Detection of Hypoglycemic Events through Wearable Sensors

Jean-Eudes Ranvier[1], Fabien Dubosson[2], Jean-Paul Calbimonte[1], Karl Aberer[1]

[1] Ecole Polytechnique Fédérale de Lausanne (EPFL) firstname.lastname@epfl.ch
[2] HES-SO Valais-Wallis firstname.lastname@hevs.ch

Abstract. Diabetic patients are dependent on external substances to balance their blood glucose level. In order to control this level, they historically needed to sample a drop a blood from their hand and have it analyzed. Recently, other directions emerged to offer alternative ways to estimate glucose level. In this paper, we present our ongoing work on a framework for inferring semantically annotated glycemic events on the patient, which leverages mobile wearable sensors on a sport-belt.

1 Introduction

Hypoglycemia characterizes a state of low glucose level in the bloodstream. While for non-diabetic people this state is relatively rare due to adequate regulation of the glucose level, it can lead to life threatening effects for diabetic patients, ranging from headaches to judgment impairment and loss of consciousness. To help diabetic users regulate their glucose level, the standard method consists in collecting a drop of blood from the finger and analyze its glucose level using a glucometer. While this method is reliable as it is performed through a direct measurement, it is not very convenient as it requires the user to pinch her finger for each new observation. Furthermore, this method does not allow for a continuous monitoring, but rather a sporadic sampling of the glucose level. Alternatively, continuous glucose monitoring can be achieved using an under-the-skin sensor which relays glucose information to an electronic receiver. This method has a granularity of a sample every few minutes. However, the position of the sensor makes it cumbersome for an extended usage, limiting its applicability. For this reason, alternative non-invasive techniques (i.e. not requiring the user to compromise her physical integrity) have been studied [3, 9, 1].

In this paper we present our work-in-progress on D1namo, a non-invasive approach to detect hypoglycemic events based on the continuous collection of sensed data from an off-the-shelf sensor belt. We base our method on two distinct models. The first one leverages a physiological consequence of hypoglycemia, namely an alteration of the user electrocardiogram's features (ECG). We additionally use the accelerometer and breathing sensor of the belt to infer the energy expenditure of the user, correlated with her food intake to estimate her glucose level. We then combine these two models to improve the accuracy of our prediction. Furthermore, previous approaches that rely on mobile wearables generate raw data, with no or little additional information to make it possible for other applications to understand and interpret this data. We propose a semantic approach for representing the hypoglycemic events, anomalous features, activities and energy expenditure, so that this annotated data can be ingested by a semantic complex event processor in a monitoring mobile platform.

The contribution of this work is a method to detect glycemic events in an everyday configuration, using semantic technology to allow advanced reasoning about the user's condition. To the best of our knowledge, combining observations about physiological symptoms and energy expenditure in order to detect glycemic events has not yet been explored and should improve the detection accuracy, on everyday (i.e. out of the hospital) settings.

2 System overview

The D1namo system taps into the data generated by a Zephyr Bioharness [12] sensor belt worn by the user. The belt generates high frequency readings for accelerometer, breathing sensor and electrocardiogram (ECG). The pipeline followed by D1namo to go from raw sensor readings to the understanding of the user's blood glucose level is described in Figure 1.

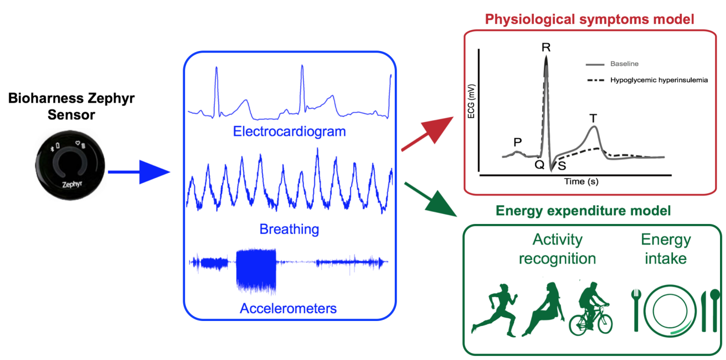

Fig. 1. *D1namo Architecture.* The data is acquired from an off-the-shelf sensor belt and preprocessed to reduce noise. It is then used to generate two semantic models for classifying hypoglycemic events, respectively based on physiological symptoms of hypoglycemia and energy expenditure.

2.1 Preprocessing

The bioharness records multiple physiological signals from the user. However, some signals are collected with an important amount of noise. While the accelerometer readings are relatively clean, the breathing signal (measuring the extension / compression of the thorax of the user) is subject to a high frequency white noise, and is also moderately affected by the re-adjustment of the belt by the user. A low pass filter isolates the oscillations due to the breathing of the user while removing the noise. As for the ECG signal, it presents variable noise: When the user stands still, the noise is very limited and the shape of the ECG is clearly distinguishable. However, under moderate and heavy activity, the ECG becomes very noisy due to artifacts generated by muscle contraction as well as displacement of the belt's electrodes on the skin. Since the noise of the ECG signal is correlated with the movement of the user, we filter the ECG signal with an adaptive filter, namely a normalized least mean squares filter. For this we use the accelerometer signal as interference signal, therefore making use of the correlation between the two to mitigate the impact of the noise.

2.2 Feature extraction

Once the noise is attenuated, we extract the features that are used by the two models to detect hypoglycemic events, as listed in Table 1.

Physiological model (ECG)	**Energy expenditure model**
HB fiducial points location	Heart rate
HB fiducial points amplitude	Breathing rate
ST segment shape	Vector Magnitude Unit (VMU)
QTc interval	Energy intake

Table 1. List of the features used in the models for classifying hypoglycemic events.

Physiological features The physiological model relies essentially on ECG features. In [6], the author explains how hypoglycemia alters ventricular repolarisation, therefore influencing the ECG of the user. Based on this assertion, we extract fiducial points of the ECG to use as features for training the model. Fiducial points are defined as the key points that characterize a heart beat. They are defined as P, Q, R, S, T labels and can be seen in Figure1. In order to extract these points, we leverage the approach taken by Yazdani et al. [11]. This approach is based on mathematical morphology. A structuring element representing coarsely a QRS complex is applied to the signal through two mathematical morphology operators: top-hat and bottom-hat. The average of the two resulting signals ideally yields non zero signal for the QRS complex of heart beats, while remaining zero outside of these complexes. However, with real life signal, artifacts appear due to noise. They are handled by applying heuristics based on the temporal limitations of human QRS complexes (i.e. min/max time between to consecutive complexes, minimum duration of a complex, etc). Furthermore, to better adapt this method to different users, the structuring element is updated with each new QRS complex detected.

While QRS complexes are relatively easy to locate on an ECG, P and T points are less obvious, and may even be missing. We do not consider P points since according to [6], they carry little information about the state of glycemia of the users. On the other hand the T points are instrumental in discriminating the different glucose states. They are therefore extracted using a gradient ascent after each QRS complex since they. Despite the noise reduction applied in the preprocessing phase, artifacts resulting from noise can lead to differences in the amplitude of the fiducial points from one complex to another. To alleviate this problem, we average the detected complexes over a one minute sliding windows. This averaging does not prevent the detection of hypoglycemic events which have a longer duration, while allowing for more reliable measurements.

Energy expenditure features As a byproduct of the QRS extraction, the interval between two consecutive R peaks corresponds to the interval between two different heartbeats, providing us with the heart rate of the user. The breathing rate is computed as the local maximums of the breathing signal preprocessed as described in the previous section. The vector magnitude feature is provided directly from the sensor belt secondary signals.

The last feature of the energy expenditure is the energy intake. During the collection campaign, the participants were asked to log their meals and snacks. This information is semantically enhanced by querying the Fitbit food database (http://dev.fitbit.com/docs/food-logging/). This database allows for a semantic annotation of the intake and activity events, which can be represented in terms of an ontology. This includes the event context, meal category, estimated calories and glucose intake, etc.

2.3 Model learning

Once the two sets of features presented in Table 1 are extract, they can be used to train in parallel two machine learning models. Rather than a regression on the estimated glucose level of the user, our system focuses on the detection of glycemic events that are of interest to the user. For this reason we take a classification approach which will output whether the user is in state of hypoglycemia, euglycemia or hyperglycemia. To this purpose, we are currently evaluating the use of decision trees to perform this classification.

Once the classification is done, the different events will be fed to a complex event processor (CEP), encoded as a stream of semantically-annotated RDF events. In the example below we show two sample Hypoglycemic and Systolic observation events that can be appended to the stream.

```
hypo1 a :HypoEvent;   :observedAt "2016-03-03T20:30:31"; :hasValue 45.3.
syst1 a :SystolicObs; :observedAt "2016-03-03T20:30:31"; :hasValue 145.
```

Then, using a CEP-enabled RDF Stream query processor, we can evaluate rules on the incoming events, e.g. sequences over a sliding window, as on the example below encoded as a CQELS-CEP [5] query:

```
SELECT ?h1,?sys FROM NAMED WINDOW :win ON ex:eventStream [RANGE  1h]
WHERE { WINDOW :win {
 SEQ({?h1 a :HypoEvent},
     {?h2 a :SystolicObs; :hasValue ?sys. FILTER (?sys>140)})}
```

3 Preliminary Experiments

In order to validate the models defined in the previous section, we are currently collaborating with medical staff in order to collect data from diabetes type 1 patients. The acquired data contains the signal acquired by the sensor belt for 5 days, but also glucose readings coming from a continuous glucose monitoring system Ipro 2 (Medtronic) which collects a glucose measurement per 5 minutes. This measurement are used as a ground truth for the training and evaluation of the models. A power analysis based on the medical literature estimated that a dataset of 21 participants should be collected in order for the study to have enough glycemic events to be statistically significant. At the time of writing, the data of 5 participants is already collected, providing a total of 260 hours of data and 9 distinct glycemic events covering 16.33 hours of these data. Not all of the participants displayed hypoglycemic events during the time of acquisition. However, the rate at which the glycemic events are collected is higher than the one considered in the power analysis. Consequently, a lower number of participants may be needed to achieve the expected statistical power.

Figure 2 depicts preliminary results of this project. It features the two main steps of the preprocessing and feature extraction task: the black signal corresponds to the raw ECG data taken from the sensor-belt, it is preprocessed using the adaptive filtering with the accelerometers as noise reference, resulting in the blue signal. Finally, the mathematical morphology component extracts the fiducial points of the QRS complexes, in red on the filtered ECG signal.

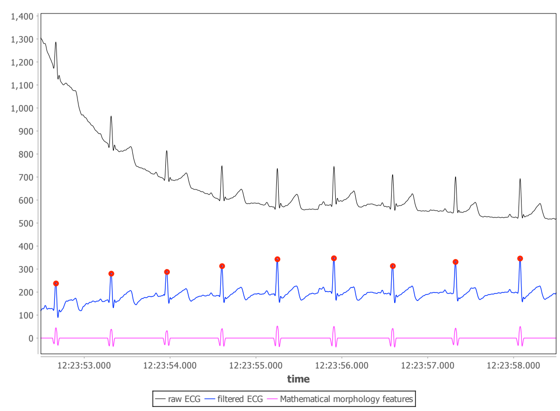

Fig. 2. Filtering and segmentation of the ECG.

4 Related work

Recent years have seen the development of non-invasive methods aiming at replacing the drop of blood to evaluate glucose level. Recently, Google introduced a smart lense [8] in order to sense glucose level from tear fluid. In [3, 4, 1], the authors leverage signals such as accelerometer data and heart rate in order to refine the insulin dosage provided by pumps and artificial pancreas. For the same purpose, in [10], the author uses energy expenditure and galvanic skin response to estimate the food intake along with glucose measurements. Closer to our concerns, [9] integrates accelerometers, heat-flux sensors, thermistors, ECG electrodes and galvanic skin response sensor to predict glucose level, physical activity and energy expenditure. While there have also been proposals for ontology-based activity detection [2, 7], to the best of our knowledge semantics-based approaches are so far unexplored for combining physiological and energy expenditure data in a glucose estimation system.

5 Conclusion

We have presented our preliminary results on D1namo, a non-invasive approach to detect glycemic events from mobile sensor data. We presented the potential of combining both a physiological and an energy expenditure model to classify these events. We plan to complete this approach, validating our inferences with diabetes type 1 patients glucose readings. We will also include the detection algorithm into a mobile platform that will exploit the semantically enriched data through a complex event processor, providing alerts and recommendations.
Acknowledgments Supported by the Nano-Tera.ch SNSF evaluated D1namo project. The authors would like to thank B. Zeydan for his insights on adaptive filtering as well as S. Yazdani for the discussions on mathematical morphology.

References

1. Breton, M.D., et al.: Adding heart rate signal to a control-to-range artificial pancreas system improves the protection against hypoglycemia during exercise in type 1 diabetes. Diabetes technology & therapeutics 16(8), 506–511 (2014)
2. Chen, L., et al.: Ontology-based activity recognition in intelligent pervasive environments. Intl. Journal of Web Information Systems 5(4), 410–430 (2009)
3. Cichosz, S., et al.: Combining information of autonomic modulation and cgm measurements enables prediction and improves detection of spontaneous hypoglycemic events. J. Diabetes science and technology (2014)
4. Cichosz, S., et al.: A novel algorithm for prediction and detection of hypoglycemia based on continuous glucose monitoring and heart rate variability in patients with type 1 diabetes. J. diabetes science and technology (2014)
5. Dao-Tran, M., et al.: Towards enriching cqels with complex event processing and path navigation. In: HiDeSt. pp. 2–14 (2015)
6. Laitinen, T., et al.: Electrocardiographic alterations during hyperinsulinemic hypoglycemia in healthy subjects. Annals of Noninvasive Electrocardiology 13(2), 97–105 (2008)
7. Riboni, D., et al.: Is ontology-based activity recognition really effective? In: PERCOM Workshops. pp. 427–431 (2011)
8. Senior, M.: Novartis signs up for google smart lens. Nature biotechnology 32(9), 856–856 (2014)
9. Sobel, S.I., et al.: Accuracy of a novel noninvasive multisensor technology to estimate glucose in diabetic subjects during dynamic conditions. J. of diabetes science and technology 8(1), 54–63 (2014)
10. Turksoy, K., et al.: Multivariable adaptive closed-loop control of an artificial pancreas without meal and activity announcement. Diabetes technology & therapeutics 15(5), 386–400 (2013)
11. Yazdani, S., Vesin, J.M.: Adaptive mathematical morphology for qrs fiducial points detection in the ecg. In: Computing in Cardiology Conference. pp. 725–728 (2014)
12. Zephyr: (2016), http://www.zephyranywhere.com/products/bioharness-3