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Development of Urine Hydration System Based on Urine Color and Support Vector Machine

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Abstract

Nowadays, to maintain hydration in human body has becoming an important issue in health research. The water needs depend on many factors like body size, dietary intake, gender and physical activity, consequently the indicator of hydration status is highly individual. Based on recent research that said the urine color is reliable indicator for hydration status, we would like to develop a prototype for detecting hydration status automatically. To use the color indicator precisely, we tested several color sensors to performance in detecting color and chose TCS34725 as the color sensor. The prototype of urine hydration system (UHS) is designed to record hydration status data in daily basis in cloud computing and the urine information can be accessed by Android smartphone. The prototype employs a set of microcontrollers and sensors as IoT devices and support vector machine (SVM) as a classifier. To evaluate the accuracy of hydration status, we compared the prediction with urine specific gravity (USG) as golden standard. The accuracy of our UHS prototype can reach up to 84%, which is nearly similar with the accuracy of manual prediction using only human eyes.

Keywords: urine hydration system; color sensor; cloud computing; support vector machine; urine specific gravity

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1. Introduction

Water is essential for human health. Without water, human body can survive only for a few days. Depending on the stage of human life, total body water (TBW) of infant is about 75% body weight, but in elderly is only about 55% [1]. Nevertheless, there are many unanswered questions about water in of our body metabolism. To prevent dehydration humans have evolved a finely sensitive system of physiological controls to maintain TBW by thirst. Humans have many reasons for drinking, but most of drinking is due to the thirst which triggered by water deficiency. Nowadays, the mechanism of thirst is understood well, and the reason why human may drink only for pleasure is associated with large capacity of the kidney to quickly remove excess water with urine secretion [2]. To maintain hydration in human body requires a complex coordination of many sensors in the body, which is done by integrative centers in the brain to process the data. Most fluid balance is controlled by mechanism of homeostasis which correspond to the TBW. This mechanism is sensitive to TBW change both water deficits or excesses, and precise to only a few hundred milliliters [2]. In the brain, there are two controlling sensors: one for drinking by sending a signal to the brain and the other for urine secretion by sending a signal to the kidneys. The kidneys play an important role in regulating TBW, which work better in the presence of a plentiful water supply. If there is only a few of water in the body, the kidneys will produce a more concentrated urine and make their tissues work harder. Therefore, drinking enough water will protect this vital organ.

It is important to know about the effects of variation in TBW on health and human performance. In the past, researches on water requirements were just based on observing the water intake from foods and drinks of the healthy individuals. Beyond this hydration state, we do not really understand how dehydration affects human, for example the influence of water intake to chronic diseases. We want to know about the influence of water intake, which is important to prevent illness and maintain health. Recently, Isabelle Guelinckx et al [3] addressed the dehydration question based on the human physiology. Previous research has associated total fluid intake or water intake with the risk for chronic kidney disease (CKD). Urine biomarkers have been linked to the risk of CKD, and these biomarkers, mainly arginine vasopressin (AVP) respond quickly to variations in fluid intake. AVP is molecule that is recognized as a very important part in water homeostasis. However, the AVP also have impacts to human health. When humans have lower intake of water, they have higher circulating AVP and thus higher urine concentration, they tend to have increased risk of developing pathologies, increased risk for diabetes mellitus or cardiovascular disease and chronic kidney disease (CKD). The interconnections between AVP, water intake and metabolic health can be seen in Fig 1.

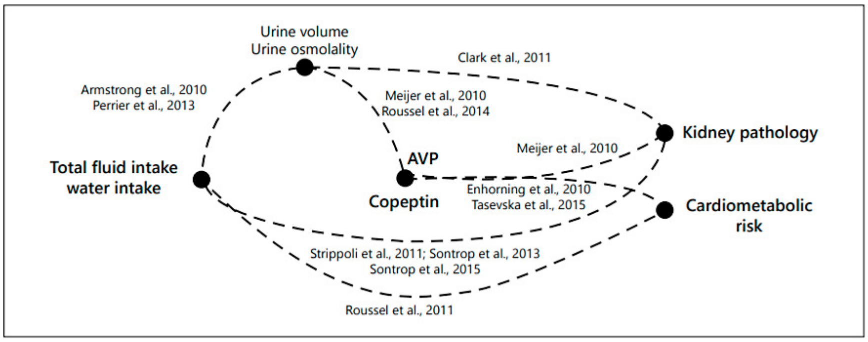


Fig. 1. Interconnection between total fluid intake to urine variables and AVP [3]

The water needs depend on internal human factors, such as body weight, dietary intake, gender, exercises, and external factors such as climate, temperature, and disease. Therefore, the indicator of hydration status is highly individual. Three simple indicators of hydration status are: body weight, thirst, and urine osmolality (the total number of solutes in a urine solution). Based on Thornton [4], increased water intake is related with loss of body weight. But its mechanisms through decreased feeding and increased lipolysis take a relatively long time, thus body weight is not suitable for tracking hydration. The second option, thirst naturally lefts behind an acute change in hydration mainly in exercise session. Moreover, the thirst responses of older persons are less sensitive comparing to younger persons [2]. These reasons make the thirst is viewed as not ideal method of tracking hydration. The last choice to monitor individual hydration status is by tracking urine osmolality or urine concentration. Urine concentration is the end-result of human metabolism required to maintain TBW in response to variation of hydration status. Thus, measuring urine concentrations has great benefits for individual assessment of daily water intake. Perrier et al [5] stated that the urine color correlates with urine concentration in situations and can be used for monitoring hydration status accurately. Substantial changes in urine color happen daily because of the amount of fluid intake. This fact suggests that individuals can use urine color to monitor their hydration status in simple way.

The results of Perrier et al [5] research states that a change in urine color by 2 shades on an 8-color scale (see Fig 2), can be attained with an assessable change in water intake about 1200 mL/day. Moreover, the change in urine color shades correspond to to change in urine volume and its specific gravity. This result has inspired us to use urine color as indicator of hydration status.

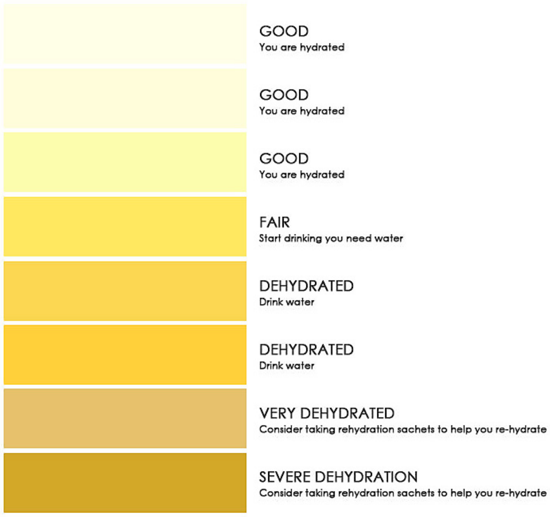


Fig. 2. 8-color scale urine hydration chart

Nowadays, many people live in sedentary lifestyle especially in urban areas. In sedentary lifestyle, people are often sitting while engaged in an activity like working, reading, socializing, watching television or using computer for much of the day. This lifestyle tends to make people ignore their daily water intake because their activity does not make a sense of thirst. Therefore, the sedentary group inclines to consume lower amounts of water and other beverages than in the other groups [6]. This habit can lead to chronic dehydration, where water that out from our body was bigger than the water continually. The risk of dehydration in the elderly is due to increased fluid loss coupled with a decrease in fluid intake associated with decreased thirst [7].

Research of The Indonesian Regional Hydration Study (THIRST) [8] found that as many as 46.1% of the 1200 Indonesians in DKI Jakarta, West Java, East Java and South Sulawesi were mildly dehydrated. It is also found that the number of adolescents who experienced mild dehydration higher than adults due to low knowledge about the function of water for the body. Another study [9] found that the dehydration risk factors in adolescents are ecological areas, gender, body temperature, hydration knowledge, and fluid intake, when to explain why adolescents got dehydration higher than adult. Another study [10] found that the dehydration factors are depends on age, gender, working time and also work load. To increase hydration knowledge, there is book [11] that shows how water can cure diseases by only adjusting the water and salt intake. Nevertheless, this approach is not effective because we do not know exactly our hydration status. Even though we can check daily the hydration status using urine color chart, we do not remember or care our history of hydration status. Due to this motivation, we would like to develop urine hydration system based on IoT technology which can monitor and store our hydration status and give recommendation about our health condition. The urine hydration system will be based on urine color aligned with the solid study [5] to identify the hydration status. There is a research [12] which use color and ammonia level in human urine to identify the hydration status. This research uses low quality color sensor and naïve Bayes classifier, so their experiments give low accuracy in the identification step. To build a better accuracy in identification of hydration status, we develop the system based on high quality color sensor and support vector machine (SVM) as classifier.

The remainder of this paper is composed as follows: first we discuss the design of urine hydration system (UHS) in section 2, and then is followed by hardware design and its implementation., in section 3. In section 4, we discuss software design including SVM algorithm for classifying the urine color. Furthermore, we report the experiment result in hydration status identification based on urine color in section 5. Finally, we summarize our work with suggestions to our future research in section 6.

2. Urine Hydration System

The urine hydration system (UHS) is designed to detect hydration status automatically based on the urine color. We relied on Perrier et al [5] research that said the urine color is reliable indicator for hydration status. To use the color indicator precisely, we tested several color sensors to performance in detecting color and compared their datasheets. The used color sensor is TCS34725 (see Fig. 3) where this color sensor has better ability in determining red-green-blue (RGB) comparing the other color sensors. The TCS34725 [13] has RGB and clear light sensing elements and also an IR blocking filter for allowing color measurements to be made accurately. The TCS34725 sensor also has an incredible 3,800,000:1 dynamic range with adjustable integration time and gain.

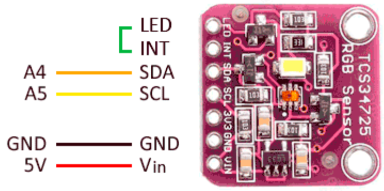


Fig. 3. TCS34725 color sensor

UHS is also designed to record hydration status data in daily basis in cloud computing Firebase. Firebase can be a platform to connect IOT with Android smartphone. It is mobile development platform that provides a database hosted in the cloud. Firebase stores data as JSON and can update the data in real-time by synchronizing to connected client. After the sensor read the urine color, UHS will send the color data to the local server for color classification. Local server which is built using python, will classify the color data based on urine hydration chart by using support vector machine (SVM) algorithm. Finally, the user profile from NFC tag, time and date, urine color data, and its classification will be sent to cloud computing Firebase. Fig 4 depicts the design of the UHS components and their interactions .

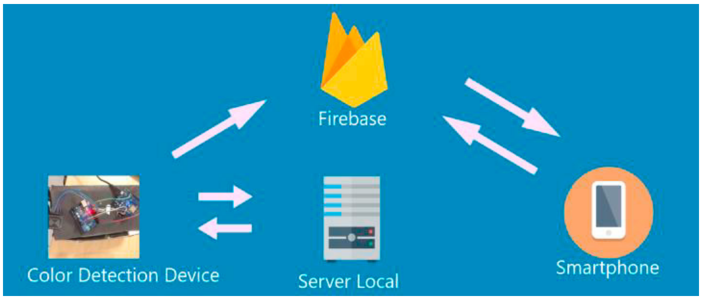


Fig. 4. The design of urine hydration system (UHS)

Furthermore, UHS is designed such that the users can monitor their hydration status conditions in the form of texts or graphs any time dan can also update their profiles. The next two sections will discuss hardware and software development of UHS in detail.

3. Hardware Design and Implementation

In this section, we would like to describe about the color detection device, which illustrates in Fig. 4. The color detection device, in principle, is an embedded device to get urine color data based on the color sensor. The components of this device consist of microcontroller Arduino Uno and Wemos D1, color sensor TCS34725, and RFID MRC522. To build the UHS prototype, the microcontroller Arduino needs to be combined with the sensor color sensor and RFID reader. Wemos D1 is Wi-Fi based board that uses layout similar to Arduino Uno. It is used to connect the UHS device with local server and cloud computing Firebase. Fig. 5 is scheme of the UHS prototype, including its wiring.

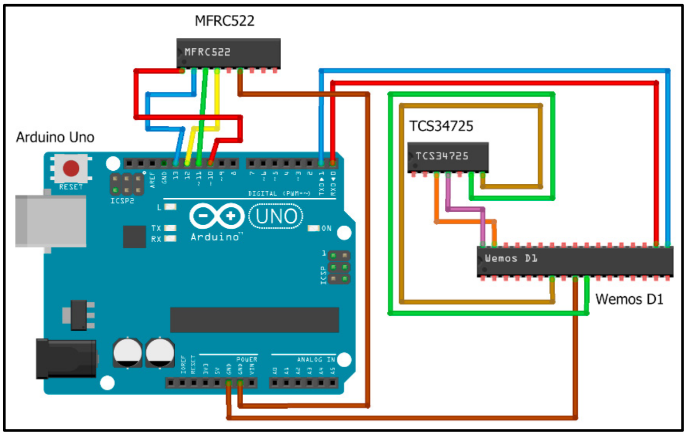
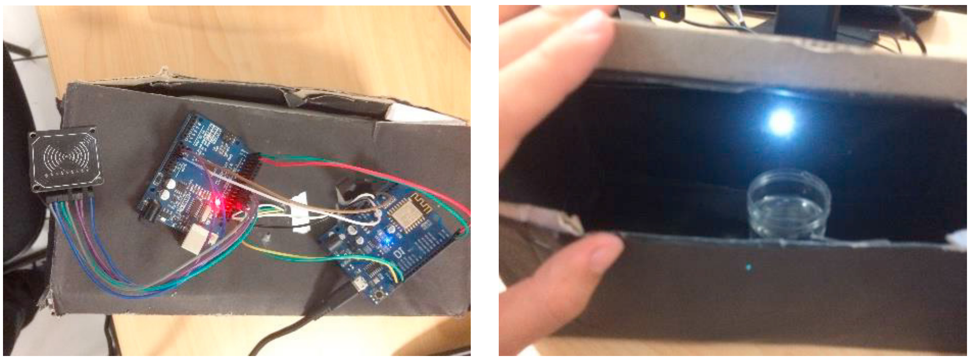


Fig. 5. The scheme of UHS prototype

The procedure to use the color detection device as follow: (1) users attach NFC or RFID tags, such as electronic ID card to the reader RFID MRC522 which connected on Arduino Uno, (2) user ID profiles which is read will be sent to Wemos D1 and integrate with the urine color data which read by the color sensor, (3) urine color data is sent to the local server for color classification, (4) Finally, all data including time and date will be sent to cloud computing. The appearance of or color detection device can be seen in Fig.6 together with illustration how to take the urine color data.



(a) (b)

Fig. 6. (a) a whole prototype (b) taking urine color data on the UHS

4. Software Design and Support Vector Machine

There are three programming languages which used in the software design of our UHS. To control and connect the microcontroller (Arduino Uno and Wemos D10) to other devices, it is used Arduino-based C language. While the local server, which implemented SVM for urine color classification, used Python as programming language. Finally, to develop android applications is used Java programming language in Android studio.

We implemented three communication types in the microcontroller based on Arduino-based C language for sensor data collection and device communication, as following:

1. To communicate between Arduino Uno and Wemos D1, we used serial port, which also known as a universal asynchronous receiver-transmitter (UART). In Arduino Uno, it communicates via digital pins 0 (RX) and 1 (TX) to the pair pins in Wemos D1 (see Fig. 5). Serial communication on pins TX/RX in Arduino Uno uses 5V TTL logic levels. This type communication is asynchronous serial communication using transmitter (TX) and receiver (RX) in which the data format and transmission speed can be configured [14].
2. To communicate between Arduino Uno and RFID reader MRC522, it is used SPI (Serial Peripheral Interface) in which communication is synchronous [14]. SPI is a synchronous serial data protocol used by microcontrollers for communicating with peripheral devices rapidly over short distances. To implement SPI communication, it needs three pins in Arduino Uno (see Fig.5), that is: (1) digital pin 11 for MOSI (Master Out Slave In), (2) digital pin 12 for MISO (Master In Slave Out), and (3) digital pin 13 for SCK (Serial Clock).
3. To communicate between Wemos D1 and the color sensor TCS34725, we used I2C (Inter-Integrated Circuit) communication protocol. I2C is a serial protocol for two-wire interface to connect microcontrollers in embedded systems, which has the following features: synchronous, multi-master and multi-slave. In Wemos D1, we can implement I2C communication by using two pins (see Fig.5), that is: (1) digital pin 16 for SDA (data line) and (2) digital pin 17 for SCL (clock line).

In local server, we developed simple HTTP server and classification function based on support vector machine (SVM). SVM is a discriminative classifier formally defined by a separating hyperplane [15]. Hyperplane in an n-dimensional Euclidean space is a flat, n-1 dimensional subset of that space that divides the space into two disconnected parts. SVM find the optimum separation hyperplane for a given finite set of learning patterns. We implemented SVM classifier by using scikit-learn library in Python programming language. For training SVM algorithm, we used 100 dataset, consisting of three RGB color as input data and one label of hydration status based on urine specific gravity (USG). The dataset is generated by normal random generator based on urine color chart (Fig. 2) and its related urine specific gravity as label (Table 1) and time data. This table is based on Minton et al [16]. Example of the training dataset can be seen in Table 2.

Table 1. Hydration status based on urine specific gravity (USG)

USG Value	Label	Meaning
1000 - 1010	0	hydrated and healthy (HH)
1011 - 1020	1	properly dehydrated (PD)
1021 - 1030	2	seriously dehydrated (SD)
>1030	3	highly dehydrated (HD)

Table 2. Example of training dataset

R	G	B	Label	USG	**Time**
85	90	75	0	1005	Noon
65	88	88	0	1000	Afternoon
77	85	85	0	1000	Noon
108	78	49	2	1023	Morning
76	88	84	0	1000	Afternoon

In our UHS prototype, Android application is mainly used to retrieved information for cloud computing Firebase. When the users register or update the profile in the application, their profile will be stored at Firebase. The user data is synchronized to their RFID or NFC tag by attaching the tag to the smartphone (see Fig. 7a) Furthermore, the application will display the urine information based on periodically measurements, in the form of sequences of text data. The information which are showed are user profile, date and time of measurements, urine RGB color, and the hydration status (see Fig. 7b). Finally, we can see the result of hydration status in graphical form. Consequently, we can see changes in hydration status more easily because the graph shows comparisons on every hour of each day (see Fig. 7c).

5. Experiment Result

For testing data, we collected urine data from 52 participants. Each participant collected one urine sample in morning, afternoon and noon randomly. As the training data, urine specific gravity of each sample as golden standard is measured by using digital refractometer and labeled based on Table 1 after that the urine color is measure using our prototype. The confusion matrix of experiments can be seen in Table 3. In general, the average accuracy of the UHS prototype is about 84%.

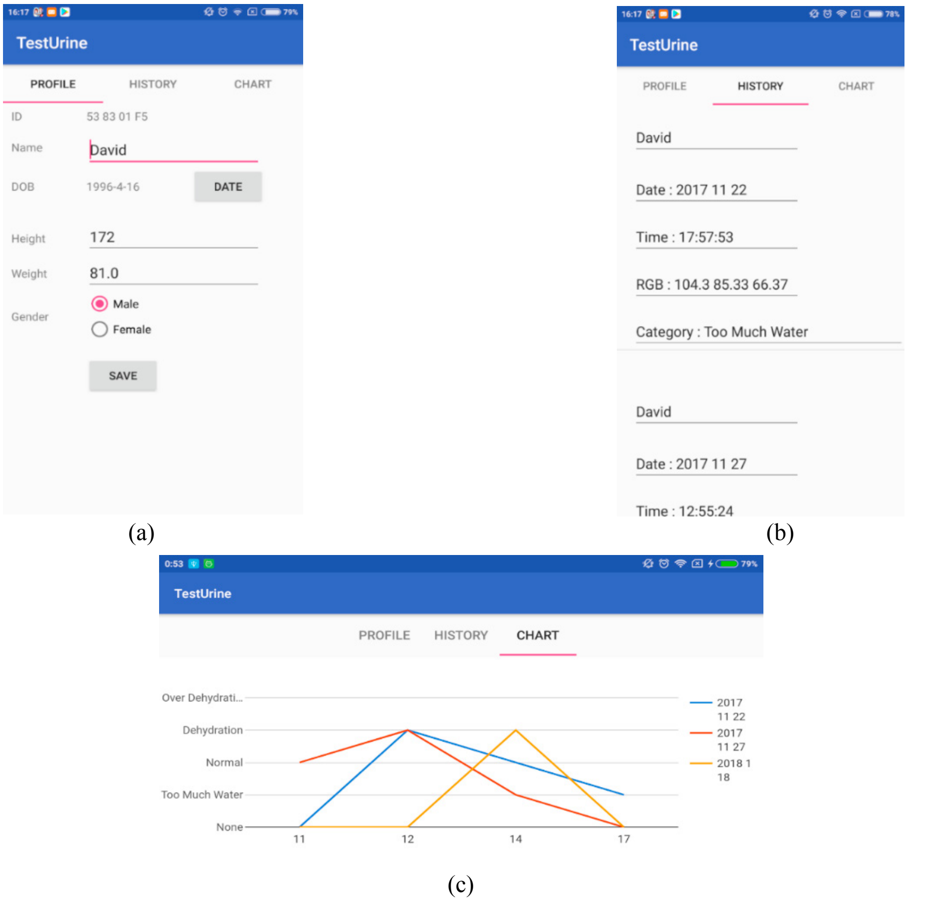


Fig. 7. (a) Form of user profile (b) urine history in text form (c) urine history in graphical form

Table 3. Confusion matrix of the experiments

	Actual				
Prediction	n =52	HH	PD	SD	HD
	HH	24	5	0	0
	PD	3	2	0	0
	SD	0	0	18	0
	HD	0	0	0	0*

Note: hydrated and healthy (HH), properly dehydrated (PD), seriously dehydrated (SD), highly dehydrated (HD). There no participants who is highly dehydrated.
Average accuracy: 84% based on 52 data
(24+2+18/52)

Here some examples of prediction of the testing data comparing to USG measurement using digital refractometer:

Table 4. Example of testing data

Urine Detection System					Comparison		Matching
Red	Green	Blue	Time	Prediction Status	USG	Hydration Status	
83	89	71	Afternoon	*HH*	1009	*HH*	✓
85	91	73	Noon	*HH*	1004	*HH*	✓
90	85	71	Morning	*SD*	1018	*PD*	x
92	92	71	Afternoon	*HH*	1014	*HH*	✓

6. Conclusion

In this paper, we have successfully developed prototype of urine hydration system (UHS) to detect and monitor urine hydration status based the urine color. Based on the experiment results, the average accuracy of this prototype is about 84%. We can still improve the prototype accuracy by adding more training dataset and tuning the SVM parameters. This result is nearly similar with the study of THIRST [8] that compares manual prediction using only human eyes with USG measurement using digital refractometer. The current implementation is still restricted for manual urine measurement. Thus, we would like to design further so that our UHS prototype can be installed in toilette as Benavides et al [14] and then detect the hydration status automatically. These are remaining for our future works.

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