# Inferring Complex Human Behavior Using a Non-obtrusive Mobile Sensing Platform

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## 1 Introduction

Thanks to the decreasing cost, increasing mobility, and wider use of sensors, a great number of possible applications have recently emerged, including applications that may impact the high-level goals in people's lives. Applications can be found in many areas ranging from medical devices to consumer devices. Information about activity and context can be inferred from sensors and be used to provide automated recommendations.

Previous research has suggested that, using simple sensors, devices can improve human life on an everyday basis. Interesting examples can be found in the area of fluid intake monitoring [2, 7]. Also, activity and context recognition from wearable sensors have been investigated [8–11].

Still, many challenges remain open in this area, including how to effectively determine the sensor data that is valuable, how to select sensors and also how to best connect the low-level sensory data with high-level goals that are explicitly or implicitly monitored by a user. As demand for these devices increases it is desired to generalize sensor platforms to monitor a broad set of activities. Moreover, it is desirable to make devices non-obtrusive and more naturally fit into our daily life. This further motivates researchers to design simple devices able to complete complex sensor-supported tasks in real-time.

In this paper we:

- Demonstrate use of a mobile sensor platform for high-level inference, with an example about water consumption recommendation while hiking;
- Highlight the selection of simple, inexpensive sensors for a non-obtrusive device running real-time algorithms;
- Build a dehydration model for implementation on a sensor platform.

To further understand applications of sensors we look at a specific problem found in outdoor activity, namely water consumption recommendation. This problem is challenging as it demands data from many sensors to be properly fused for inference and recommendation.

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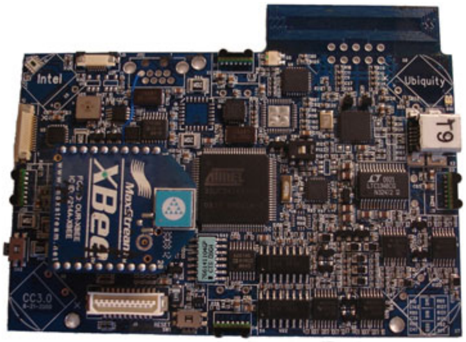


**Fig. 1.** Intel Ubiquity Lab sensing platform providing the following features: triaxial accelerometer, 3D compass, triaxial gyroscope, capacitive touch sensors, light sensor, thermometer, barometer, ZigBee radio and switches

## 2 System Description

Towards the goal of demonstrating high-level inference with a mobile sensor platform, we design a system that recommends appropriate water intake during a hike. Hiking can be a physically demanding exercise that becomes dangerous if hikers get dehydrated. This makes this application useful in a practical sense because learning how to avoid dehydration can be extremely difficult. Although many guidelines exist in the literature [1, 5, 6], little effort has been made in integrating them in a unified model. More importantly, this also raises the issue of how to connect high-level goals (such as "maintain healthy water intake") to low-level sensory data (such as "your acceleration is currently [x, y, z]"). The amount of water that needs to be consumed is strictly related to the level of dehydration. It is advisable to drink at rates comparable to a person's sweating rate [1]. Different variables affect the dehydration rate, including intensity of activity and environment conditions.

**Hardware**: our prototype system is implemented using the Intel Ubiquity Lab mobile sensing platform, depicted in Figure 1, providing the following features: triaxial accelerometer, 3D compass, triaxial gyroscope, capacitive touch sensors, light sensor, thermometer, barometer, ZigBee radio and switches. This hardware allows for a non-obtrusive implementation, where the device can be carried anywhere over the outerwear or on the user's backpack. The most relevant sensors to activity and environment inferencing were chosen as a subset of the available features, as described in the following.

**Sensor selection**: the accelerometer is used to achieve information about the intensity of the user's activity, as physical activity recognition using acceleration data has been shown to be successful in the literature [3]. Dehydration rate is also affected by temperature, altitude and degree of exposure to sunlight [1, 5, 6]. For this reason, the light sensor, the barometer and the thermometer are employed to make inferences about the environment conditions in which the

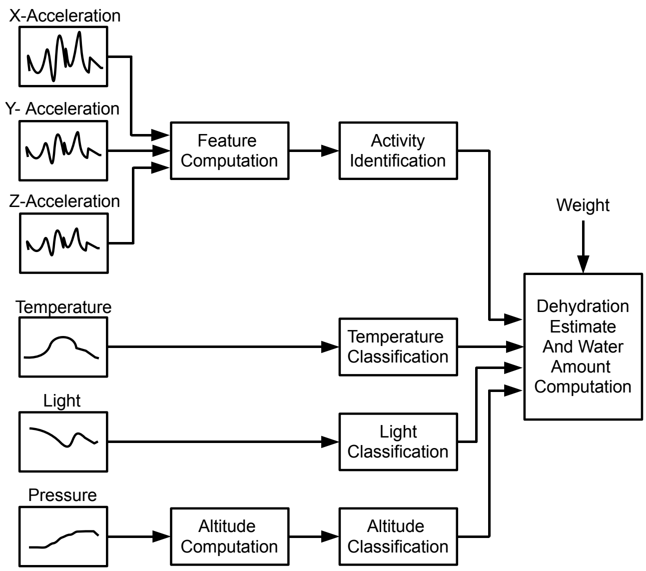


**Fig. 2.** Overview of the prototype system: acceleration data is used for activity identification while temperature, pressure and light intensity are used to make environmental inferences. Information about intensity of activity and environment conditions is then combined to estimate dehydration rate.

activity is performed. Altitude is computed from the pressure by inverting the barometric formula [4]. These sensors were preferred to perspiration and $CO_2$ sensors because of their non-obtrusive and inexpensive nature.

**Classification**: the system is depicted in Figure 2. We use classification as opposed to more complex interpolation to mitigate computational load. The following four common hiking activities are considered, listed in increasing intensity level: resting, walking level, walking downhill and walking uphill. This particular choice of actions is able to characterize a general hiking experience providing a reasonable estimate of the amount of undertaken work and, as a consequence, a recommendation about the amount of water that the user should drink. The model makes use of a well-known approach [3] to recognize activity using acceleration data.

We address the modeling of the external environment conditions by considering a number of temperature, light and altitude classes. Exploiting the guidelines present in the literature, a different dehydration rate is associated with each possible combination of classes. The following temperature classes are used: low (under 20°C), medium (over 20°C but below 30°C) and high (above 30°C) [1]. Altitude is classified as either low or high based on a threshold set to 6000 feet [5]. In a similar way, illumination is classified as low or high based on a threshold set to 800 lux, distinguishing between direct and indirect sunlight exposure [6].

**Inference**: starting from the identified activity and the temperature, altitude and light classes, the estimated dehydration rate $d$ is computed according to the following equation:

$$d = (1 + k_a a)(1 + k_l l)\left[d_{00} + \frac{d_{23} - d_{03}}{2}t + \frac{d_{03} - d_{00}}{2}i\right]$$

where $a \in \{0, 1\}$, $l \in \{0, 1\}$, $t \in \{0, 1, 2\}$ and $i \in \{0, 1, 2, 3\}$ represent altitude, light, temperature and activity intensity, respectively. The algorithm was designed to minimize processor load. The constants $k_a, k_l, d_{00}, d_{23}$ and $d_{03}$ were estimated from the literature [1, 5, 6]. Dehydration rate is then used to estimate the amount of water that should have been consumed over the hike to keep dehydration below 2% of body weight.

## 3 Conclusion

We demonstrated use of a mobile sensing platform for complex behavior inference, developing an application for recommending water intake when hiking. Our prototype system meets the design criteria including use of simple sensors and algorithms, non-obtrusive nature and real-time operation. Preliminary experiments provided results within reason of current sport medicine expectations. Upon completion of a 30 minute level walk in direct sunlight, low altitude and moderate temperature, a water amount of 0.22 liters was recommended for a 70 kg person, which is in the range of 0.25 liters expected.

With regards to the hiking application, more research has to be formalized on the effect of weather conditions and intensity of exercise on dehydration. Also, the use of additional sensors can be investigated to achieve a richer description of the environment and a more detailed activity classification. Possible improvements include using a flow rate sensor to detect amount of water consumed and microphones to monitor user breathing and conversation level.

In a more general frame, future work includes formalizing the design process to choose appropriate sensors and algorithms. More research is needed to bring machine learning algorithms to low computational power platforms.

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