Towards NLG for Physiological Data Monitoring with Body Area Networks

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Abstract

This position paper presents an on-going work on a natural language generation framework that is particularly tailored for summary text generation from body area networks. We present an overview of the main challenges when considering this type of sensor devices used for at home monitoring of health parameters. This paper describes the first steps towards the implementation of a system which collects information from heart rate and respiration rate using a wearable sensor. The paper further outlines the direction for future work and in particular the challenges for NLG in this application domain.

1 Introduction

Monitoring of physiological data using body area networks (BAN) is becoming increasingly popular as advances in sensor and wireless technology enable lightweight and low costs devices to be easily deployed. This gives rise to applications in home health monitoring and may be useful to promote greater awareness of health and prevention for particular end user groups such as the elderly (Ahmed et al., 2013). A challenge however, is the large volumes of data which is produced as a result of wearable sensors. Furthermore, the data has a number of characteristics which currently make automatic methods of data analysis particularly difficult. Such characteristics include the multivariate nature of the data where several dependent variables are captured as well as the frequency of measurements for which we still lack a general understanding of how particular physiological parameters vary when measured continuously.

Recently many systems of health monitoring sensors have been introduced which are designed to perform massive and profound analysis in the area of smart health monitoring systems (Baig and Gholamhosseini, 2013). Also several research have been done to show the applications and efficiency of data mining approaches in healthcare fields (Yoo et al., 2012). Such progress in the field would be suitable to combine with state of the art in the NLG community. Examples of suitable NLG systems include the system proposed by Reiter and Dale (2000) which suggested an architecture to detect and summarise happenings in the input data, recognise the significance of information and its compatibility to the user, and generate a text which shows this knowledge in an understandable way. A specific instantiation of this system on clinical data is BabyTalk project, which is generated summaries of the patient records in various time scales for different end users (Portet et al., 2009; Hunter et al., 2012). While these works have made significant progress in the field, this paper will outline some remaining challenges that have yet to be addressed for physiological data monitoring which are discussed in this work. The paper will also present a first version of an NLG system that has been used to produce summaries of data collected with a body area network.

2 Challenges in Physiological Data Monitoring with BAN

2.1 From Data Analysis to NLG

One of the main challenges in healthcare area is how to analyse physiological data such that valuable information can help the end user. To have a meaningful analysis of input signals, preprocessing the data is clearly an important step. This is especially true for wearable sensors where the signals can be noisy and contain artifacts in the recorded data. Another key challenge in physiological data monitoring is mapping from the many data analysis approaches to NLG. For example finding hidden layers of information with unsuper-

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vised mining methods will be enable the system to make a representation of data which is not producible by human analysis alone. However, domain rules and expert knowledge are important in order to consider a priori information in the data analysis. Further external variables (such as medication, food, stress) may also be considered in a supervised analysis of the data. Therefore, there is a challenge to balance between data driven techniques that are able to find intrinsic patterns in the data and knowledge driven techniques which take into account contextual information.

2.2 End User / Content

A basic issue in any design of a NLG system is understanding the audience of the generated text. For health monitoring used e.g. at home this issue is highly relevant as a variety of people with diverse backgrounds may use a system. For example, a physician should have an interpretation using special terms, in contrast for a lay user where information should be presented in a simple way. For instance, for a decreasing trend in heart rate lower than defined values, the constructed message for the doctor could be: *"There is a Bradycardia at ... "*. But for the patient itself it could be just: *"Your heart rate was low at ... "*. It is also important to note that the generated text for the same user in various situations should also differ. For instance a high heart rate at night presents a different situation than having a high heart rate during the high levels of activity. Consequently, all the modules in NLG systems (data analysis, document planning, etc.) need to consider these aspects related to the end user.

2.3 Personalisation / Subject Profiling

Personalisation differs from context awareness and is effective to generate messages adapted to the personalised profile of each subject. One profile for each subject is a collection of information that would be categorised to: metadata of the person (such as age, weight, sex, etc.), the history of his/her signals treatments and the extracted features such as statistical information, trends, patterns etc. This profiling enables the system to personalise the generated messages. Without profiling, the represented information will be shallow. For instance, two healthy subjects may have different baseline values. Deviations from the baseline may be more important to detect than threshold detection. So, one normal pattern for one in-

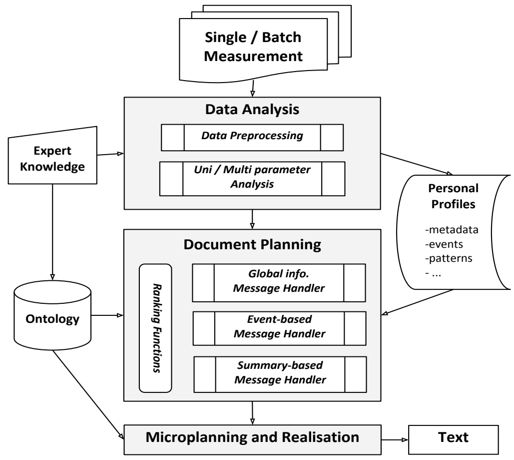

Figure 1: System architecture of text generation from physiological data.

dividual could be an outlier for another individual considering his/her profile.

3 System Architecture

In this section we outline a proposed system architecture, which is presented in Figure 1. So far the handling of the single and batch measurements and the data analysis have been implemented as well as first version of the document planning. For microplanning and realisation modules, we employed the same ideas in NLG system proposed by Reiter and Dale (2000).

3.1 Data Collection

By using wearable sensor, the system is able to record continuous values of health parameters simultaneously. To test the architecture, more than 300 hours data for two successive weeks have been collected using a wearable sensor called Zephyr (2013), which records several vital signs such as heart rate, respiration, temperature, posture, activity, and ECG data. In this work we have primarily considered two parameters, heart rate (HR) and respiration rate (RR) in the generated examples.

3.2 Input Measurements

To cover both short-term and long-term healthcare monitoring, this system is designed to support two different channels of input data. The first channel is called single measurement channel which is a continuous recorded data record. Figure 2 shows an example of a single measurement. In the figure, the data has been recorded for nine continuous hours of heart rate and respiration data which capture health parameters during the sequential activi-

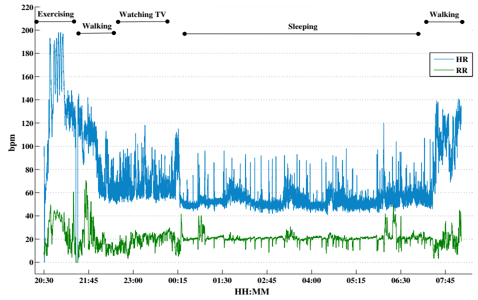

Figure 2: An example of single measurement, 13 hours of heart rate (HR) and respiration rate (RR).

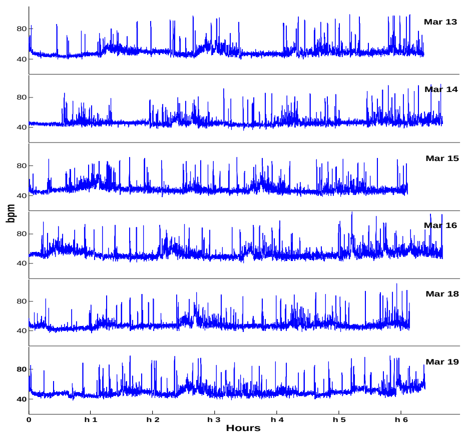

Figure 3: An example of batch measurement included heart rate for 6 nights.

ties such as exercising, walking, watching TV, and sleeping. To have a long view of health parameters, the system is also designed to analyse a batch of measurements. Batch measurements are sets of single measurements. Figure 3 presents an example of a batch of measurements that contain all the readings during the night for a one week period. This kind of input data allows the system to make a relation between longitudinal parameters and can represent a summary of whole the dataset.

3.3 Data Analysis

To generate a robust text from the health parameters, the data analysis module extracts the informative knowledge from the numeric raw data. The aim of data analysis module is to detect and represent happenings of the input signals. The primary step to analyse the measurements is denoising and removing artifacts from the raw data. In this work, by using expert knowledge for each health parameter, the artifact values are removed. Meanwhile, to reduce the noise in the recorded data, a series of smoothing functions (wavelet transforms and linear regression (Loader, 2012)) have been applied.

In this framework an event based trend detection algorithm based on piecewise linear segmentation methods (Keogh et al., 2003) for the time series has been used. In addition, general statistics are extracted from the data such as mean, mode, frequency of occurrence etc. that are fed into the summary based message handler. As an ongoing work, the system will be able to recognise meaningful patterns, motifs, discords, and also determine fluctuation portions among the data. Also for multi-parameter records, the input signals would be analysed simultaneously to detect patterns and events in the data. Therefore the particular novelty of the approach beyond other physiological data analysis is the use of trend detection.

3.4 Document Planning

Document planning is responsible to determine which messages should appear, how they should be combined and finally, how they should be arranged as paragraphs in the text. The messages in this system are not necessarily limited to describing events. Rather, the extracted information from the data analysis can be categorised into one of three types of messages: global information, event based, and summary based messages. For each type of message category there is a separate ranking function for assessing the significance of messages for communicating in the text. The order of messages in the final text is a function based on (1) how much each message is important (value of the ranking function for each message) (2) the extracted relations and dependencies between the detected events. The output of document planning module is a set of messages which are organised for microplanning and realisation. Document planning contains both event based and summary based messages as described below.

Event based Message Handler: Most of the information from the data analysis module are categorised as events. Event in this system is an extracted information which happens in a specific time period and can be described by its attributes. Detected trends, patterns, and outliers and also identified relations in all kinds of data analysis (single/batch measurement or uni/multi parameter) are able to be represented as events in the text. The main tasks of the event based message handler are to determine the content of events, construct and combine corresponding messages and their relations, and order them based on a risk function.

The risk function is subordinate to the features of the event and also expert knowledge to determine how much this event is important.

Summary based Message Handler: Linguistic summarisation of the extracted knowledge data is a significant purpose of summary based message handler. With inspiration from the works done by Zadeh (2002) and Kacprzyk et. al (2008), we represent the summary based information considering the possible combination of conditions for the summary of data. The proposed system uses fuzzy membership function to map the numeric data into the symbolic vocabularies. For instance to summarise the treatments of heart rate during all nights of one week in linguistic form, we define a fuzzy function to identify the proper range of low/medium/high heart rate level or specify a proper prototype for representing the changes such as steadily/sharply or fluctuated/constant. Here, the expert knowledge helps to determine this task.

The validity of these messages is measured by a defined formula in linguistic fuzzy systems called truth function which shows the probability of precision for each message. The system uses this indicator as a ranking function to choose most important messages for text. The main tasks of summary based message handler are: determining the content of the summaries, constructing corresponding messages, and ordering them based on the truth function to be appeared in the final text. The summary based message handler is not considered in previous work in this domain.

3.5 Sample Output

The implemented interface is shown in Figure 4 which is able to adapt the generated text with features such as health parameters, end user, message handler etc.. Currently our NLG system provides the following output for recorded signals which covers global information and trend detection messages. Some instances of generated text are shown, below. The first portion of messages in each text is global information which includes basic statistical features related to the input signals. An example of these messages for an input data is:

"This measurement is 19 hours and 28 minutes which started at 23:12:18 on February 13th and finished at 18:41:08 on the next day."

"The average of heart rate was 61 bpm. However most of the time it was between 44 and 59 bpm. The average of respiration rate was 19 bpm, and it was between 15 and 25 bpm."

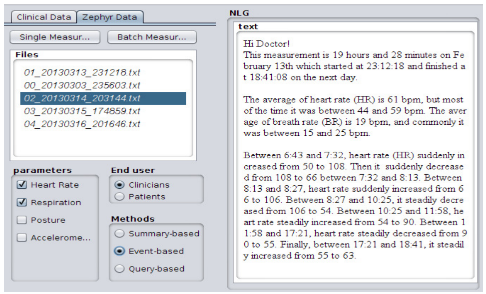

Figure 4: A screenshot of the implemented interface.

Regarding to the event based messages, an example of the output text extracted from the trend detection algorithm is:

"Between 6:43 and 7:32, the heart rate suddenly increased from 50 to 108 and it steadily decreased from 90 to 55 between 11:58 and 17:21."

4 Future Work

So far we have described the challenges and the basic system architecture that has been implemented. In this section we outline a number of sample outputs intended for future work which captures e.g. multivariate data and batch of measurement. We foresee that there is a non-trivial interaction between the event message handler and the summary message handler. This will be further investigated in future work.

Samples for single measurement:

"Since 9:00 for half an hour, when respiration rate became very fluctuated, heart rate steadily increased to 98."

"Among all high levels of heart rate, much more than half are very fluctuated."

Samples for batch of measurements:

"During most of the exercises in the last weeks, respiration rate had a medium level."

"During most of the nights, when your heart rate was low, your respiration rate was a little bit fluctuated."

Other messages could consider the comparison between the history of the subject and his/her current measurement to report personalised unusual events e.g.:

"Last night, during the first few hours of sleep, your heart rate was normal, but it fluctuated much more compared to the similar times in previous nights."

In this work we have briefly presented a proposed NLG system that is suitable for summarising data from physiological sensors using natural language representation rate. The first steps towards an integrated system have been made and an outline of the proposed system has been given.

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