Smart Cup for Festival Alcohol Consumption Awareness

Smart Cup for Festival Alcohol Consumption Awareness

Maxence Bobin*, Hamdi Amroun*, Margarita Anastassova†, Mehdi Boukallel†, Mehdi Ammi*
*LIMSI-CNRS
{maxence.bobin, hamdi.amroun, mehdi.ammi}@limsi.fr
†CEA-LIST
{margarita.anastassova, mehdi.boukallel}@cea.fr

***Abstract*—This paper presents a platform prototype to monitor alcohol consumption for festival's attendees. The platform also aims to raise awareness about alcohol consumption in order to help people control or even reduce their alcohol consumption. The platform consists of a self-contained smart cup which the attendee uses during the day. This platform allows to easily follow the user's alcohol intake based on a model in order to display alerts if necessary. The smart cup embeds sensors to detect the liquid level and its movements. In addition, activity recognition is performed from the collected data in order to recognize when the user drinks and enhance the alcohol intake assessment. The smart cup also embeds LEDs visual displays that provides information about the alcohol intake estimation. This paper presents the design concept of the smart cup along with the technical implementation. Then, the data processing and analysis is presented for the alcohol intake estimation method using activity recognition with a Support Vector Machine classifier. An experiment have also been carried out and shows a good level of recognition above 90% for the "drinking" activity. Next, the feedback identification for the alcohol intake estimation is detailed in the last section. Finally, perspectives for the detection of abnormal behavior based on the alcohol intake assessment and the movements of the cup are introduced.**

***Index Terms*—Festival, Alcohol Awareness, Alcohol Estimation, Activity Recognition**

I. Introduction

Festivals are temporary sites constructed to host an event celebrated by a community and centered on culturals activities. They regroup many people at the same place, for example the Burning Man (USA)[1] with approximately 50 thousand attendees. Festival participants are outside of their daily routines and it is suggested they often treat festivals as a bubble away from the on-going concerns of their day-to-day lives. This temporary re-configuration of priorities and bounds can be critical for some people who abuse of alcohol and suffer from lack of sleep. Festivals often include alcohol consumption that can lead to abnormal behavior and generate road safety problems for example (eighth cause of death in the world with one million victims each year [1]). In order to avoid these situations and raise awareness on alcohol consumption, the alcohol intake as well as the physical activity of attendees could be monitored and alerts could be provided.

Several research groups have investigated new technological approaches to provide information on the alcohol consumption such as abnormal gait detection or alcohol detection. Some of these approaches use smartphones combined with a number of basic sensors such as an accelerometer to analyze the user's gait [2], [3]. Others monitor the blood alcohol level detection with breath analysis [4] or drink composition analysis [5]. Generally, these applications require to use an external device (smartphone) or a dedicated device (breath analyzer) which make the use difficult during a festival.

The emergence of smart objects and more generally Internet of Things (IoT) in recent years allows to go beyond the constraint of using an external or dedicated device. Indeed, IoT is a network of devices embedding electronic, software, sensors and actuators. It is therefore possible to use common objects to collect and process data. Some research investigated the IoT concept in order to retrieve health data. For example, Baek et al. developped a chair that is able to measure biological signals (ECG, PPG and BCG) in a nonintrusive way [6]. However, this device is not portable and cannot be used continuously. In order to offer portable solution for monitoring, wearable devices have been developped such as Movital, that is a personal device for diabetes therapy management [7]. This device is portable but required the use of a glucometer which is a medical device. Other wearable devices allow a continuous monitoring of patient's vital signals such as PhysioDroid which combine a wearable device embbeding sensors and a remote computer [8]. Such devices open the door for activity recognition and monitoring through wearables and smart objects. Actually, many researchs performed activity recognition with accelerometers or proximity sensors [9], [10]. Activity recognition algorithms are varied (HMM [11], SVM [12], Decision Trees, Random Forest [13], KNN and NN [14]) and present different benefits according to the situation. However, activity recognition is often presented as an end and not as a tool for improving wearable monitoring.

The proposed platform prototype is based on a common object, a cup, embedding several sensors and displays, and provides a powerful tool for a continuous monitoring of the alcohol intake during the day. The platform provides relevant information on the state of the object manipulated by the user such as the liquid level inside the cup and its movements.

[1]https://fr.wikipedia.org/wiki/Burning_Man

Furthermore, the movements sensor embedded into the cup allow to recognize when the user drinks in order to enhance the alcohol intake estimation. Moreover, the cup also includes visual displays that alert users on their alcohol intake. The two feedback provide helpful sensory feedback when the user's visual or cognitive abilities are affected by alcohol. Finally, the combination of the liquid level information and the movements of the cup could allow to detect abnormal behavior due to alcohol consumption such as liquid spilled off the cup.

This paper begins with a presentation of the design concept of the platform. Then, the technical implementation of the smart cup prototype (See Figure 1), called FrACTAl (Festival Alcohol ConsumpTion Awareness) is detailled including the data collection from sensors and hardware architecture. Furthermore, the alcohol intake estimation is introduced and the "drinking" activity recognition process is explained with results. Besides, the detection of abnormal behavior based on the alcohol intake estimation and the movements of the cup is developped. Finally, future works and perspectives are introduced.

Fig. 1. Example of use of FrACTAl: (a) user is sober, (b) the user's behavior is abnormal and (c) the user has a loss of balance.

II. The platform prototype

This section aims to present the design concept of the platform as well as its implementation.

A. Design Concept

FrACTAl is a smart cup designed to help festival's attendees to manage their alcohol consumption by monitoring the alcohol intake via embedded sensors and data processing. The design process of FrACTAl is divided into four steps: (1) identification of the information to monitor, (2) implementation of the prototype, (3) data processing and (4) feedback for alert.

1) Monitored information: In order to help festival's attendees to manage their alcohol consumption, the cup needs to collect relevant information related to the alcohol intake of the user.

The alcohol intake is estimated via the Widmark model (Equation 1). This model determine the theoretical maximum blood level alcohol concentration according to the following parameters : (1) the absorbed mass of alcohol, (2) the mass of the person and (3) the reduction or distribution factor in the body.

$$C = A/(m.r) \tag{1}$$

where :

- C : the mass fraction of alcohol in the body in mg/g
- A : the absorbed mass of alcohol in grams (g)
- m : the mass of the person in kilograms (kg)
- r : the reduction or distribution factor in the body :
  - Mens : 0.68 to 0.70
  - Womens / Adolescents : 0.55 to 0.60
  - Babies and childrens : 0.75 to 0.80

The only parameter depending on the situation is the absorded mass of alcohol. Indeed, the r and m parameters are specific to the user. The absorbed mass of alcohol can be calculated from the quantity of liquid that the user ingested over time. We therefore decided to monitor the quantity of liquid into the cup with a liquid level sensor in order to estimate the quantity of liquid drank during the day. Based on this estimation, we can estimate the alcohol intake on the user. For example, if a person (28 years old, 80kg) drank six pints of beer, being three liters with a 5% alcohol percentage on a period of six hours, this person ingests the equivalent of 150mL of pure alcohol (5% of 3000mL). As alcohol has a density of 789 kg/m^3, the absorbed mass of alcohol is 118 grams. According to the Widmark model, his blood alcohol level is approximately equal to 2.10 mg/g ($118 \div (80 \times 0.7)$) or 199.7 $mg/100mL$ ($mg/100mL = mg/g \times 100 \div 1.055$ where 1.055 is the density of the human blood). The alcohol blood level is therefore 1.99 g/L ($199.7 \times 10 \div 1000$). Moreover, blood alcohol level decreases to 0.15 g/L every hour. As he drank during six hours, 0.9 g/L (0.15×6) has to be substracted to the previous blood alcohol level. The final estimated blood alcohol level for this attendee is 1.09 g/L ($1.99 - 0.9$).

However, it can happens that the user spills by accident the content of the cup or empties the cup. This behavior has to be take into account by the platform in the calculation of the estimated alcohol intake. In order to enhance the alcohol intake monitoring performed by the liquid level sensor, the system can differentiate when the user really drinks or not. Support Vector Machine (SVM) machine learning model have been implemented to detect the activity of "drinking" (See Section III). If we suppose that two pints were spilled most likely due to a rush or inattention in the previous example, this person only drank two liters of beer (only 79g of pur alcohol). After six hours, his alcohol level is 0.44 g/L.

Therefore, we created a model (Figure 2) that estimate the alcohol intake based on two parameters : (1) the liquid level inside the cup and (2) the detection of "drinking" activity. The model takes different parameters as input: the absorbed mass of alcohol, the mass of the person, the reduction or distribution factor in the body as well as the detection of "drinking". The output of the model is the estimated level of the user's physical state i.e. the alcohol intake estimation.

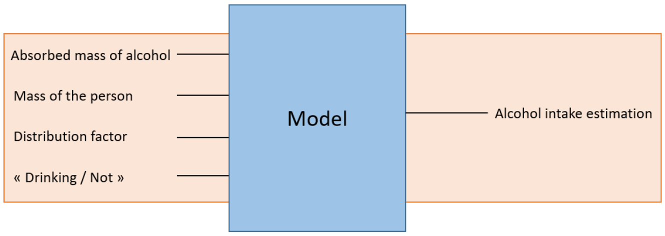

Fig. 2. Representation of the model to estimate the user's physical state.

B. Implementation of the cup prototype

FrACTAl cup prototype embeds a series of sensors to access the required data. The following sections detail the sensors specifications and the data collection.

1) Liquid level sensor: Due to the constraints of industrial liquid level sensors (low-reactivity, size, etc.), FrACTAl cup embeds its own custom sensor to monitoring its liquid level. The designed sensor is based on the measurement of the liquid conductivity which is modified when liquid reach an electrode. Five conductive electrodes were placed vertically inside the cup. The electrodes were connected to tension divider bridges to measure electric tensions. Each electrode are spaced of one centimeter vertically which gives a sensor resolution of 100mL. According to this data, feedback can be displayed (Figure 1).

2) Movements sensor: FrACTAl cup embeds an Inertial Measurement Unit (IMU, the 9-axis Motion Tracking device "Invensense MPU-9150") that embeds an accelerometer, a gyroscope and a magnetometer. It presents a good compromise between performance, energy efficiency, size and cost. Specifications of each sensor is presented on the adjacent table (See Table I). Each of these sensors returns three values on the three axis x, y, z.

Sensor	Value	FSR
Accelerometer	Acceleration	± 2 m.s^{-2} (g)
Gyroscope	Angular velocity	± 1000 $^{\circ}$.s^{-1}
Magnetometer	Magnetic field	± 1200 μT

TABLE I
IMU SPECIFICATIONS.

FSR (Full-Scale Range) allows mapping of raw data from registers from $[-2^{15}, 2^{15}$ - 1] to FSR value.

The data of the IMU sensor are used to calculate the movements of the cup and analyze and classify the "drinking" activity by the machine learning algorithm.

3) Electronic architecture and data transfert: The electronic part of FrACTAl is based on the Raspberry Pi Zero. The RPi Zero is a tiny computer (65.0 mm x 31.0 mm x 5 mm) which embeds a 1GHz Single-core CPU, 512MB RAM and GPIO. Pi Zero is inexpensive (5$) and very easy to use for prototyping. The data from the IMU sensor are retrieved over I^{2}C (Inter-Integrated Circuit). Moreover, as the Pi Zero does not have analog GPIO while the liquid level sensor is based on analog values, Analog-to-Digital Converters are used to convert a continuous physical quantity (usually voltage) to a digital number. Visual display is composed of RGB LEDs from NeoPixels. In order to light up all the LEDS (14 for alcohol intake alert), a PowerBoost is used to provide a constant 5V output voltage with a minimum output current of 1A. Finally, a power switch allows to power off the device (See Figures 3 and 4).

FrACTAl have been equiped with a Wi-Fi dongle to transfert data which present a good transfert rate. The main constraint for a real-time wireless communication is power consumption. However, data is logged locally into the cup. Saved data are sent to a mobile application over Wi-Fi. FrACTAl cup embeds a 3.7 V and 2500 mAh battery. The power autonomy of the cup is approximately 2 days with the LEDs indicators, and up to 2 weeks without this visual feedback.

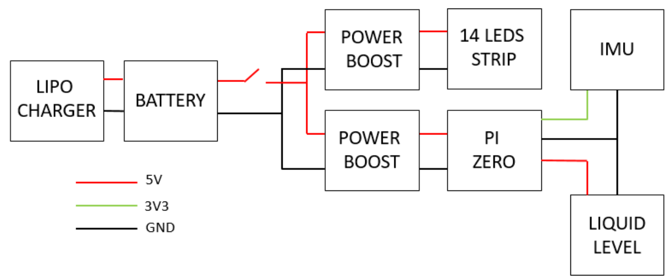

Fig. 3. Power Supply Architecture.

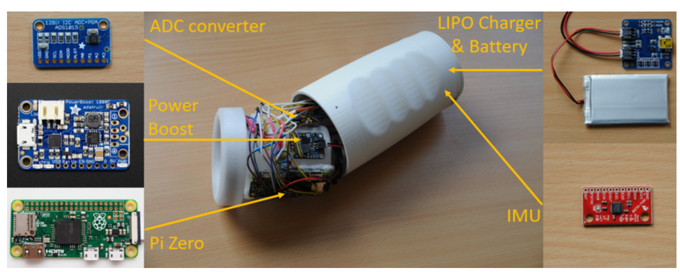

Fig. 4. FrACTAl cup components.

III. ALCOHOL INTAKE ESTIMATION

The alcohol intake estimation is based on the Widmark model presented before. The estimation of the alcohol intake is divided into two parts: (1) recognition of the drinking activity and (2) the estimation of the C parameter of Widmark model (the theoretical maximum blood level alcohol concentration). Recognize when the user drinks allow to only take the ingested liquid into account and avoid false-positive with the liquid level sensor such as when liquid is spilled of the cup. This section explain the method used to recognize the activity of "drinking" with the IMU data collected during the cup usage.

A. Protocol

The data was recorded at a sampling frequency of 30Hz via Wi-Fi under controlled conditions in a laboratory corridor. Fifthteen participants were involved in this experiment for data collection. Each participant was asked to wear glasses that simulate a drunk vision and perform two tasks during 10 minutes continuously: (1) drinking while walking and (2) drinking while sitting. The simulated features appear to be relevant in order to detect all configurations where the participant can drink and easily controllable.

Fig. 5. Photos of the tasks performed by the participants: a) Drinking while walking and b) Drinking while sitting.

All results have been obtained by using Support Vector Machines (SVM) which is a linear algorithm classifier.
The activity analysis method includes the following steps:

1 Signal segmentation
2 Descriptors calculation
3 Classification performances
4 Creation of the database for future learning

B. Signal segmentation

We decided to perform a segmentation of the signals which gives stable, similar and therefore non-noisy periodic signal sequences.

C. Descriptors calculation

Compress the data before using any learning algorithm is mandatory. It is required to find representatives key points of a signal (called descriptors or features) that characterize this signal. The discrete cosine transform DCT-II was used as a descriptor [15]. Indeed, the DCT is a good signal decorrelator, but is also able to regroup the energy in the low frequency coefficients thanks to its approximation of the Karhunen-Love transform of main component analysis.

The DCT of a sample X(n), n=0, 1, (N-1) is given by:

$$X(0) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n) \tag{2}$$

$$X(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} x(n) \cos \frac{(2n+1)\pi k}{2N}, k = 1..(N-1) \tag{3}$$

As the IMU signals are not homogeneous, we need to cut them in regular and equal portions. Indeed, overfitting can appear when the entire signal is analyzed, in other words, the learning model will learn by heart the data and the generalization will be inaccurate.

We need therefore to set the size of the signal cutting window and study the contribution of overlapping in terms of precision in the calculations. We investigated three cutting sizes (∆t) with and without overlap. We set the size of the cutting to 128 samples (1.06 seconds), 256 samples (2.13 seconds) and 512 samples (4.26 seconds). It appears that better performances are observed for accelerometer, gyroscope and magnetometer signals with overlap and a cutting size of 512. The performances are respectively equal to 89.62%, 88.02% and 87.09% for "drinking while walking" activity and 90.0%, 88.77% and 83.05% for "drinking while sitting" activity. The size of 512 will be used to calculate the signal descriptors of the three sensors.
After determining the cutting size, tests have been carried out to determine the size of each sensor descriptor (Figure 6) which gives better performances for classifier with a cutting size of 512.

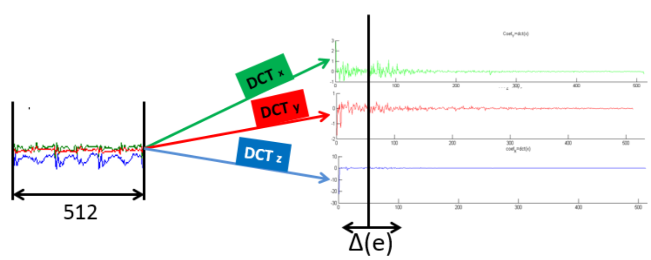

Fig. 6. Calculating descriptors for each axis for each sensor (accelerometer, gyroscope and magnetometer)

The ∆(e) value (size of the descriptor) was set between 2 and 64 in order to find the ∆(e) which gives the best classification performances.

A descriptor size of 32 gives better classification performance for the accelerometer (For example Figure 7) and magnetometer. Moreover, a descriptor size of 48 gives better classification performance for the gyroscope.

D. Classification performances

Once the size of the cutting window and the size of the descriptors for each sensors have been determined, it seems interesting to see whether using only one axis of a sensor (accelerometer, gyroscope and magnetometer have three axis) is enough to reach a good precision or merging axis allow

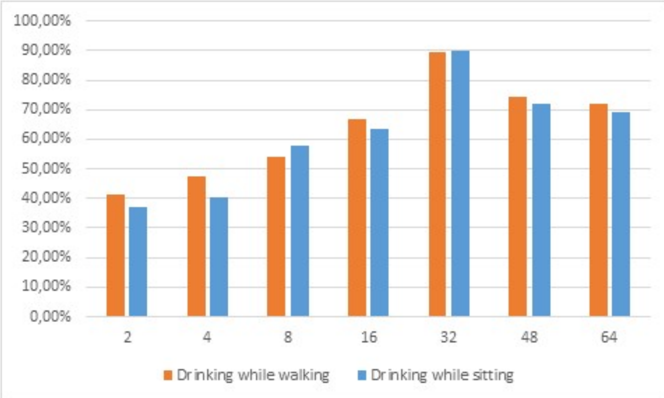

Fig. 7. Classification performance according to the value of Δ(e) (Accelerometer).

to have a better precision. The obtained classification performances used a 512 cutting window with an overlap of 256 and a descriptor size of 144 (48 * 3) (for the gyroscope), 96 (32 * 3) for the accelerometer and the magnetometer. The concatenation of the three axes of each sensors (accelerometer, gyroscope and magnetometer) gives better classification performance equal to respectively 89.62%, 88.02% and 87.09% for "drinking while walking" activity and 90.0%, 88.77% and 83.05% for "drinking while sitting" activity.

E. Creation of the database for learning

Once the determined DCTs of each axis (X, Y, Z) of each sensor have been concatenated to form descriptors, we stored these descriptors in a database used for classification. We divided the data-set in a training set and a test set. The learning phase is performed by the 10-fold cross validation method.

F. Results

We first extracted non-noisy periodic signal using segmentation. Then, we calculated descriptors by using the DCT algorithm. Afterwards, we managed to find that the performancesare far much better with a cutting size of 512 for each sensor (accelerometer, gyroscope and magnetometer) with overlap. We set the descriptor size to 32 for the accelerometer and magnetometer and 48 for the gyroscope. Then, we demonstrated that the concatenation of the descriptors of each axis (X, Y and Z) for each sensors shows a better classification performance. We also created a database using the 10-fold-cross validation method in order to perform the activity recognition. Finally, we obtained the best recognition result with the concatenation of the three sensors (accelerometer, gyroscope and magnetometer) with a precision of 91.09% for "drinking while walking" activity and 92.17% for the "drinking while sitting" activity with the SVM classifier algorithm. This good precision allows to enhance the alcohol intake estimation by excluding liquid from the model when the user do not really drinks.

IV. Feedback identification for alert

The information computed from the sensors embbeded into FrACTAl needs to be displayed to the user with a sensory feedback. A sensory feedback refers to an additional information feedback provided with a sensory channel (e.g. visual channel) that enables the user a better perception of an information.

The selected feedback for alcohol intake representation is a visual feedback around the top of the cup (See Figure 8). Indeed, the cup is used in a noisy environment and audio feedback can not be provided. Moreover, visual display around the top of the cup allow the feedback to be visible whatever the orientation. A circle of fourteen LEDs is placed on the top of the cup under the semi-transparent material. The LEDs displayed colors according to the alcohol consumption. A series of discriminable colors (green, orange and red) have been selected in relation to the European culture. Using discriminate colors contributes to avoid the ambiguity of perception for the user under alcohol effects. The following color/alcohol consumption associations were used: green when user is sober, orange when the user's behavior is starting to be affected by alcohol and red if the user is considered as drunk.

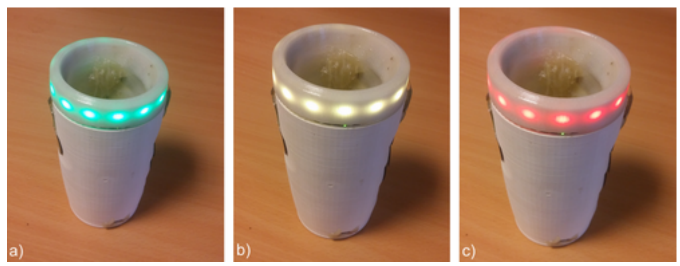

Fig. 8. Visual feedback according to alcohol intake estimation: a) sober, b) modified behavior due to alcohol, and c) drunk.

V. Abnormal behavior detection perspective

Drunk people often encounter a loss of balance [16] or disorder in movements coordination [2]. In order to detect abnormal behaviors, we plan to reuse the signals of the IMU sensors to monitor the movements of the cup in terms of accelerations and orientation during manipulation. The orientation of the cup will allow to detect if the cup is held correctly while fusion with the orientation and the accelerations will allow to detect a loss of balance due to alcohol consumption. Moreover, reuse the alcohol intake estimation could reinforce the loss of balance detection. Indeed, the cup will be able to distinguish an unusual orientation of the cup due to alcohol consumption from an unusual orientation of the cup due to a stumbling for example. Furhtermore, feedback on the abnormal behavior will be provided by adding another visual feedback to the cup. Indeed, LEDs used for the alcohol estimation will be reused and will blink when abnormal behavior will be detected.

The detection of the user movements will includes two measurements. First of all, the acceleration measurements would

[2]https://www.stop-alcool.ch/une-substance-psychoactive/les-effets-immediats

allow to detect sudden movements of the cup. Accelerations would also be used to detect a cup fall. Second, the 3D orientation of the cup, also called pose, will be computed from the IMU data by using the RTQF fusion algorithm. RTQF is a simplified version of a Kalman filter designed for an effective fusion of data from the accelerometer, gyroscope, and magnetometer. The fusion algorithm returns a quaternion computed from two quaternions: a predicted quaternion from the gyroscope measures and a ground frame-referenced measured quaternion from the accelerometer and magnetometer.

We already thought to enhanced the first model (Figure 2) by using a Support Vector Machine algorithm to merge the movements of the cup with the alcohol intake estimation from the previous section, allowing to detect the abnormal behaviors due to alcohol consumption. The complete model is presented in the Figure 9.

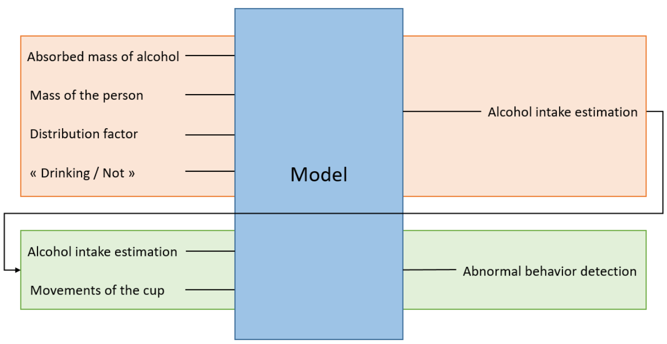

Fig. 9. Representation of the model to detect abnormal behavior.

VI. Conclusion and Future Works

The paper presents the design methodology and the prototype of FrACTAl cup, a self-contained smart cup for monitoring and alert festival's attendees on their alcohol consumption. A model have been created in order to assess the alcohol intake and provide alert to the user. The alcohol intake estimation is based on the liquid level sensor values as well as predefined parameters (m and r). The recognition of "drinking" activity allow to enhance the alcohol intake estimation by merging data from the liquid level sensor and the recognition of "drinking" activity with a recognition precision above 90%.

As perspectives, the detection of abnormal behavior by merging data from movements detection and activity recognition will be investigated. Data from the accelerometer, gyroscope and magnetometer of the smartphone could be retrieved and merged with the cup to detect falls. The fall detection could lead to link the attendees and the emergency services of the large scale event. Moreover, a mobile application will be created in order to set custom parameters for alcohol intake estimation such as sex and weight. The application will allow to visualize the data recorded by the cup and display alerts on the smartphone. An interesting future work would be to provide services based on the activity of the user (sitting, standing, etc.). For example, services such as geolocalisation friends or toilets finder could be available when the user is standing up or walking. When the user is sitting, nearest food stall could be displayed. Finally, a study will be carried out during a large scale event in order to evaluate the prototype in non-controlled real conditions.

VII. Acknowledgments

We would like to thank ISN for their financial support.

References

[1] W. H. O. Violence, I. Prevention, and W. H. Organization, *Global status report on road safety 2013: supporting a decade of action*. World Health Organization, 2013.

[2] H.-L. C. Kao, B.-J. Ho, A. C. Lin, and H.-H. Chu, "Phone-based gait analysis to detect alcohol usage," in *Proceedings of the 2012 ACM Conference on Ubiquitous Computing*. ACM, 2012, pp. 661–662.

[3] A. Veenendaal, E. Daly, E. Jones, Z. Gang, S. Vartak, and R. S. Patwardhan, "Drunken abnormal human gait detection using sensors," *Computer Science and Emerging Research Journal*, vol. 1, 2013.

[4] K.-C. Wang, Y.-H. Hsieh, C.-H. Yen, C.-W. You, Y.-C. Chen, M.-C. Huang, S.-Y. Lau, H.-L. C. Kao, and H.-H. Chu, "Soberdiary: A phone-based support system for assisting recovery from alcohol dependence," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*. ACM, 2014, pp. 311–314.

[5] D. Dand, "Cheers: alcohol-aware strobing ice cubes," in *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 2013, pp. 2795–2796.

[6] H. J. Baek, G. S. Chung, K. K. Kim, and K. S. Park, "A smart health monitoring chair for nonintrusive measurement of biological signals," *IEEE transactions on Information Technology in Biomedicine*, vol. 16, no. 1, pp. 150–158, 2012.

[7] A. J. Jara, M. A. Zamora, and A. F. Skarmeta, "An internet of things–based personal device for diabetes therapy management in ambient assisted living (aal)," *Personal and Ubiquitous Computing*, vol. 15, no. 4, pp. 431–440, 2011.

[8] O. Banos, C. Villalonga, M. Damas, P. Gloesekoetter, H. Pomares, and I. Rojas, "Physiodroid: Combining wearable health sensors and mobile devices for a ubiquitous, continuous, and personal monitoring," *The Scientific World Journal*, vol. 2014, 2014.

[9] J. M. Fontana, M. Farooq, and E. Sazonov, "Automatic ingestion monitor: A novel wearable device for monitoring of ingestive behavior," vol. 61, no. 6, pp. 1772–1779, 2014.

[10] T. Isoda, Y. Nohara, S. Inoue, M. Shirouzu, Y. Sugiyama, M. Hirata, K. Machida, and N. Nakashima, "Experiment for nursing activity analysis using mobile sensors and proximity sensors," in *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*. ACM, 2015, pp. 153–156.

[11] C. Zhu and W. Sheng, "Multi-sensor fusion for human daily activity recognition in robot-assisted living," in *Proceedings of the 4th ACM/IEEE international conference on Human robot interaction*. ACM, 2009, pp. 303–304.

[12] K. Ouchi and M. Doi, "Smartphone-based monitoring system for activities of daily living for elderly people and their relatives etc." in *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*. ACM, 2013, pp. 103–106.

[13] A. Ghosh and G. Riccardi, "Recognizing human activities from smartphone sensor signals," in *Proceedings of the 22nd ACM international conference on Multimedia*. ACM, 2014, pp. 865–868.

[14] L. Gao, A. K. Bourke, and J. Nelson, "A comparison of classifiers for activity recognition using multiple accelerometer-based sensors," in *Cybernetic Intelligent Systems (CIS), 2012 IEEE 11th International Conference on*. IEEE, 2012, pp. 149–153.

[15] F. M. de S Matos, L. V. Batista *et al.*, "Face recognition using dct coefficients selection," in *Proceedings of the 2008 ACM symposium on Applied computing*. ACM, 2008, pp. 1753–1757.

[16] K. Dunlap, "Effects of alcohol on hand and eye coordination," *Psychobiology*, vol. 2, no. 3, pp. 187–191, 1920.