Study of Seven Regression Techniques

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Keywords: Dehydration, Electromyography Sensors, Fluid Intake, Volume Quantifying, Swallowing.

Abstract: Insufficient fluid intake in older adults, in particular, is a worrying problem and an actual concern that warrants scrutiny. Monitoring fluid intake is essential to avoid dehydration and overhydration problems. This paper presents an investigation to estimate the fluid intake volume using surface Electromyographic (sEMG) sensors. Eleven subjects participated in the experiment, and sEMG recordings of swallows from cups, bottles, and straws were collected. Four features were extracted from the EMG signals. Seven regression algorithms were implemented for quantifying the volume of swallowed fluid: Random Forest (RF), Support Vector Regressor, K-nearest neighbour (KNN), Linear Regressor (LR), Decision Tree (DT), Lasso and Ridge. The mean sip volume across subjects was 14.85 $\pm$ 5.05 ml. Results showed that using Random Forest, the root mean square (RMSE) for estimating fluid intake volume using one the Mean Absolute Value feature gave 1.37 $\pm$ 1.1 ml. These results indicate a step forward in estimating fluid intake volume based on sEMG for hydration monitoring.

1 INTRODUCTION

The terms ”hydration” and ”healthy” can be used interchangeably because water is necessary for every organ, cell, and tissue in the body to function normally. In other words, being hydrated is essential to good health because it aids in processes like lubricating joints, avoiding infections, feeding cells nutrients, and preserving the general health of the body's organs. Yet, older adults experience considerable hydration concerns since their bodies contain $10-15\%$ less water. This can be a significant contributing factor to the majority of health problems that older adults experience. Studies show that most older individuals are more susceptible to renal issues and electrolyte abnormalities due to medications that lead to dehydration, making them more susceptible to changes in conditions and illnesses (El-Sharkawy, 2021). Dementia, Alzheimer's, diabetes, and poor mobility are just a few of the health problems that older adults may experience that cause their ability to feel thirst decreases, making them less conscious of their body's need for water. Dehydration is an issue for many older persons as a result. It also increases the risk of death in seniors relative to the general population and is one of the most common reasons for hospital admissions.

Dehydration occurs when the human body uses or loses more fluid and minerals, such as sodium and potassium than it takes in. The body cannot perform everyday tasks due to the lack of water and other liquids. Thus, if the body cannot replace the lost fluids, it will become dehydrated, which is very dangerous. Therefore, monitoring the quantity of intaken fluid is essential to decrease the risk of dehydration. Fluid charts are one of the vital clinical methods used to monitor patients' fluid intake and output throughout the day in hospitals and care facilities where nurses stay with the patients to try to keep an eye on their consumption of meals and liquids. The medical team uses the data to make later clinical decisions, such as whether to perform surgery or prescribe medication. It is crucial to fully complete the fluid balancing charts to detect changes in the fluid's input or output. Any fluid intake should be precisely measured and its type recorded on a fluid balance chart. That technique can be used to estimate and record any output fluid, including urine, loose stools, and vomiting. These fluid charts may only be used to monitor fluid levels; however, they are not always accurate because doctors or nurses sometimes fail to note a patient's input or output (Malvuccio and Kamavuako 2021). According to the study, only 25% of the fluid charts at Kettering General Hospital had precise measurements, and only

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Ismail, I. and Kamavuako, E.
Estimation of Fluid Intake Volume from Surface Electromyography Signals: A Comparative Study of Seven Regression Techniques.
DOI: 10.5220/0011795600003414
In *Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2023) - Volume 4: BIOSIGNALS*, pages 118-124
ISBN: 978-989-758-631-6; ISSN: 2184-4305

14% had thorough records of all intakes and outputs (Asogan, 2021).

Many technologies use machine learning and other techniques to monitor fluid intake in older persons, according to a survey of literature reviews on methods of monitoring dehydration. One of these technologies is wearable technology, including accelerometers, inertial sensors, smartwatches, cellphones, acoustic sensors, and psychological sensors. These items are widely available on the commercial market and have helped detect drinking activities (Cohen, 2021). Still, wearables cannot reliably quantify consumption volume, despite research showing that they can detect drinking events with an accuracy of ¿ 80%. Furthermore, some senior citizens dislike these devices and do not wish to wear them (Wellnitz, 2019). For textile techniques to be useful in daily life, they must be connected to the clothing and securely laundered in the washing machine. Respiratory Inductance Plethysmography (RIP), for example, has produced positive results for swallowing detection but hasn't calculated the volume of fluid consumed. Accordingly, none of these methods has been used to quantify the volume of fluid intake in the clinic, despite the encouraging results of these methods for detecting swallowing and drinking events (Dong, 2017, Cheng, 2010 - Tatulli, 2020).

Another approach to measure fluid intake is surfaces with embedded sensors. These surfaces require the users to lift the containers used for drinking and place them on the surface every time they drink to determine the drinking actions and to record the amount of the drink. Any additional object placed on the surface will give inaccurate information, leading to erroneous detections. Further, some vision and environmental approaches, like wearable cameras and radar, have concentrated on intake detection. Still, the detection accuracy depends on the camera resolution and the surrounding environment (lighting, processing power, and data storage), most of which have not operated in real-time. Although these techniques can recognise drinking events with a 90% accuracy using deep learning techniques, they cannot calculate the volume of fluid consumed (Cohen, 2021).

The use of smart containers paired with Inertial Measurements Units (IMU) placed outside the bottle to estimate the sip volume according to the event orientation and duration is another effective method that has been used to quantify fluid intake. Though, the usability of these containers remains low. Numerous research has examined ultrasonic sensors to calculate the volume of fluid being absorbed using the container, but they have not evaluated how accurate the sensors are. Nevertheless, these techniques have not found their way to the clinics routinely.

Methods based on physiological signals to monitor fluid intake include sEMG and acoustic sensors, such as microphones. Nakafuji et al. (2015) obtained a classification accuracy of 84% using microphones to record swallowing noises to discriminate between discrete fluid volumes (Nakafuji, 2014). Using the frequency and amplitude characteristics of the recorded signals, Kobayashi et al. (2014) captured swallowing sound using a throat microphone to accurately detect fluid intake with 95% accuracy using the cross-validation of SVM and estimate how much the individual was drinking with a 3.33 ml RMSE using the amplitude characteristic of swallowing sound (Kobayashi, 2014). Malvuccio and Kamavuako (2021) have also applied sEMG recordings of individual and continuous swallows to distinguish between liquid and saliva swallows using Fine KNN with an accuracy of 86.69 ± 5.52% to classify between the noise and swallows using Fine Gaussian SVM with an accuracy of 99±1.31 (Malvuccio Kamavuako, 2021). Surface electromyography (sEMG) and microphones have been used for continuous monitoring of the swallowing events by Amft and Tröster to discriminate between solid and liquid meals in a single participant (Amft, 2006).

To the best of our knowledge, there is a limited number of studies using the sEMG to estimate fluid intake volume effectively. Among the above three cited studies, only one attempted to use a continuous estimation approach using artificial neural networks. The challenge is not to classify discrete values but to estimate continuous volume. Therefore, this study aims to compare the capability of different regressors in estimating fluid intake volume using sEMG. Novel contributions of this paper include (1) investigating different machine learning regressors to find the optimum regressor in estimating fluid volume (2) unravelling the dependency between the choice of regressor and features; and (3) proposing optimum placement of sEMG electrodes with minimum error.

2 METHODOLOGY

2.1 Dataset

This study uses a previously recorded dataset; details can be found in (Malvuccio Kamavuako, 2021). In brief, three females and eight men, ranging in age from 20 to 67 years, participated in this study. Two of the Delsys Tringo sensors were placed on the belly of the suprahyoid muscles, and two were placed on the belly of the infrahyoid muscles. Drinking events occurred through various classes (drinking using a cup, straw, bottle, and scale). After data checks, two subjects had poor EMG data and were removed from the investigation.

2.2 Experimental Procedure

Subjects consumed water using: a bottle, a cup, and a straw, referred to as containers for simplicity. Each subject had to swallow water five times for each container while taking regular sips. We used a digital scale to weigh the container before and after drinking to quantify the true sip volume. A sip is a drink, taking only a small amount at a time. For the final group of drinks, 5 ml were added to the highest cup volume that could be computed, and this assignment was only done once.

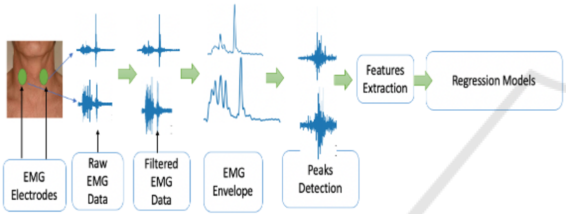

Figure 1: A graphical representation of the experimental approach and data analysis pipeline.

2.3 Data Analysis

On Google Collab, we carried out data analysis using Python 3.8 and preprocessing consisted of bandpass filtering between 6–400 Hz. As shown in Figure 1, the EMG signals were rectified, and the signal envelope was computed to detect the highest peak where the swallowing event occurred. The EMG burst was then extracted using the peak position. From that burst, features of the Mel frequency cepstral coefficients (MFCCs), Mean Absolute Value (MAV), Waveform Length (WL), and Willison Amplitude (WAMP) were calculated on the raw data of the EMG. These features had positive outcomes when applied to EMG signals in earlier investigations.

- Mean Absolute Value (MAV): It is a method for identifying and evaluating the intensity of muscular contractions. It can be represented as the moving average of the full wave rectified EMG signal, as shown in equation 1[49].

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|X_i| \tag{1}$$

  While N is the length of the segment, i is the segment increment, and Xi is the signal amplitude value.

- Mel-frequency cepstral coefficients (MFCCs): MFCCs are coefficients that form the Mel-frequency cepstrum (MFC) based on a linear cosine transform of a log power spectrum on a non-linear Mel scale of frequency. It works by segmenting the signal to a number of windows, then applying the Discrete Fourier Transform (DFT) and taking the log of the magnitude. Then, it makes wrapping the frequencies on a Mel scale and, in the end, applies the inverse Discrete Cosine Transform (DCT).

- Willison Amplitude (WAMP): The WAMP feature counts the number of changes in the amplitude of the EMG signal that surpass a specific threshold, as shown in equation 2 (Negi, 2016).

$$WAMP = \sum_{i=1}^{N}[f(|X_i - X_{i+1}|)];$$

$$f(x) = \begin{cases} 1, x >= \text{threshold} \\ 0, \text{otherwise} \end{cases} \tag{2}$$

- Waveform Length (WL): It is the total length of the waveform for the segment. The results obtained from the WL computation indicate the waveform's amplitude, frequency, and duration as shown in equation 3 (Spiewak, 2018).

$$WL = \sum_{i=1}^{N-1}|X_{i+1} - X_i| \tag{3}$$

We used a regression approach to estimate drinking volume from sEMG. Our analysis included the following techniques: Random Forest (RF), Support Vector Regressor (SVR), K-Nearest Neighbor Regressor (KNN), Linear Regression (LR), Decision Tree (DT), Lasso, and Ridge regressors. For each subject, we had 16 observations; thus, a leave-one-sample-out was used employed with permutation, with the Root Mean Square Error (RMSE) as the performance metric. In the first part of data analysis, we investigated the impact of using all four channels versus the two lower (infrahyoid muscles) and upper (suprahyoid muscles) channels using all regressors, single features and all features together. We used a three-way repeated measures analysis of variance (3-ANOVA) with factors (Channels, Regressors and features) to test for statistical differences between the factors and interactions. In the second part of the data analysis, we selected the three regressors and three features with the lowest RMSE to investigate the effect of using single and mixed channels (one upper and one lower) on performance. Similarly, we used 3-ANOVA to test for statistical differences. Results are expressed as mean ± standard error.

3 RESULTS

The overall grand mean of the sip volume across subjects and estimation RMSE across channels, regressors and features were 13.91 ± 1.27 ml and 1.37 ± 0.39 ml, respectively.

The Effect of Regressors and Features: The RMSE of all four channels was 2.65 ± 0.32 ml, not significantly lower than the infrahyoid (2.90 ± 0.35 ml) and suprahyoid (2.76 ± 0.33 ml) pairs. There was a statistical difference between regressors ($P = 0.003$), with RF (2.25 ± 0.25 ml), SVR (2.29 ± 0.30 ml) and KNN (2.41 ± 0.37 ml) performing better than the others, also summarised in Figure 2 There was no interaction between channels and regressors ($P = 0.379$).

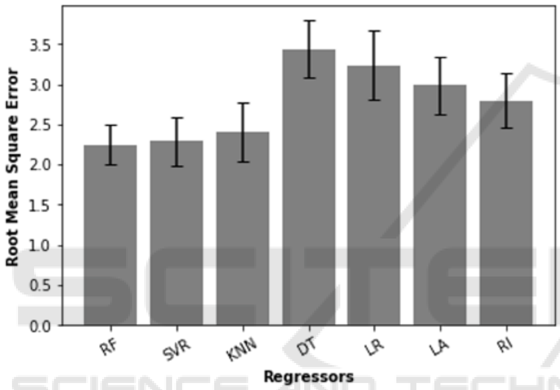

Figure 2: An error bar plot that summarizes the RMSE and the STD for the seven regressors.

The mean performance of each feature in ascending order, was 1.37 ± 0.39 ml for MAV, 1.82 ± 0.45 ml for MFCC, 1.82 ± 0.45 ml for all features combined, 1.99 ± 0.60 ml for WAMP and 2.12 ± 0.44 ml for WL, not statistically different ($P = 0.132$) from each other. There was an interaction ($P = 0.01$) between regressors and features, meaning that the choice of features affects the performance of the regressors, as summarised in Table 1. Figure 3 depicts the relationship between regressors and features when using the two suprahyoid muscles, figure 4 depicts the relationship between regressors and features when using the two infrahyoid muscles, and figure 5 depicts the relationship between regressors and features when using the two suprahyoid and the two infrahyoid muscles.

Table 2 indicates that performance can be maximised using suprahyoid muscles with Random forest as regressor with the MAV feature. Nevertheless, SVR and KNN are good regressor candidates with the MFCC feature.

Table 1: Association between features and best regressor for different channels.

Features	Four channels	Infrahyoid muscles	Suprahyoid muscles
MFCC	RF 2.26±0.27ml	SVR 2.27±0.41ml	KNN 1.82±0.45ml
MAV	RF 1.44±0.25ml	Lasso / Ridge 2.19±0.42ml	**RF 1.37±0.39ml**
WAMP	KNN 1.99±0.60ml	KNN 2.09±0.57ml	KNN 2.03±0.57ml
WL	SVR 2.24±0.36ml	SVR 2.15±0.44ml	RF 2.12±0.44ml
ALL	SVR 2.06±0.60ml	SVR 1.97±0.36ml	KNN 1.82±0.45ml

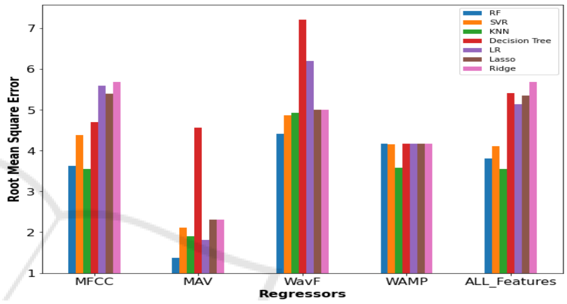

Figure 3: The bar plot with the root mean square error for the seven regressors with the features using the Suprahyoid.

Single channel investigation showed no difference between channels nor their combinations (infrahyoid and suprahyoid). It is worth noting that using the left infrahyoid or left suprahyoid channel alone with the RF regressor with either MAV or MFCC provided RMSE values close to 1.6 ml. The combined left supra and right infra channels performed down to 1.5 ml using RF and MAV. Combination of MAV and MFCC using the two suprahyoid channels with the RF has not improved the RMSE results. Table V demonstrates the average sip volume and the Root Mean Square error for each subject using the upper two suprahyoid muscles with RF.

4 DISCUSSION

This study aimed to compare the power of various regressor techniques in estimating fluid intake volume using surface Electromyographic (sEMG) sensors. The study's regression findings strongly suggest that estimation of fluid intake volume is feasible using surface EMG. This study demonstrated how regression performance differed depending on whether signals were coming from the upper two muscles

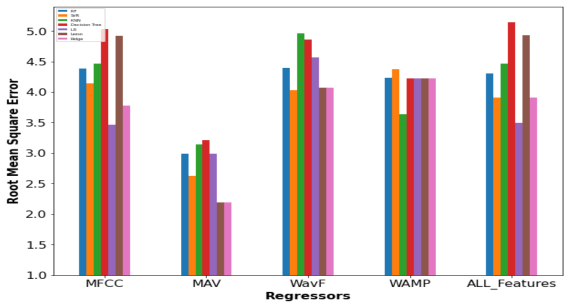

Figure 4: The bar plot with the root mean square error for the seven regressors with the features using the Infrahyoid Muscles.

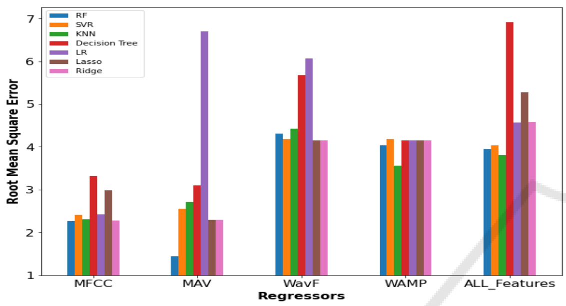

Figure 5: The bar plot with the root mean square error for the seven regressors with the features using the Infrahyoid Muscles and the Suprahyoid muslecs.

(Suprahyoid muscles), the lower two muscles (Infrahyoid muscles), or all the muscles. We found that solely employing suprahyoid muscles did not produce significant superior results to those of the infrahyoid muscles. The seven regression models were run on each feature individually and then on all four features collectively to select the best features.

This demonstrated that no single regressor works best for all features and that the regressor depends on the feature. There was a signficant difference between the regressors. For example, Random Forest regressor performs best using the Mean Absolute Value feature. Except for the Willison amplitude and MFCC features, statistical analysis did reveal significant variation in how different regressors performed with various features. Therefore, utilising a single characteristic can be advantageous since it will decrease computing costs and time, particularly for online jobs. Using single channels of the infrahyoid or the suprahyoid muscles or combining a single channel of each to estimate the volume has not improved the results of RMSE. However, the error difference was not too high, indicating that single EMG channels may be used to record the intake data. As a result, in a subsequent study, single channels will be used to record the intake data and will be investigated if the fluid estimation performance will be improved or not.

Table 2: Final Results for the Best Regression Model (RF) using Mean Absolute Volume feature.

Subjects	**Average Sip Volume (ml)**	**RMSE (ml)**	**Percentage error (%)**
S1	19.42 ± 5.00	1.07 ± 1.67	5
S2	8.72 ± 2.95	1.42 ± 0.98	16
S3	12.18 ± 4.19	0.82 ± 1.4	6
S4	11.4 ± 3.59	2.99 ± 1.19	26
S5	18.71 ± 5.94	0.13 ± 1.98	1
S6	12.72 ± 3.85	1.85 ± 1.28	14
S7	21.32 ± 8.47	0.39 ± 2.82	2
S8	13.66 ± 3.15	0.29± 1.05	2
S9	7.14 ± 2.86	3.35 ± 0.95	47
Average	13.91 ± 1.27	1.37 ± 0.39	13.22

The number of studies aiming at fluid volume estimation from sEMG is very limited. Kobayashi et al. attempted to measure the amount of liquids consumed using a throat microphone with an RMSE value of 3.33 ml (Kobayashi, 2014). Malvuccio also estimated the amount of fluid consumed using sEMG recordings of both individual and continuous swallows, but her work had an RMSE than ours (Malvuccio, 2021). Despite the similar performance, decreasing the error further will be beneficial, and thus our future study should include a larger sample size with advanced techniques.

Although the sEMG performance in estimating fluid intake volume has shown encouraging results compared to other approaches, further validation of these data is necessary. We aim to increase the sample size to improve the outcomes and model performance. Additionally, the test volunteers must be older adults since their swallowing habits change as people age, which may impact the system's functionality. Finding out if the performance would be affected by age and by increasing the number of subjects is required because this study only used a small number of participants. Additionally, this study did not consider other variables that could impact the sip volume, such as the liquid temperature and composition. These factors may cause the sip volumes to differ from subject to subject, compromising the fluid intake volume technique's estimation ability.

5 CONCLUSIONS

We have compared for the first time the capability of various regressors to estimate fluid intake from sEMG signals recorded during swallowing events. The results of utilizing only the suprahyoid or infrahyoid muscles did not differ statistically; however, there were statistical differences between the various regressors. RF, then SVM regressors were the best ones using the Mean Absolute Value feature in estimating the fluid volume with the lowest error. Furthermore, there is an indication that regressor performance is feature dependent. This outcome is a step forward in using sEMG for hydration monitoring. Further research is needed to investigate the use of single EMG channels to record and estimate the fluid data and whether two channels work better for regression and the other are better for classification.

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