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Estimating Caloric Intake in Bedridden Hospital Patients with Audio and Neck-worn Sensors

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ABSTRACT

We present an approach for estimating calorie intake given a limited number of foods provided to patients in an in-bed setting. Data collected from a proximity sensor, inertial measurement unit, ambient light, and audio sensor placed around the neck are used to classify food-type consumed by second using a random forest classifier. A multiple linear regression model is then developed for each food-type to map second-level features to calories per second. We conducted a user study in a patient simulated setting, where 10 participants were asked to eat on a patient bed. A user-independent analysis demonstrated food-type detection at 97.2% F1-Score, and an average Absolute Error of 3.0 kCal per food-type. Our method shows promise in distinguishing food items and predicting calorie intake in a bedridden setting given a limited set of food items.

CCS CONCEPTS

• **Human-centered computing → Mobile computing**; **Mobile devices**; **Ubiquitous computing**;

KEYWORDS

Calorie intake estimation, hospital malnutrition, wearable sensor, food identification, eating behavior

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1 INTRODUCTION

One in three patients that arrive at a hospital in developed countries suffer from malnutrition, and another one-third become malnourished during their stay [5]. Malnutrition leads to poor patient health outcomes, hospital-acquired conditions and longer length of hospital stays [2]. Self-report and existing hospital dietary logs suffer from inaccuracy resulting from recall bias, and hospital understaffing. Hospitals and rehabilitation centers are beginning to integrate wearable sensors with their patients to monitor their motion and physical activity during their stay. Patients that are at-risk for being malnourished can be effectively monitored using a neck-worn sensor during their hospital stay. Such a system could trigger a just-in-time intervention to provide enteral feeding (i.e. feeding that uses the gastrointestinal tract either through normal oral diet, liquid supplements or tube feeding) or parenteral feeding (i.e. delivery of nourishment and calories into the vein) to deliver the calories and nutrients needed by the patient for improved recovery. In this paper we test the effect of a neck-worn sensor, and the benefits of using audio to identify food-intake and estimate calorie intake.

2 RELATED WORK

Several sensors have been proposed to monitor nutrition in free-living people, some sensors attempt to measure proxies to caloric intake that are behavioral in nature such as feeding gestures [3] and swallow or chew rates [4]. Audio sensors, both in-ear and around the neck have been used extensively in recent literature to detect eating activities like chewing and swallowing [1]. While each of these systems has shown promise, none have been able to show efficacy in bedridden patients. We test our calorie estimating wearable system in a clinic environment, with 10 people in-bed, consuming a limited number of food items on a tray.

3 SYSTEM EVALUATION

3.1 Study Design

We recruited 10 participants (22-25 years of age, 9 male). Participants wore the devices around the neck and ate while laying on a patient bed in a clinical setting. They each were asked to consume one or more of the following four food items: traditional bagel (N=12), turkey chili soup (N=13), Fuji apple (N=13), and potato chips (N=13). The patient bed and portable food tray were adjusted according to the participants height (see Figure 1). A Mandometer scale is placed under the meal tray to monitor food weight.

3.2 Sensors

As shown in Figure 1 a neck-worn sensor is attached around each subjects neck. The neck-worn sensor comprises a proximity, ambient-light (VCNL4010), and an inertial motion sensor (IMU) (BNO055). Proximity and ambient light sensors are oriented towards the chin of the subject to capture periodic chewing patterns. The IMU measures the lean forward angle (LFA), the angle between the Earth's surface and the necklace. To differentiate food items, a lavalier microphone (MAONO) is placed on the shirt collar of the subject.

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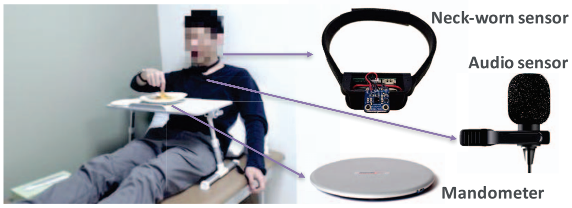

Figure 1: Sensing platform consists of a neck-worn sensor, audio sensor and Mandometer.

4 METHODS

We estimate calories at the second level by first building a classification model to determine food-type, given a predefined set of food items. Then a separate regression model is built for each food-type to map second-level features to kilocalories (kCal). Once the food-type is detected, the appropriate regression model is applied to estimate kCals.

4.1 Food Type Identification

We extracted time-based and frequency-based features from the audio device. We extracted 34 predictive features from the audio signal for each second. Then we calculated the average and standard deviation of the 34 features across 5 seconds (centered at each second), resulting in 68 final audio features. We also extracted 98 predictive features from the proximity, ambient-light and LFA signal. Details of the features are shown in Table 1. We developed three models: audio-only, necklace-only, and a combined model. Given that each food item is likely to have distinguishing eating sounds and chewing/eating patterns, we train a random forest classifier (RFC) (n=100 trees) to identify food-type based on all the corresponding features extracted from the sensors. We apply a Leave One Food Out (LOFO) approach from each participant for evaluation.

Table 1: List of features from necklace and audio

Device	Domain	Features
Necklace	Stat.	Max, min, mean median, variance, RMS correlation, skewness, kurtosis 1st and 3rd quartile, interquartile range
	Freq.	Amplitude at 0.25 Hz, 0.5 Hz, 0.75 Hz, 1 Hz, 1.25 Hz, 1.5 Hz, 1.75 Hz, 2 Hz, 2.25 Hz, 2.5 Hz
	Stat. of Freq.	Skewness and kurtosis of spectrum from frequency features
Audio	Time	Zero Crossing Rate, Energy, Entropy of Energy
	Stat. of Freq.	Spectral Centroid, Spectral Spread, Spectral Entropy, Spectral Flux, Spectral Rolloff, MFCCs (13), Chroma Vector (12), Chroma Deviation

4.2 Calorie Estimation

Audio and neck-worn features are also descriptive in estimating kCals. Out of the 166 combined features, for each food-type we selected the top 5 features using the forward feature selection algorithm. We then trained a separate multiple linear regression (MLR) model for each food-type using those features, using a LOFO evaluation method, to estimate kCals. When training the model, to identify the kCals for each second of data (for ground truth) we divide the total kCals of each food item by the number of seconds it took to consume it (each food was consumed in sequence). We then build a MLR model for each food item using the top 5 features.

5 RESULTS

Figure 2 shows the F1-Score across the 10 subjects for each RFC model. The average F1-Score is 88.8% using the necklace-only model, 94.0% using audio-only model, and 97.2% when using the combined model. Subsequently, for each predicted second, we calculate the calorie using the corresponding regression model and achieve a 3.0 kCal Absolute Error (on average), and a 96.6% accuracy on average (See Figure 3 for results across food-type).

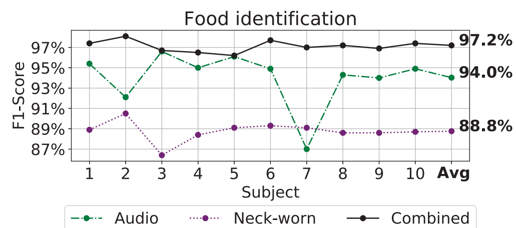

Figure 2: F1-Score of food-type identification using audio-only, necklace-only, and combined models.

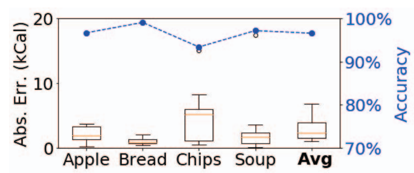

Figure 3: Leave one food out (LOFO) calorie estimate.

6 CONCLUSION AND FUTURE WORK

We show, given a limited number of known food items provided to a bedridden participant the ability to identify food-type with 97.2% F1-Score, and estimate calories with a 96.6% accuracy using audio, proximity, IMU, and ambient-light sensors around the neck. Future work will incorporate testing in real patients in a hospital setting while consuming a greater variety of food items.

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