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Abstract

Water has been widely acknowledged as an essential part of all living things. It is the fundamental necessity for all life 19s activities and most biochemical reactions in human body are executed in water. Therefore, the type and quantity of liquid intake everyday have a critical impact on individuals 19 health. In this paper, we demonstrate HydraDoctor, a real-time liquids intake monitoring system which is able to detect drinking activities, classify the categories of liquids and estimate the amount of intake. The system runs on multiple platforms including a smartwatch to detect the motion of hands and a smartglass to capture the images of mugs. A smartphone is also used as an edge computing platform and a remote server is designed for computationally intensive image processing. In HydraDoctor, multiple state-of-the-art machine learning techniques are applied: a Support Vector Machine (SVM)-based classifier is proposed to achieve accurate and efficient liquids intake monitoring, which is trained to detect the hand raising action. Both of them are well optimized to enable in-situ processing on smartwatch. To provide more robust and detailed monitoring, the smartglass is also incorporated and trigged to capture a short video clip in the front of the user when potential drinking activity is detected. The smartglass will send the video clip to the remote server via its companion smartphone and a Faster-RCNN is performed on the server to confirm the detected drinking activity and identify the type of intake liquid. According to our evaluation on the real-world experiments, HydraDoctor achieves very high accuracy both in drinking activity detection and types of liquids classification, whose accuracy is 85.64% and 84% respectively.

HydraDoctor: Real-time Liquids Intake Monitoring by Collaborative Sensing

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ABSTRACT

Water has been widely acknowledged as an essential part of all living things. It is the fundamental necessity for all life's activities and most biochemical reactions in human body are executed in water. Therefore, the type and quantity of liquid intake everyday have a critical impact on individuals' health. In this paper, we demonstrate HydraDoctor, a real-time liquids intake monitoring system which is able to detect drinking activities, classify the categories of liquids and estimate the amount of intake. The system runs on multiple platforms including a smartwatch to detect the motion of hands and a smartglass to capture the images of mugs. A smartphone is also used as an edge computing platform and a remote server is designed for computationally intensive image processing. In HydraDoctor, multiple state-of-the-art machine learning techniques are applied: a Support Vector Machine (SVM)-based classifier is proposed to achieve accurate and efficient liquids intake monitoring, which is trained to detect the hand raising action. Both of them are well optimized to enable in-situ processing on smartwatch. To provide more robust and detailed monitoring, the smartglass is also incorporated and trigged to capture a short video clip in the front of the user when potential drinking activity is detected. The smartglass will send the video clip to the remote server via its companion smartphone and a Faster-RCNN is performed on the server to confirm the detected drinking activity and identify the type of intake liquid. According to our evaluation on the real-world experiments, HydraDoctor achieves very high accuracy both in drinking activity detection and types of liquids classification, whose accuracy is 85.64% and 84% respectively.

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CCS CONCEPTS

• **Networks → Cyber-physical networks**; • **Human-centered computing → Ubiquitous and mobile computing systems and tools**; • **Computing methodologies → Machine learning approaches**; • **Applied computing → Health care information systems**;

KEYWORDS

Liquid intake Monitor, Activity Recognition, Liquid Identification

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1 INTRODUCTION

The proportion of water in body composition ranges from 45% to 75% for an healthy adult and a sedentary man or woman consumes at least 2900 ml and 2200 ml fluid per day respectively. Therefore, the amount of water intake has a significant effect on human beings' health status. Water is important, however, easily overlooked in our daily life without dedicated reminder mechanism to remain people drinking enough water. For that reason, a drinking activity monitoring system with pervasive devices (e.g., smartphone, smartwatch and smartglass) is needed to aid people's daily liquid intake.

The success of smart wearables has enabled a spacious range of new application through collecting and analyzing physiological data generated by individuals in daily life. For example, heart rate sensor is embedded on various models of smartwatch and smartband to collect the realtime dynamics of heartbeats. The statistics can be used to infer the status of individuals during workout or analyze their sleep qualities.

Literally, there have been some existing studies on liquids intake monitoring systems. However, most of them require bespoke devices, such as special designed wearable microphone [15], to detect drinking patterns. As a result, they cannot be used handily. On the contrary, our new real-time liquid intake monitoring system which facilitates multiple sensing and computing platforms including smartglass, smartwatch and smartphone to help users to establish a healthy lifestyle by reminding them taking sufficient liquid in time.

This real-time liquid intake monitoring system, HydraDoctor, only expedites the commercialized platforms which can be easily accessed. As shown in Fig.1, it detects hand raising action as a hint for drinking activity from the motion data produced by IMUs on the smartwatch, then the smartglass are triggered to capture a short video clip and send the image frames to the remote server through a smartphone to perform intensive image processing. We design and optimize multiple state-of-the-art machine learning models including Support Vector Machine (SVM), Conditional Random Field (CRF) and Faster-RCNN to enable real-time and robust drinking activity detection and liquid amount estimation. The contributions of this paper are as follows:

- We propose HydraDoctor, a robust and real-time liquid intake monitoring system, which is capable to detect drinking activity, identifying the type of liquid and estimating the amount of intake using multiple commercialize wearable and mobile devices.
- To enable HydraDoctor running smoothly on the resource-constrained wearable devices, we come up with a new recognition algorithm based on multiple state-of-the-art machine learning methods and ameliorate its computational complexity and energy efficiency.
- We conducted intensive real-world experiments to evaluate the performance of HydraDoctor. The resultant accuracy of drinking activity detection is 85.64% and the recognition accuracy of differentiating 6 the types of liquids is 84.30%.

This paper is organized as follows. Section 2 reviews the related work. Section 3 demonstrates system design and key algorithms. Finally, Section 4 concludes the contribution of this project and outlines some possible future work.

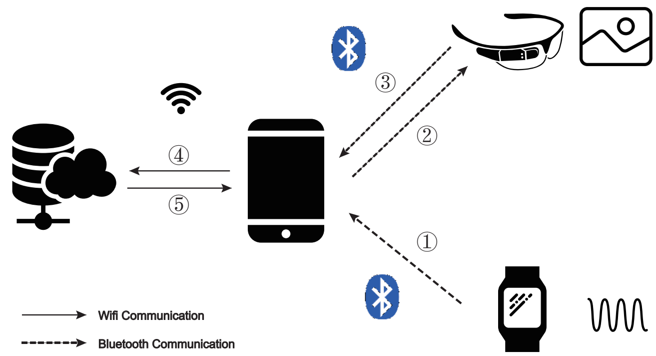


Figure 1: The Components of HydraDoctor

2 RELATED WORK

2.1 Human Activity Recognition

Human activity recognition is essential for most human-centered systems and applications. Voluminous sensors have been applied to solve this problem. In the past decades, this problem was extremely important in computer vision area and various technologies has been proposed from 3D data [1]. The activity recognition based on WIFI utilizes channel state information to identify 7 different activities, including running, walking, sitting down and opening refrigerator, achieving an average accuracy of greater than 96% [21].

Besides these general activity recognition approaches, some special methods are taken to detect drinking and eating activity. A liquid intake monitoring system, using the batteryless Ultra High Frequency Radio Frequency Identification (RFID) technology, has been developed [9]. RFID data stream is detected by fluid container with RFID tags and this method achieves F-scores of 85% for the young and 79% for the older in recognizing drinking activity. For wearable devices, a necklace with a piezoelectric sensor is a direct method to detect whether people is drinking or eating [10]. Using inertial sensor, Feature similarity search(FSS) is employed performing 84% recall and 94% precision [3].

2.2 Intake Detection

Detecting the type of food and liquid is crucial to help users form a healthy life style. AutoDietary utilizes a high-fidelity microphone on user's neck to collect acoustic data, which is used to recognize food types using the lightweight decision-tree-based algorithm [4]. The miniature microphones in the outer ear canal are developed to classify eating seven types of food and consuming one drink and are detected by a finite-state grammar decoder based on the Viterbi algorithm [16]. Some methods based on images are also employed for measuring nutrition intake [2].

Generous methods have been applied to detect the type of food, but there still are few approaches to solve the liquid problem. The method to recognize the type of fluid depends on their density, special character and container. Radio frequency signal is used to penetrate trough special material, and the different amounts of phases and received signal strength (RSS) changes are observed [20]. This way achieves higher than 94% accuracy among 10 liquids.

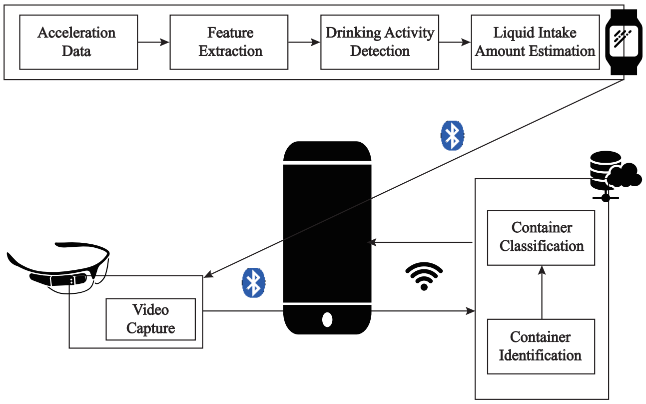


Figure 2: The Architecture and Workflow of HydraDoctor

2.3 Local Processing on Wearable Sensors

Generally, data from wearable sensors is analyzed on remote servers due to the limitation of processor and battery. Even a simple application to differentiate statuses whether a smartwatch is worn or not still need to send real-time sensor data to remote servers to calculate and analyze [11]. For energy consuming part, Snoopy, a deep sequence learning algorithm, runs on smartwatch, and it consumes extra 4%-8% battery per hour [14]. Google glass can work for video capture and OpenCV face detection lasting for 43 minutes and 38 minutes respectively [13]. It is extremely difficult to keep balance between the real-time property and energy consumption. Taking the ability of precessing and the status of battery into consideration, the wearable devices will always send their data to smartphone and smartphone will transmit the data to the remote servers to process.

3 SYSTEM DESIGN

3.1 System Architecture

The workflow of HydraDoctor is shown in Fig. 2. It facilitates multiple sensing and computing resources: the smartwatch detects user's drinking activities through the accelerometer recording the hand raising motion of user (we assume that the smartwatch is worn on the dominant hand). If a potential drinking activity is detected, further processing is triggered to estimate the amount of liquid intake based on the data from accelerometer and gyroscope. Then the smartglass is triggered to capture a short video clip in the front of the user. The video clip is sent to the remote server via smartphone. HydraDoctor on the server side detects and classifies the types of the containers and sends the results back to smartphone for display.

3.2 Feature Extraction from Acceleration Data

Inertial Measurement Unit (IMU) sensors are widely embedded on mobile devices. Generally, it contains accelerometer, gyroscope and magnetometer. During drinking activity detection, only accelerometer is active as gyroscope consumes significantly more energy while accelerometer itself is sufficient to provide robust detections.

The time-series recored is segmented using 1-second sliding window and the stride is 250ms. Multiple features are extracted from each segment including mean, variance, amplitude, skewness, peak and correlation in time domain. The computation of feature extraction is lightweight and implemented locally on smartwatch. The types of features extracted from accelerometer signals are listed in TABLE 1.

Table 1: Features Extracted from Accelerometer Data

Features	Description
Mean	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \bar{y}, \bar{z}$
Variance	$\sigma_x^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2, \sigma_y^2, \sigma_z^2$
Amplitude	$A(x) = max(\lvert x_1\rvert, \lvert x_2\rvert, \ldots, \lvert x_n\rvert), A(y), A(z)$
Skewness	$skew(x) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{(n-1)\sigma_x^3}, skew(y), skew(z)$
Kurtosis	$kurt(x) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sigma_x^4}, kurt(y), kurt(z)$
Correlation	$\rho(x,y) = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sigma_x\sigma_y}, \rho(y,z), \rho(x,z)$

3.3 Drinking Activity Detection

The features extracted from accelerometer data are used to detect the potential drinking activity by finding the starting and ending points of the event. The beginning of drinking activity is a hand raising action and followed by a reverse action as the ending. We apply Support Vector Machine (SVM) [6] classifier to detect the actions. We collect 6 different actions include writing, opening doors, typing, walking, raising hand up and down. The same feature vectors of these actions are extracted to train SVM classifier. SVM classifies different activities by constructing a hyperplane according to the feature vectors,

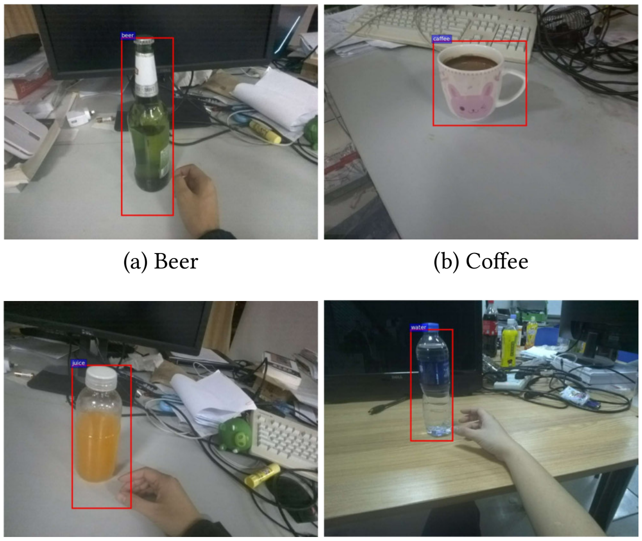
$$\vec{w}^T\vec{x} + b = 0 \tag{1}$$

where $\vec{w}$ is the parameter vector, $\vec{x}$ is the feature vector and b is the scalar vector. We build two SVM classifiers for hands raising up and down actions respectively.

When a pair of actions containing hand moving up and down are detected within a reasonable period, a potential drinking activity is recorded. The SVM classifiers are implemented on smartwatch and obtain the results which reduce the response time compared with the offloading strategy. It is worth noting that the accelerometer is running on low frequency mode to save energy.

3.4 Video-based Container Identification and Classification

The smartwatch also facts as switch to trigger smart glasses to capture the images. When the smartwatch detect the end of drinking, smartwatch will send a message to smartphone via bluetooth, and smartphone will trigger smart glasses to capture a serial images for further identifying exactly drinking activity and classifying. Because the combination of hand movement is a candidate drinking activity, some resemble motions, such as putting on glasses, are also recognized as candidate drinking activity. Therefore, the images from smart glasses are benefit to identify drinking action



(a) Beer (b) Coffee

(c) Juice (d) Water

Figure 3: The Identification and Classification of Container

more exactly and classify liquid type by container. In another word, When a potential drinking activity is detected, the smartglass is triggered to record a short video clip in the front of the user which aims to find and classify the containers that the user is using.

When a user is drinking, the smart glasses is not able to capture the whole part of container. Even if the image includes the integrate part, the container is still difficult to be recognized because of the position and the vision angle. This is the result why HydraDoctor captures images after drinking activity is finished.Besides, the container identification and classification cannot be decided only by a single images, because the movement and angle of smart glasses lead to the poor-quality image. A set of images may overcome this weakness. If the images captured by the camera includes a container, the period of drinking can be decided. Then the video clip is sent to remote server immediately via WIFI to execute the container identification and classification. The container identification confirms whether the potential drinking activity is a true detection or not in the previous stage and the containers classification can be used to infer the type of liquids.

As remote server can be treated as limitless computation and energy resources. The accurate resources consuming deep learning techniques can be adopted. In HydraDoctor, we employ a Faster-RCNN [18] for extracting the container area and classifying its type. During training stage, images of bottles and cups in ImageNet [7] dataset are used to train the deep learning model. To improve its robustness, the faster-RCNN model is also fine-tuned by the bottle and cup images obtained from search engine and collected by ourselves using smartglass. Some examples of the identified and classified containers are shown in Fig. 3

After the classification, the quantity of liquid will be added to this category, and the total amount of different liquid will be displayed in smartphone. users can check how much hydration they have drunk by the app in smartphone.Beside the design of algorithm, An Android App has been also developed to record the amount of each liquid intake and an easy statistics can been view in such App.

Table 2: Hands Up Action Detection Table

		Prediction		**Recall**
		Hand Up	Others	
Type	Hand Up	200	3	98.52%
	Others	82	307	78.92%
Precision		70.92%	99.03%	

Table 3: Hands Down Action Detection Table

		Prediction		**Recall**
		Hand Down	Others	
Type	Hand Down	343	46	88.17%
	Others	53	357	87.07%
Precision		86.62%	88.59%	

Table 4: Container Identification Result

		Prediction		**Recall**
		Not Container	Container	
Image Type	Not Container	17	12	58.62%
	Container	1	104	99.05%
Precision		94.44%	89.66%	

4 EVALUATION

In this section, we recruit 11 volunteers to participate in multiple real-world experiments to evaluate the performance of HydraDoctor on drinking activity detection, liquid intake amount estimation, containers identification and classification. Besides the performance on detection or classification accuracy, we also evaluate the energy consumption of HydraDoctor on the wearable platforms.

4.1 Drinking Activity Detection Accuracy

Drinking activity detection is the first step of HydraDoctor. We collect motion data of six different hand moving actions including writing, opening doors, walking, typing, hand raising up and hand moving down from all participants. We segment the continuous time series of motion data using 1-second sliding window. We collect 593 segments to evaluate the performance of detection accuracy. The recall and precision of hand raising up and moving down is shown in TABLE 2 and TABLE 3 respectively. We can find that the precision and recall of hand raising up is up to 70.92% and 98.52% respectively, while those of hand moving down detection are 86.62% and 88.17% respectively.

4.2 Container Identification and Classification

Container identification is evaluated using 134 video clips including 188 videos with containers and the rest (16) without containers. The results of precision and recall of container identification are shown in TABLE 4. As a result we can observe that the precision and recall of container identification is 89.66% and 99.05% respectively.

Table 5: Container Classification Result

Container	Right Number	Total Number	Accuracy
Juice	13	25	52.00%
Coffee	24	24	100%
Cola	11	14	78.57%
water	13	16	81.25%
milk	10	10	100%
beer	14	15	93.33%
Total	**102**	**121**	**84.30%**

Besides the container identification, HydraDoctor is also able to distinguish different types of liquid containers. After identification, there are totally 121 containers being identified from original images. These images with containers are fed into faster-RCNN to generate the classification results. The accuracy of classification on each type of containers is listed in TABLE 5. The results show that HydroDoctor achieves an overall accuracy 84.30% for containers classification while it especially achieves 100% on categories of coffee and milk.

5 CONCLUTION

In this paper, we present HydraDoctor, a real-time liquid intake monitoring system using multiple off-the-shelf smart devices (e.g., smartwatch, smartglass and smartphone) under the assist of cloud computing. In this system, the smartwatch is utilized to collect wrist movement data while smart glasses is used to capture the image when a user is doing a drinking action. We conduct intensive real-world experiments to evaluate the performance on detection and classification accuracy as well as the resource consumptions. During the experiment, both the smartwatch and smart glasses are connected to the smartphone in order to transfer the data via Bluetooth, and smartphone intend to send these data to the remote server by WIFI. This system is able to identify whether the user is drinking by the wrist movement and images and these images are used to classify what kind of hydration the user is drinking. Our experimental results show that the system can recognize drinking activity efficiently, classify the hydration type precisely and estimate liquid intake accurately. By using multiple state-of-the-art machine learning techniques including SVM, CRF and faster-RCNN, HydraDoctor is able to robustly detect the drinking activity, estimate the amount of intake and classify different types of containers. The results show that HydroDoctor is able to provide accurate monitoring on liquid intake and realtime feedback displayed to the users. HydraDoctor achieves very high accuracy both in drinking activity detection and types of liquids classification, whose accuracy is 85.64% and 84% respectively.

Further work can be done to improve the accuracy of hydration intake measurement. However, due to the limitation of the data scale in this system, the results would be better if more training data can be used to improve the recognition algorithm. In the future, with the increasing number of health-related application and system appearing, new wearable technologies will lead human beings to live in a healthier life.

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REFERENCES

[1] Jake K Aggarwal and Lu Xia. 2014. Human activity recognition from 3d data: A review. *Pattern Recognition Letters* 48 (2014), 70–80.

[2] Rana Almaghrabi, Gregorio Villalobos, Parisa Pouladzadeh, and Shervin Shirmohammadi. 2012. A novel method for measuring nutrition intake based on food image. In *Instrumentation and Measurement Technology Conference (I2MTC), 2012 IEEE International*. IEEE, 366–370.

[3] Oliver Amft, David Bannach, Gerald Pirkl, Matthias Kreil, and Paul Lukowicz. 2010. Towards wearable sensing-based assessment of fluid intake. In *Pervasive Computing and Communications Workshops (PERCOM Workshops), 2010 8th IEEE International Conference on*. IEEE, 298–303.

[4] Yin Bi, Mingsong Lv, Chen Song, Wenyao Xu, Nan Guan, and Wang Yi. 2016. Autodietary: A wearable acoustic sensor system for food intake recognition in daily life. *IEEE Sensors Journal* 16, 3 (2016), 806–816.

[5] Jingyuan Cheng, Mathias Sundholm, Bo Zhou, Marco Hirsch, and Paul Lukowicz. 2016. Smart-surface: Large scale textile pressure sensors arrays for activity recognition. *Pervasive and Mobile Computing* 30 (2016), 97–112.

[6] Corinna Cortes and Vladimir Vapnik. 1995. Support-vector networks. *Machine learning* 20, 3 (1995), 273–297.

[7] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. 2009. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 248–255.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 770–778.

[9] Asangi Jayatilaka and Damith C Ranasinghe. 2017. Real-time fluid intake gesture recognition based on batteryless UHF RFID technology. *Pervasive and Mobile Computing* 34 (2017), 146–156.

[10] Haik Kalantarian, Nabil Alshurafa, and Majid Sarrafzadeh. 2014. A wearable nutrition monitoring system. In *Wearable and Implantable Body Sensor Networks (BSN), 2014 11th International Conference on*. IEEE, 75–80.

[11] Matin Kheirkhahan, Hiranava Das, Manoj Battula, Anis Davoudi, Parisa Rashidi, Todd M Manini, and Sanjay Ranka. 2017. Power-efficient real-time approach to non-wear time detection for smartwatches. In *Biomedical & Health Informatics (BHI), 2017 IEEE EMBS International Conference on*. IEEE, 217–220.

[12] Susan M Kleiner. 1999. Water: an essential but overlooked nutrient. *Journal of the American Dietetic Association* 99, 2 (1999), 200–206.

[13] Robert LiKamWa, Zhen Wang, Aaron Carroll, Felix Xiaozhu Lin, and Lin Zhong. 2014. Draining our glass: An energy and heat characterization of google glass. In *Proceedings of 5th Asia-Pacific Workshop on Systems*. ACM, 10.

[14] Chris Xiaoxuan Lu, Bowen Du, Hongkai Wen, Sen Wang, Andrew Markham, Ivan Martinovic, Shen Yiran, and Trigoni Niki. 2017. Snoopy : sniffing your smartwatch passwords via deep sequence learning. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* (2017).

[15] Yehenew Mengistu, Minh Pham, Ha Manh Do, and Weihua Sheng. 2016. AutoHydrate: A wearable hydration monitoring system. In *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on*. IEEE, 1857–1862.

[16] Sebastian Päßler, Matthias Wolff, and Wolf-Joachim Fischer. 2012. Food intake monitoring: an acoustical approach to automated food intake activity detection and classification of consumed food. *Physiological measurement* 33, 6 (2012), 1073.

[17] Erica Perrier, Agnès Demazières, Nicolas Girard, Nathalie Pross, Dominique Osbild, Deborah Metzger, Isabelle Guelinckx, and Alexis Klein. 2013. Circadian variation and responsiveness of hydration biomarkers to changes in daily water intake. *European journal of applied physiology* 113, 8 (2013), 2143–2151.

[18] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster R-CNN: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*. 91–99.

[19] Edison Thomaz, Irfan Essa, and Gregory D Abowd. 2015. A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 1029–1040.

[20] Ju Wang, Jie Xiong, Xiaojiang Chen, Hongbo Jiang, Rajesh Krishna Balan, and Dingyi Fang. 2017. TagScan: Simultaneous Target Imaging and Material Identification with Commodity RFID Devices. In *Proc. ACM MobiCom*. 1–14.

[21] Wei Wang, Alex X Liu, Muhammad Shahzad, Kang Ling, and Sanglu Lu. 2015. Understanding and modeling of wifi signal based human activity recognition. In *Proceedings of the 21st annual international conference on mobile computing and networking*. ACM, 65–76.