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Real-time fluid intake gesture recognition based on batteryless UHF RFID technology

Asangi Jayatilaka*, Damith C. Ranasinghe
Auto-ID Lab, School of Computer Science, University of Adelaide, Australia

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ABSTRACT

Automatic fluid intake monitoring can be used to ensure adequate hydration in older people. In this study, a real-time fluid intake monitoring system based on the batteryless Ultra High Frequency Radio Frequency Identification (RFID) technology is proposed. The system is simple, unobtrusive, low cost and maintenance-free. Despite the noisy RFID data stream, we demonstrate the efficacy of using a batteryless RFID enabled fluid container to recognize individual instances of drinking (i.e. drinking episodes), in the presence of non-drinking gestures. We conducted experiments with 10 young and 5 older volunteers and achieved F-scores of 87% and 79% for recognizing drinking episodes, respectively.

1. Introduction

With rapidly growing aging populations around the world and increasing number of cognitively impaired older people, poor fluid intake is becoming a common problem [1]. Dehydration and incorrect fluid intake behaviors in older people are extremely complex and can have long term devastating effects such as reduced mental and physical capabilities and even death [2,1]. Older people, especially the those diagnosed with cognitive impairments, may forget to initiate drinking or get distracted and fail to complete it [2].

Monitoring drinking behaviors of older people living at home is important not only to ensure that they maintain an adequate fluid intake but also to identify any deviations in their fluid intake patterns [1–3]. To date, approaches to monitor such behaviors are mostly based on manually filled questionnaires [4]. However, manual techniques are error-prone and hence unsuitable for older people with cognitive impairments. Automatic fluid intake monitoring approaches can alleviate limitations in manual methods, but only limited research towards automatic fluid intake monitoring have been carried out. In fact, most of the research on automatic dietary monitoring focus on eating activity [5,6] but drinking activity is mostly overlooked.

Similar to automatic monitoring of eating activity [5], automatic monitoring of drinking activity involves two key challenges: (i) recognizing the periods where drinking takes place and (ii) identifying the type of liquid and amount of liquid. Continuous monitoring of the individual instances of where drinking takes place can reveal information about timing and the rate of fluid consumption [3,7]. Furthermore, such information may be later used to infer the volume of liquids consumed by linking with human activity profiles.

Common approaches for automatic monitoring of fluid intake include attaching battery-powered sensors to users [8,3,7] or to objects [9,10], because of their capability to provide information rich sensor data. However, these sensors are bulky, maintenance prone (i.e. need battery replacement or recharging) and expensive. As a result, they are unsuitable for

* Corresponding author.
E-mail address: asangi.jayatilaka@adelaide.edu.au (A. Jayatilaka).

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older people in free living conditions. In contrast, computer vision techniques do not require instrumenting a person, hence they are unobtrusive and do not require maintenance such as changing or replacing batteries [11,12,10,9]. However, the use of cameras has raised privacy concerns among community-dwelling older people despite the use of silhouettes to preserve privacy [13].

Batteryless (passive) Ultra High Frequency (UHF) Radio Frequency Identification (RFID) tags are small, inexpensive and has an infinite lifetime making them ideal candidates for unobtrusive monitoring of human behavior in real world settings [14,15]. These tags can be easily embedded into everyday objects, creating possibilities for users to carry out their normal routines without any alterations. Up to date, only a limited amount of work has been carried out on passive UHF RFID based lower level gesture recognition [16–19]. However, no research attempts have been made for recognizing natural dietary intake gestures based on passive RFID technology.

In this study, we investigate the efficacy of recognizing periods of drinking, henceforth referred to as drinking episodes, using passive UHF RFID tags by attaching them to drinking containers. We define a drinking episode as the time period of moving the fluid container towards the mouth, having a sip and moving the fluid container away the mouth. Recognizing such human movements can be considered a gesture recognition problem [7,3]. In particular, there are two types of human gestures [7]: (i) artificial and (ii) natural. Artificial gestures are controlled movements, mostly designed to provide strong discrimination for human computer control applications. On the other hand, natural human gestures such as fluid intake related human gestures are not well defined and occur unconsciously, hence challenging to spot than artificial gestures.

Despite the clear advantages of using passive UHF RFID technology for fluid intake gesture recognition, accurate and real-time recognition of drinking episodes embedded in RFID data streams is challenging. Firstly, a drinking episode involves non-repetitive movements that have very short durations in contrast to steady or repetitive movements such as walking, running and sitting [7]. Secondly, previous studies [20,21] clearly illustrated that due to the unreliable, inconsistent nature (noise) of Received Signal Strength Indicator (RSSI) information, it cannot be used as an accurate measure of the distance. Thirdly, RSSI values are directly affected by water based liquids and the material of the drinking container. Water based liquids can significantly affect read range and backscatter power characteristics of the RFID tag. Additionally, cold drinks cause water vapor to condense on the outer surface of the drinking container and can affect the performance of the RFID tag. Fourthly, participants may cover RFID tags with their fingers or palm or might move objects or parts of the human body in between the reader antenna and the tagged cup blocking radiation from the reader antenna to the RFID tags. Therefore, our focus is to design an RFID tagged drinking container suitable for recognizing drinking episodes and accurately determining drinking episodes based on streaming RFID information. The contributions of this paper are listed below.

- We propose a simple drinking container design (henceforth referred to as *smart cup*) with sensing and unique identification capability based on commercially available passive UHF RFID technology (Section 3). The design enables the *smart cup* to be used for recognizing natural drinking episodes without the need for any body-worn devices.
- We collected data from (i) ten young volunteers based on broadly scripted activity routines and (ii) five older volunteers in an unscripted setting (Section 5). We have made the anonymized and annotated datasets publicly available to support other researchers as well as to serve as a baseline for future research.[1]
- We propose a machine learning based approach capable of recognizing natural drinking episodes embedded in the RFID data stream in real time (Section 4).
- We evaluate the capability of the proposed system to recognize natural drinking episodes based on the data collected from young participants. Then, based on the machine learning models trained from data collected from young participants, we evaluate the performance of the system to recognize drinking episodes for data collected from older participants. The promising results demonstrate the efficacy of the proposed approach to recognize natural drinking episodes for both young and older participants (Sections 6 and 7).

2. Related work

We review related literature in three aspects: (a) monitoring fluid intake based on body-worn sensors; (b) monitoring fluid intake based on environmental sensors; and (c) passive RFID based gesture recognition.

2.1. Body-worn sensors for monitoring fluid intake

Single or multiple sensors attached to various parts of the human body, such as arms [7,3,22] and neck [23], are proposed to monitor fluid intake. For example, in [7] commercially available inertial sensors were attached to different parts of the body, such as lower and upper arms, to recognize the periods of drinking and eating. Even though [3] significantly reduced the number of body-worn sensors compared to [7], it still required instrumenting a person with a bulky battery-powered device.

Although body-worn sensors provide rich sensor data, evidence in the literature suggest that older people, especially those with memory impairments, may forget to wear the devices or purposely refuse to use them due to obtrusiveness and

[1] http://autoidlab.cs.adelaide.edu.au/research/inutricare.

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requirement for maintenance (such as charging batteries) [24]. Furthermore, as highlighted in [22] body-worn approaches to recognize drinking can suffer from false recognition because drinking gestures, for example, can have a similar motion to eating gestures.

2.2. Environment sensors for monitoring fluid intake

Previous work on body worn sensor free fluid intake monitoring are based on (i) sensors attached to objects and (ii) vision based techniques using cameras. Both these approaches are unobtrusive as they do not require the users to be instrumented with sensors.

Monitoring drinking episodes using data from battery-powered environmental sensors attached to everyday objects have been proposed in [9,25–27]. For instance, in [9], a pre-defined tilt angle threshold based on acceleration signals obtained from a mobile phone attached to a drinking container was used to recognize drinking motions. In [25], an ordinary dining table was augmented with weight scales, a wireless networking module for communications and nine RFID antennas. Here, RFID technology was used for unique identification of RFID tagged objects and dietary intake was identified by the weight changes. However, researchers in [25] revealed that the time period of a drinking motion is less than the amount of time the RFID reader performed one round of reading over nine antennas; hence, they were unable to recognize the periods of drinking accurately. Recently, a fine grained pressure textile matrix and a weight sensitive tablet have been proposed to monitor dining activities including drinking [26].

Apart from identifying the periods of drinking, in [27,28], sensors attached to drinking containers were used to automatically recognize levels of fluids. In [27], a drinking container embedded with a high resolution capacitive sensor was used to monitor the fluid level where a coil embedded in a dining table was used to power the drinking container using inductive coupling and the same set up was used for data exchange. In [28], a passive RFID tag attached to the side of a drinking container was used to identify when a refill was needed at a restaurant setting based on the full and empty states. These two states were mainly identified using the sudden detection of the attached RFID tag. According to the cup design [28], the RFID tag was only visible when the glass was empty. However, we are interested in recognizing drinking episodes based on the variations in RSSI and phase data obtained from the *smart cup*. Therefore, the RFID enabled cup design proposed in [28] is not suitable for our work.

Although the above described battery-powered environmental sensors produced rich sensor data, their higher per unit cost [9,25] and the need for maintenance [26] make them less applicable in the real world. On the other hand, vision based approaches [11,12,10,9] for fluid intake monitoring have also been proposed. For example, in [11], four cameras were employed at a dining table to produce multi-view videos and they were processed in real time to recognize eating and drinking actions. Furthermore, in [9], images acquired by a mobile phone attached to a drinking container were used to monitor fluid levels. In [10], an Xbox Kinect 3D sensor, which recorded human behaviors using an infra-red camera, was used to identify when drinking took place. Even though vision based techniques are unobtrusive and do not require maintenance, as discussed in [29], robustness of vision based recognition techniques can be challenged due to multiple reasons such as changing illumination, clutter, dynamic backgrounds and occlusion. Furthermore, [13] states that among community-dwelling older people cameras raised greater privacy concerns than other technologies, even when methods for extracting silhouettes were in place to preserve privacy.

2.3. Passive RFID based gesture recognition

The research focused on passive UHF RFID based gesture recognition is limited [16–19]. They mostly focus on specific well defined gestures and require multiple RFID reader antennas and reference tags. For example, in [16], a tag created by combining four passive RFID tags – super tag – was moved in a 2D space on a square table. Three antennas were placed around the table and reference tags were employed to localize the super tag. In [17], gesture recognition using a regression based algorithm in a smart home environment was the focus. In addition to the simulated gestures, their experiments involved a human subject, reproducing the gestures proposed in [16], using an RFID tagged coffee cup, in a smart kitchen equipped with four wall mounted antennas.

Researchers in [14] proposed a real-time action recognition system based on spatial relationships among RFID tagged everyday objects. They conducted experiments in a kitchen environment and the proposed approach is capable of recognizing meal preparation actions. Subsequently, recognized actions were used to infer high level activities such as making cereal [14]. In [19], fixed set of passive RFID tag motions such as still, cover, rotate, swipe were recognized using a single antenna placed near the ceiling. They also recognized high level activities such as making cereal and drinking milk by associating the higher level activities with movement events of relevant RFID tagged objects. People may use a drinking container besides drinking such as dragging hence directly mapping movement events of a drinking container to the high level activity of drinking may result in false recognitions. However, unlike our study, identifying individual drinking instances was not the focus in [19].

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2.4. Summary

Body-worn approaches for fluid intake monitoring are not suitable for older people with cognitive impairments as they may forget to wear those monitoring devices daily. Particularly, battery-powered sensors for fluid intake monitoring have disadvantages in free living conditions as they require maintenance. Vision based techniques can raise privacy concerns among community-dwelling older people. Most of the fluid intake recognition studies [7,3,9] have evaluated their approaches with data collected using young participants, thus their performance with older people cannot be guaranteed. Passive UHF RFID can serve as a practical, unobtrusive, battery-less solution for fluid intake monitoring. However, the ability to recognize natural human gestures, particularly those related to fluid intake, based on passive RFID technology is still not explored.

3. Design and realization of the *smart cup*

3.1. RFID preliminaries

Here, we provide an insight into passive RFID technology in which we ground our *smart cup* design. Passive RFID tags harvest energy radiated by RFID reader antennas. Once successfully powered, they respond by backscattering the Radio Frequency (RF) signal back to the RFID reader via the RFID antenna. In this study, we particularly use UHF RFID technology and the communication is governed by the RFID air interface protocols ISO-18000-6C [30]. Apart from the unique identification of the tag, modern RFID readers are able to measure detailed RF communication related properties such as RSSI and phase. RSSI is an indicator of the power received from the RFID reader antenna. Phase is a measure of the phase angle between the RF carrier transmitted by the reader and the return signal from the tag. RFID reader performs frequency hopping from one channel to another, as a result, phase values are dependent on the frequency [31]. RF phase (Ψ) is generally affected by even small movements of an RFID tag and RSSI is primarily affected by much larger movements.

RSSI is affected by the distance between the reader and the tag as well as the orientation of the tag antenna. Based on the Friss transmission equation [32], RSSI of a backscattered signal that is captured by an RFID reader has the form of $P_t G_t^2 G_{path}^2 K$. Here, P_t is the output power of the reader, G_t is the gain of the reader antenna, K is the backscatter gain. The G_{path} is the one-way path gain of the deterministic multipath channel determined as $G_{path} = \left(\frac{\lambda}{4\pi R}\right)^2 |H|^2$. R is the line of sight distance between the tag and the reader antenna, and H is the channel response due to multipath. Although RSSI is sensitive to channel characteristics, RSSI is also determined by R as $RSSI \propto 1/R^4$. The tag radial velocity can be estimated by measuring the phase of the tag signal at two time instances, as $V_r \propto \frac{\partial\Psi}{\partial t}$ [31]. Additionally, the distance between reader and the RFID tag is proportional to the partial derivative of the phase with respect to the derivative of frequency as $d \propto \frac{\partial\Psi}{\partial f}$ [31]. Unlike in [28], our aim is to recognize variations in RSSI and phase data extracted from tag replies to recognize drinking episodes.

3.2. Design considerations

Water based fluids can largely reduce the readability of the tag due to absorption of incident RF energy from reader antennas as well as the resulting detuning of the RFID tag antenna in the presence of moisture. Furthermore, water vapor can get condensed over the outside surface of the cup due to the presence of a colder fluid inside. Additionally, people may cover RFID tags with fingers or palm affecting the performance of the tag and possibly even move objects or parts of the human body in between the reader antenna and tagged objects blocking radio frequency paths to RFID tags. As a result of the issues discussed above, detection of RFID tags can be severely reduced and variations in RSSI and phase information may not relate to the movements of the *smart cup*. More importantly, in order to recognize drinking episodes, at least a single RFID tag must be observable. Therefore, the proposed *smart cup* design should (i) increase the possibility of detecting at least a single RFID tag even when the cup is filled with liquids and (ii) facilitate reliable RSSI and phase patterns from the *smart cup*.

3.3. Smart cup prototype

We realized a *smart cup* prototype by attaching four commercially available passive UHF RFID tags to a regular tempered glass cup as shown in Fig. 1(a). Three RFID tags were attached to the side of the *smart cup* while another RFID tag was attached to the bottom. As discussed earlier, liquids or a human hand may yield RFID tags undetectable. We believe redundancy with multiple tags can increase the drinking episode recognition performance. In the *smart cup* data stream, a single tag reading consisted of the 5-tuples: (i) RSSI; (ii) phase; (iii) frequency; (iv) antenna ID; and (v) time stamp.

In order to increase the possibility of having at least one RFID tag visible most of the time, even when the *smart cup* was completely filled with liquids, a Styrofoam base was used to separate the RFID tag at the bottom of the cup (i.e. tag 4). Styrofoam's dielectric constant is very close to that of air (see Table 1) and as a result the effects of liquids on the tag are reduced and the possibility of successfully reading the tag is increased. In order to further increase the detectability

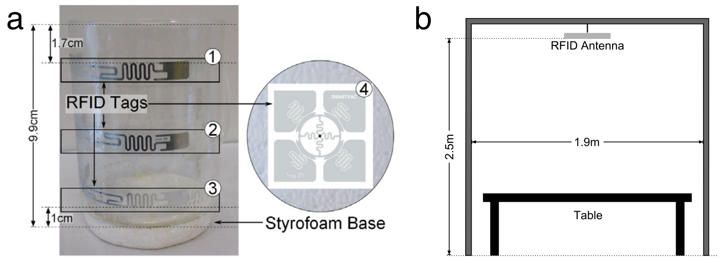

Fig. 1. (a) Re-created dining room setting. (b) The *smart cup* used in the experiment.

Table 1
Typical relative permittivity of materials reported in the literature.

Air	Styrofoam	Water (20 °C)	Water (0 °C)	Tempered glass	Porcelain	Glass	Plastic
1	1.03	80.4	88	7.3	5–6.5	5–10	1.5–3.5

of the bottom tag, we specifically selected Smartrac Frog 3D tag[2] due to its orientation insensitivity to the reader antenna and larger operational range (>6 m). Furthermore, Smartrac Frog 3D tag was well suited to be placed at the bottom of the drinking container due to its size (53 × 53 mm) and symmetrical shape.

We observed that, due to the relatively large dimensions of the Smartrac Frog 3D tags, placing them on the side of the drinking container can lead to poor tag performance as a consequence of the following: (i) tags being in the vicinity of a liquid at most times and (ii) increased obstructions of the tag from a human hand. Based on a preliminary study, we selected Alien Squiggle tags (ALN 96 402[3]) with a good operational range (>4.6 m) and small size (94.8 × 8.1 mm) as a more suitable candidate for attaching to the side wall of the drinking container. We used a horizontal tag placement on the side of the *smart cup* to (i) increase the possibility of reliably reading the tags to obtain information rich RSSI and phase data when water level changes and the distance of tags on the wall to liquids in the drinking container increases and (ii) facilitate liquid level detection in the future using the same *smart cup* design. Three Alien Squiggle tags were attached opposite to the handle of the *smart cup* so that they are less likely to be obstructed by a human hand or occluded by a human body while drinking takes place. As demonstrated in [28], the detectability of the RFID tags is affected by the fluid level. Therefore, in future, we are considering to extend the work in [28] to determine the fluid level to a reasonable granularity in real time using information from the multiple tags on the *smart cup*.

4. Drinking episodes recognition

We treated the problem of determining whether a tag reading corresponded to *drinking* or *non-drinking* to be a binary classification problem and a continuous series of drinking predictions were considered as a drinking episode.

4.1. Data segmentation and feature extraction

The collected data stream is a time series. We segmented the time series as a single tag reading is inadequate to obtain sufficient amount of information about human movements [33]. We used a fixed time overlapping segmentation method. A segment size (δw) of 5 s, which is advanced each 0.1 s, was selected based on the mean duration of drinking episodes in the dataset collected with young people (see Section 5). We considered two segmentation schemes for feature extraction: (i) full window approach and (ii) sub-segmented window approach. In the sub-segmented window approach, the 5 s segment is equally divided into three sub-segments. We believe that such a sub-segmentation window approach can capture the typical drinking behavior of a person that includes a sequence of movements involving the cup: (i) moving the cup towards the mouth; (ii) having a sip; and (iii) moving the cup away from the mouth. For each segment, we extracted statistical features (mean, median, mode, standard deviation and range) with respect to RSSI and Phase. In the case of the sub-segmented window approach, for the central tendency measures, we obtained the differences between the corresponding values for each sub-segment as features by taking advantage of having three sub-segments and other measures were used as it is.

Before extracting phase based features, raw phase values need to be corrected for flipping and wrapping. RFID readers wraps the phase signal in the range of 0 to 2π and flipping can occur randomly where an ambiguity of π is added to the original phase measure. RFID readers also hops the transmitted frequency in a pseudo-random manner in order to reduce interference. Given a stationary tag, the phase value depends on the frequency and therefore phase should be corrected

2 https://www.smartrac-group.com/frog-3d.html.
3 http://www.alientechnology.com/wp-content/uploads/Alien-Technology-Higgs-3-ALN-9640-Squiggle.pdf.

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considering the reader selected frequency. In this study, statistical features with respect to phase was calculated based on differences in phase between consecutive tag reading belonging to the same tag. Feature extraction considered each tag individually and the full window approach and sub-segmented approach consisted of 40 and 120 features, respectively.

4.2. Classification

We investigated five machine learning algorithms for binary classification: (i) Naïve Bayes (NB) [34]; (ii) Linear Support Vector Machine (LSVM) [35]; (iii) Non-linear Support Vector Machines (NSVM) [35]; (iv) Random Forest (RF) [36]; and (v) Linear Conditional Random Fields (LCRF) [37].

These five classification algorithms have different characteristics. NB is a simple generative model that assumes features are conditionally independent [34]. NB implementation provided in Matlab (R2015a) is used in this study. Support Vector Machine (SVM) is a state of the art discriminative machine learning algorithm which has a strong theoretical generalizability [35]. NSVM supports non-linear decision boundaries using kernels. In this study, we used LSVM and NSVM using Radial Basis Function (RBF) kernel. We use libraries LIBLINEAR [38] and LIBSVM [39] for LSVM and NSVM classifiers, respectively.

RF is an ensemble classifier based on the CART algorithm [36]. Output from RF is obtained considering the majority votes of all trees (nTrees) in a Decision Tree (DT) ensemble. As a result, based on the concept of law of large numbers, RF achieves a higher generalization performance than a single DT. RF implementation provided in Matlab (R2015a) is used in this study.

LCRF is a probabilistic graphical model which models a Markov chain. As a result, LCRF is capable of modeling the relationships between consecutive elements in a sequence. Inferencing in traditional LCRF algorithms consider the entire input sequence. Therefore, traditional LCRF can only work in finite sequences, hence cannot be used for real-time sequence prediction. We used the LCRF proposed in [33] where the sum–product algorithm is used during inferencing to obtain real-time predictions. In summary, in the case of real-time applications, the goal is to efficiently find the marginal probability of the current hidden variable given the past and current observations. Therefore, given a sequence of feature vectors $X = (x_t)_{t=1}^{T}$, where $x_t \in \mathrm{R}^d$ and T is the length of the sequence, the marginal probability of variable y_k is calculated as

$$p(y_k|x_{1:k}, \lambda) = \frac{1}{Z(x_{1:k}, \lambda)}\, \psi(y_k; x_{1:k}, \lambda)\, m_{y_{k-1},y_k}(y_k; x_{1:k}, \lambda)$$

where messages $m_{i,j}$ are calculated as

$$m_{i,k}(s_k) = \sum_{s_i} \psi(s_i)\psi(s_i, s_k) \prod_{t\in N_i\setminus\{k\}} m_{t,i}(s_i)$$

where s_i represents variable node i, $N_i \setminus \{k\}$ represents the set of neighbors of variable node i with the exception of node k, and $\psi(s_i)$ and $\psi(s_i, s_k)$ are node and edge potentials, respectively [33].

5. Data collection

Similar to [7,5,25,26], our experiments were conducted in a re-created dining room setting. During the experiments a single RFID antenna was placed above the dining table, near the ceiling and focusing downwards as illustrated in Fig. 1(b). Ten young volunteers (age: 30.7 ± 1.6 years) and five older volunteers (age: 69.0 ± 4.6 years) participated in this study. The older participant cohort also included an older adult diagnosed with Parkinson's disease. Parkinson's is a progressive neurological condition. Shakiness, muscular rigidity and imprecise movements are common symptoms of Parkinson's disease.

Experiment with young volunteers. Broadly scripted activity routines were employed to collect data from young participants. Such activity routines permit greater variability in participant behaviors compared to well scripted activity routines and ensure diversity and complexity of the collected data by making sure the existence of realistic other gestures involving the *smart cup* and avoiding long periods of inactivity [3,7].

During the experiments, participants were requested to select any type of drink according to their preference from a given set of choices: (i) water (hot/cold); (ii) cold soft drinks; (iii) apple/orange juice; (iv) tea or coffee. Then they were requested to drink their choice of beverage as they would normally do (see Fig. 2). The participants had the freedom to drink as much as they like and freely mix the drinking activity with other high level activities (such as eating, reading, and working on the computer) according to their preference. Even though we were not interested in recognizing high level activities such as eating and reading, this set up ensured that drinking movements occurred naturally. Furthermore, the experiments were conducted during lunch time, early morning and tea time allowed participants to undertake drinking normally during their lunch, breakfast or tea time.

The broadly scripted activity routines ensured the existence of non-drinking gestures involving the *smart cup*. These non-drinking gestures were created based on different ways users typically interacted with the cup apart from drinking and involved: (i) moving the cup while changing the sitting position; (ii) dragging the cup while changing the sitting position; (iii) getting interrupted by a phone call and as a result not completing an already initiated drinking episode; (iv) bringing the cup to the dining area; and (v) taking the cup away from the dining area. Participants were not given specific instructions except to perform these gestures with the *smart cup* multiple times during the experiment and they were free to decide how and when to perform them. For the telephone interruption, a researcher rang a telephone as soon as the participant

Fig. 2. (a) a young participant drinking water while having her lunch; (b) a young participant drinking orange juice while reading the news paper; (c) an older participant drinking cold white wine while reading a message on the phone and having his lunch; and (d) an older participant getting a refill of orange juice while enjoying his lunch.

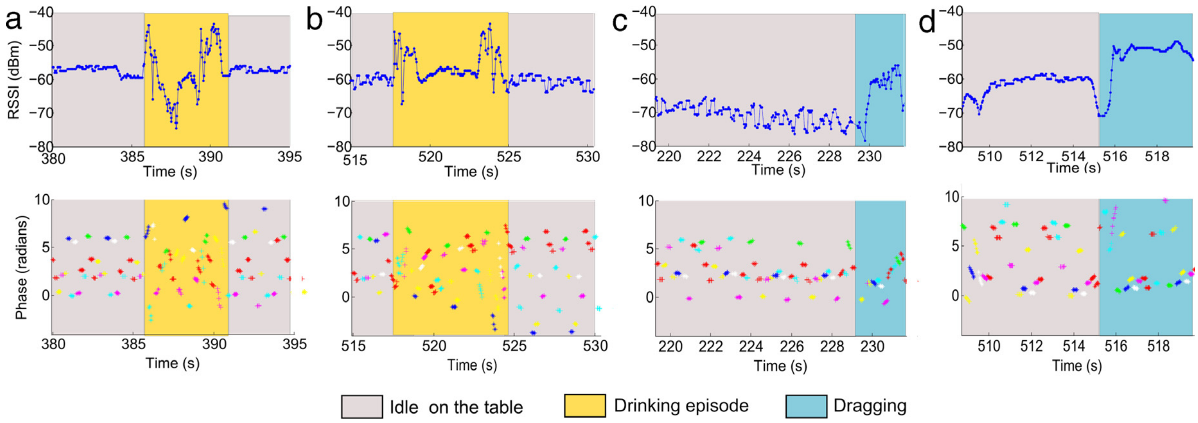

Fig. 3. Typical RSSI and unwrapped per channel phase patterns for tag 4: (a) a drinking episode of a young participant; (b) a drinking episode of an older participant; (c) young participant dragging the drinking container; (d) older participant dragging the drinking container. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

lifted the *smart cup* to drink. As informed before the experiment, the phone ringing cue prompted the participants to answer the incoming call without completing the drinking episode. An example of a broadly scripted activity routine is given in the Appendix.

The dataset collected from young participants contained 196 drinking episodes, 133 non-drinking movement episodes and 296 idle episodes. On average, a trial lasted for 621.1 ± 194.8 s and a drinking episode lasted for 5.0 ± 1.4 s. The dataset contained 348,116 tag readings where 56,329 of them related to drinking episodes. The read rate of the RFID platform was approximately 55 tags per second. Due to the effects of liquids, the read rate of individual tags varied and tag 4 reported the highest average read rate of 23 tags per second. This was followed by tag 1 with an average read rate of 21 tags per second.

Experiment with older volunteers. The data collected from older participants were unscripted. Prior to the experiments, the participants were asked to nominate a beverage of their choice. The requested beverage was made available during the experiment. Such requested beverages included cold soft drinks, fruit juice, coffee and wine. During the experiments, the participants filled the *smart cup* with any amount of their preferred liquid and drank it as they wish (see Fig. 2(c) and Fig. 2(d)). According to their preference, the participants performed one or more other high level activities while drinking. Other activities carried out during the experiments included eating, solving puzzles, reading, and using the mobile phone for texting and calls. They also had the freedom to refill the cup with their preferred liquid, if needed, and were not given any other specific instructions.

The dataset collected from the older participants contained 79 drinking episodes. On average, a trial lasted for 827.5 ± 200.4 s and a drinking episode lasted for 6.4 ± 1.5 s. The dataset contained 240,707 tag readings where 29,481 of them were related to drinking episodes. The read rate of the RFID platform was approximately 58 tags per second. Due to the effects of liquids the read rate of individual tags varied and tag 4 reported the highest average read rate of 26 tags per second. This was followed by tag 1 with an average read rate of 22 tags per second. These read rates are similar to the read rates reported for data collected from young participants.

Dataset annotation. After the experiments, a researcher labeled the ground truth using video recordings. Although drinking episode recognition was formulated as a binary classification problem, to get a deeper understanding, the dataset was annotated at a fine grained level using the labels: (i) up (the movement of the cup towards the mouth); (ii) sip (having a sip); (iii) down (movement of cup away from the mouth); (iv) moving; (v) dragging; (vi) telephone interruption; (vii) taking; (viii) bringing; (ix) idle; and (ix) holding. Holding indicates the time periods where participants were holding the drinking container in between drinking episodes without placing it back on the table. During the classification, tag readings that did not belong to a drinking episode were grouped together as the *non-drinking* class and tag readings related to drinking

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Table 2
Mean binary classification performance (%) for young participants based on full window approach and sub-segmented window approach.

		NSVM (256, 0.25)	LSVM (64)	CRF (100)	RF (100)	NB
Full	Precision	73.7 ± 5.6	47.7 ± 3.1	65.9 ± 5.3	82.6 ± 4.5	66.5 ± 5.0
	Recall	66.4 ± 5.1	63.7 ± 11.7	65.5 ± 5.2	79.4 ± 4.0	70.4 ± 8.5
	F-score	68.6 ± 5.5	60.1 ± 11.5	65.6 ± 5.1	80.5 ± 3.4	67.7 ± 6.0
		NSVM (1, 0.25)	LSVM (4)	CRF (1)	RF (100)	NB
Sub-segmented	Precision	88.5 ± 3.1	85.5 ± 3.7	76.8 ± 5.0	87.9 ± 3.8	69.1 ± 4.0
	Recall	86.2 ± 4.0	79.7 ± 4.7	78.2 ± 4.9	85.4 ± 4.1	73.8 ± 8.0
	F-score	**87.2 ± 3.4**	**82.0 ± 4.3**	**77.3 ± 4.9**	**86.6 ± 3.9**	**70.7 ± 5.2**

The model parameters for (i) NSVM (c and g); (ii) LSVM (c); (iii) CRF (λ); and (iv) RF (nTrees) are shown in parenthesis with respect to each classifier.

episodes were given the *drinking* class label. Fig. 3 illustrates typical RSSI and phase data streams collected from young and older participants.

6. Statistical analysis

We selected precision (P) and recall (R) for our evaluation and measured performance using the F-score, which is the harmonic mean of precision and recall [40]. Precision is also known as Positive Predictive Value (PPV) and recall is known as True Positive Rate (TPR) or sensitivity in the literature.

We defined a True Positive (TP) drinking episode as a drinking episode that occurs during an actual drinking episode. A False Positive (FP) is an incorrectly recognized drinking episode based on the above definition of TP. False Negative (FN) is a missed recognition of a drinking episode. We calculate precision as $P = TP/(TP + FP)$. Precision measures the number of true positives with respect to all drinking episode recognitions by our system and higher precision indicates lower false recognitions of drinking episodes. We calculate recall as $R = TP/(TP + FN)$. Recall measures the true positives with respect to all actual drinking episodes and higher recall indicates lower number of missed drinking episode recognitions. Finally, based on precision and recall, F-score was calculated as $(2 \times P \times R)/(P + R)$.

We analyzed the performance of the system for data collected from young people using the leave one person out cross validation scheme. This evaluation scheme allows us to measure the performance of the system for data that it has never seen before. The data collected from young participants were partitioned into three subsets as training, validation and testing. The testing set was from data of a single young participant. The model parameter selection was carried out by training the models using the training sets and evaluating the performance using the F-score based on the validation sets. The performance was then evaluated using the testing set based on the selected model parameters. This process was repeated for all the participants to obtain the mean performance measures.

Collecting training data from young participants is more convenient given the difficulty in recruiting older people to collect labelled training data. Therefore, we considered it more appropriate to train the model used for testing the performance of our system with older people using data collected from young people. This evaluation scheme also created the opportunity to ascertain the realistic performance of the system for older participants in a practical deployment where the learnt model needs to make predictions for unseen participants. At this stage, the data collected from young participants were partitioned into two subsets for training and validation. The model parameters were selected by training the model using the training set and evaluating the performance using the F-score based on the validation set. Finally, performance was evaluated by using data from older participants.

We only recognized a drinking episode if it is longer than $\mu/2$ time period, where μ is the mean drinking episode duration in training data. This mitigates the effects of noise in RFID data and consequently increases the drinking episode recognition precision.

7. Results

7.1. Young participants

The performance of drinking episode recognition depends on the selection of the segmentation approach. Therefore, before evaluating the performance of our system for recognizing drinking episodes, we selected the best segmentation approach based on the binary classification results for data collected from the young participants. Table 2 illustrates the binary classification results for data collected from the young participants based on the full window and the sub-segmented window approaches. From Table 2, it is evident that the sub-segmented window approach has outperformed full window approach in all classifiers. Therefore, the sub-segmented window approach was used in the subsequent analysis.

Table 3 illustrates the drinking episode recognition performance for data collected from young participants based on the sub-segmented window approach. According to Table 3, NSVM has depicted the highest performance (F-score ≈87%) for recognizing drinking episodes. The dataset collected from young participants was particularly challenging as it contained

Table 3
Mean drinking episode recognition performance (%) for young participants using the sub-segmented window approach.

	NSVM	LSVM	CRF	RF	NB
Precision	97.8 ± 3.9	96.8 ± 5.7	85.8 ± 12.0	97.7 ± 3.8	74.7 ± 4.5
Recall	79.0 ± 13.3	68.5 ± 13.9	74.7 ± 12.8	71.3 ± 15.7	72.7 ± 17.2
F-score	**86.8** ± **8.7**	79.5 ± 9.9	79.1 ± 9.9	81.6 ± 11.3	72.8 ± 9.3

Table 4
Detailed drinking episodes results for each young participant using NSVM classifier based on the sub-segmented approach.

Participant ID	1	2	3	4	5	6	7	8	9	10	Total
Ground truth (GT)	29	24	21	14	14	13	15	37	15	14	196
True positive (TP)	23	19	11	14	12	10	14	24	12	11	150
False positive (FP)	1	0	0	1	0	0	0	3	0	0	5

Table 5
Mean binary classification performance (%) for older participants based on the sub-segmented window approach.

	NSVM (1, 0.25)	LSVM (1)	CRF (100)	RF (100)	NB
Precision	87.1 ± 3.4	87.2 ± 4.3	82.8 ± 6.5	86.8 ± 4.7	71.1 ± 11.7
Recall	78.5 ± 6.1	74.4 ± 8.7	71.5 ± 4.8	78.6 ± 4.9	70.2 ± 11.0
F-score	81.6 ± 5.3	77.8 ± 9.4	75.4 ± 5.4	81.8 ± 4.8	70.0 ± 10.6

The model parameters for (i) NSVM (c and g); (ii) LSVM (c); (iii) CRF (λ); and (iv) RF (nTrees) are shown in parenthesis with respect to each classifier.

Table 6
Mean drinking episode recognition performance (%) for older participants using the sub-segmented window approach.

	NSVM	LSVM	CRF	RF	NB
Precision	94.1 ± 5.9	93.1 ± 7.2	59.3 ± 5.6	95.8 ± 4.1	81.5 ± 12.5
Recall	70.4 ± 23.2	63.7 ± 21.4	89.4 ± 11.2	70.8 ± 24.9	74.4 ± 17.7
F-score	78.8 ± 15.6	74.3 ± 14.9	71.1 ± 6.1	**79.1** ± **18.5**	76.7 ± 12.5

non-drinking gestures involving the *smart cup* due to the broadly scripted nature of activity routines (ratio between non-drinking movements and drinking episodes is 133:169). However, the results indicate that the proposed approach has successfully recognized drinking episodes with a precision of ≈98% and recall of ≈79%. It is also important to note that, although NSVM and RF depicted similar performance for binary classification, NSVM clearly outperformed RF in drinking episode recognition. The main reason for this observation is that RF has not been able to predict *drinking* continuously exceeding $\mu/2$ duration compared to NSVM. This is also indicated by the lower recall for drinking episode recognition in RF despite similar recall for binary classification compared to NSVM.

Table 4 illustrates the details of the TPs and FPs with respect to each young participant. We can see from Table 4 that the number of TPs for participant 3 is relatively low compared to the other participants. Close observation revealed that participant 3 has multiple consecutive short drinking episodes, where some of them have not been recognized by the system.

7.2. Older participants

Tables 5 and 6 illustrate mean binary classification performance and mean drinking episode recognition performance based on the sub-segmented window approach for older participants, respectively. Generally, for older people, a decrease in performance compared to young people was observed. The main reason for this is, although the RSSI and phase patterns for drinking episodes of older people are similar to that of young people, older people depicted a higher mean drinking episode duration (see Section 5). As a result of selecting a segment size based on young people dataset, all the classifiers have performed less accurately with the older people dataset.

According to Table 6, both NSVM and RF have depicted similar performance (≈79%). However, RF has obtained a marginally higher mean F-score albeit a large standard deviation in relation to NSVM.

Table 7 illustrates the TPs and FPs with respect to each older participant. In Table 7, participant 5 represents the older participant with Parkinson's disease. Closely analyzing the results presented in Table 7, we can see that the proposed approach has achieved a precision >94% and recall >66% for participant 5. Furthermore, we noticed that the $\mu/2$ filter improved the precision in most cases. However, it has also resulted in reducing the recall metric for drinking episode recognition in certain instances, especially for participant 3.

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Table 7
Detailed drinking episodes results for each older participant using RF classifier and sub-segmented approach.

Participant ID	1	2	3	4	5	Total
Ground truth (GT)	15	16	9	15	24	79
True positive (TP)	14	15	3	10	16	58
False positive (FP)	0	1	0	1	1	3

8. Conclusion

In this study, for the first time, we investigate the use of batteryless UHF RFID technology for automatic monitoring of fluid intake gestures. We proposed a fluid intake monitoring approach that includes an RFID enabled *smart cup* capable of monitoring drinking episodes based on underlying patterns in RSSI and phase data variations. The promising results achieved for drinking episode recognition for data collected from young participants (F-score ≈87%, precision ≈98% and recall ≈79%) and older participants (F-score ≈79%, precision ≈96% and recall ≈71%) demonstrate the efficacy of using passive RFID technology for recognizing natural fluid intake gestures in real time.

There are several systems to recognize drinking gestures. However, it is difficult to make a fair comparison with these recent studies mainly due to differences in the experimental settings. In [3], drinking gestures have been recognized with a 84% recall and a 94% precision. The authors conducted experiments using broadly scripted activity routines with six young volunteers. In [7], drinking gestures were recognized with an 83% recall and an 88% precision based on data collected from 4 young participants. However, none of the previous research have evaluated their approaches with older people.

Even though our the results are promising, our study is not without limitations. Due to the diversity of human behavior, drinking episode durations can depict inter subject and intra subject variabilities. Therefore, a dynamic segmentation approach as oppose to a fixed time segmentation approach may further improve the drinking episode recognition performance. Even though our experiments were conducted in a realistic but controlled setting, it is also interesting to investigate the performance of our approach over a longer period in a real-world deployment.

In conclusion, promising results achieved in our study demonstrate the efficacy of recognizing short duration, short distance natural human gestures, particularly related to fluid intake, based on passive UHF RFID technology. We believe this work will open up a new research paradigm where useful applications for individuals, caregivers as well as health researchers can be developed. In future, we are considering to extend the present work to a comprehensive fluid intake monitoring system by also recognizing the liquid level in the *smart cup* in real time.

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Appendix. Scenario for reading the paper while having a drink

Go to your kitchen (simulated) and choose any type of drink (tea/coffee/soft drink/water) you like to consume. Fill the *smart cup*, as much as you like, with your preferred drink. Come to the dining table with your drink and any material you would like to read. Drink as you would normally do, while reading your paper. You are free to move your *smart cup* when ever you want during the experiment. Change your sitting posture multiple times as you wish. Each time you change your sitting position, move the cup to a convenient place for you. During the experiment, when you have lifted the cup to have a sip, you might get a phone call (simulated). However, consider this as an interruption and put the cup down without having a sip (i.e without completing the drinking action) to answer the phone call. When you finish the drink get it refilled, come back to the dining table and continue drinking as usual. Finally, when you finish drinking, leave the table. You can choose to leave the cup at the table or take it to the kitchen.

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