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Missing-data imputation using wearable sensors in heart rate variability

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Abstract. The objective of this work is to set up a methodology that considers missing data from a connected heartbeat sensor in order to propose a good replacement methodology in the context of heart rate variability (HRV) computation. The framework is a research project, which aims to build a system that can measure stress and other factors influencing the onset and development of heart disease. The research encompasses studying existing methods, and improving them by use of experimental data from case study that describe the participant's everyday life. We conduct a study to modelize stress from the HRV signal, which is extracted from a heart rate monitor belt connected to a smart watch. This paper describes data recording procedure and data imputation methodology. Missing data is a topic that has been discussed by several authors. The manuscript explains why we choose spline interpolation for data values imputation. We implement a random suppression data procedure and simulate removed data. After that, we implement several algorithms and choose the best one for our case study based on the mean square error.

Key words: data imputation, spline interpolation, linear interpolation, HRV, IoT.

1. Introduction

The Internet of things (IoT) represents a vision of ambient intelligent devices to support smart environments, lifestyles and hyper-connectivity based on the semantic interoperability of network-centric sensor devices as connected objects [1]. It illustrates the inter-connectivity of devices through a wireless network, via Bluetooth or a pre-established protocol. The connected objects are sensors such as the smartwatch, the connected lock, thermostat, smart car, connected scale, etc., that are linked and connected to record, communicate and exchange data in real time. By 2020, it is estimated that the number of the connected objects in the world will almost double to reach 50 billion sensors worldwide, compared to 25 billion objects in 2015 [2]. Montaigne [3] claimed that the use of these devices combined with big data tools would contribute to an increase of the French gross domestic product (GDP) by 3.6% in 2020 and 7% by 2025.

Hata [4] maintains that our world is essentially divided into three main areas: the environment and its influence on human beings, the technology that enables the sensing and perception of the environment, and physiological and emotional data of the human beings themselves, which in our study are connected through sensor devices in multimodal HealthCare Monitoring. This is a complex system-of-systems using many operators and the IoT architecture. Patient data retrieved from the healthcare system can be used and analyzed as long as the patient's environment guarantees their security and safety. The number of sensors and the need to record data in a continuous, anonymous, and accurate way, using a self-synchronized data acquisition method, constitute the paradigmatic challenges in this domain. The sensors measure various parameters and provide real-time data streams, which need to be processed for data fusion and model building. Hata's health management framework [4] is based on a causality model, as is our case study. Sensors measure the psycho-physiological states of the user as well as the relevant states of their living environment and the interaction between them. Human emotions and reactions are related to hormone balance and the environment (lifestyle, work-style). To analyze emotions, we have to consider the fact that the interpretation of feelings is subjective. Some people are not able to identify their feelings. Moreover, even if they do, it is still a personal subjective assessment. For example, a person might state: "I feel stressed", but physiologically, it may show that the person is just "tired", or one may say "I feel relaxed" while data shows that they are stressed, etc. Interactions between different levels, the complexity of data management and decision-making must be examined.

The presented project focuses on the results of using connected sensors in data health area by applying data analytics tools in databases extracted from connected sensors. It explores applications in the healthcare industry and considers a few connected devices being used for monitoring cardiovascular disease (CVD) patients. In this context an experiment was conducted in collaboration with INSEAD (European Institute of Business Administration) to monitor people during their routine life. The participants were selected by INSEAD. Candidates were assigned coded identities, which were transmitted once the trial started. The protocol ID is ID February 2018/1. Both

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the protocol and all the procedures were approved by the Ethical Committee in INSEAD. The data collected were treated anonymously [5, 6].

Data was extracted from connected sensors (tensiometer, smart watch and monitor heart belt). To solve missing data problem, we have used appropriated data analysis technique.

The originality of this study consists in monitoring people during their daily life. When our participants wear sensors, they do it all day long, and not only for a few minutes or hours. So, our first objective is to analyze HRV data and separate emotions based on real life databases. We do not make people stressed, happy or angry under specific constraints. We analyze objectively the "real life" feelings for 15 days per participant. On the other side, this research was also conducted to highlight different relations between physiological and emotional data, by using the right algorithms and methodology to analyze different variations of theses variables simultaneously.

The complexity of this project consists in the fact that we will be dealing with data of huge volume, velocity and veracity. One of the problems is described in sections thereafter. The major issue of our analysis is to ensure a coherent, reliable database. We must treat correctly missing and biased data extracted from several sensors. This paper proposes our solution for data imputation.

In this paper we will present only HRV analysis. In the process of collecting and cleaning data extracted from connected sensors, some parts of data are missing. Analyzing blood pressure data will be the subject of future work.

To resolve the problem of missing data, we aim at choosing the best practice algorithm for data imputation. It is an important step in our study, as we are working with heart rate frequency. The different methods used to impute the data and the methodology followed are listed to choose the best one. The paper structure is as follows: we begin with describing the state of the art, then we consider the different materials used and the experimentation conducted, present the problem and propose a solution. Finally, the results are presented and discussed.

2. State of the art

To our knowledge, there have been no previous studies deploying a similar methodology of longitudinal real-life study of the psycho-physiological correlates of evolution and exacerbation of cardiovascular conditions. This study was initiated with reference to earlier, mainly clinically controlled studies, as reported in [7–10]. They involved data capture in the context of a few specifically detectable activities (such as preparing food, climbing stairs, using a smartphone, etc.). As Huysmans and al. [11] reported in 2018, the treatment concerning mental stress detection has been concerned mainly with feature extraction; others have used various approaches to stress detection, e.g., a survey approach [12], saliva and cortisol levels [5]. Others have used controlled studies to evaluate the impact of fast food consumption [6] and lifestyle in terms of cardiovascular disease risk. Some have involved data capture in an IoT-enabled, controlled smart home context [13]. However, our approach is different, being based on an ambulatory setting (rather than clinically controlled). It involves connected-devices-enabled continuous data measurement including contemporaneous self-expression recordings of participants' perceived feelings and mood. The purpose of this project is to determine relationships between heterogeneous categories of data (physiological and emotional) and to study their impact on chronic conditions, such as cardiovascular diseases (CVD). The experiments started with data acquisition involving healthy individuals, paving the way for addressing sensor integration, data acquisition, storage and integration issues, as well as evaluating the experimental set-up for the future [14–15]. Besides explaining the project methodology, this paper will show one of the main problems during data analysis: data imputation for missing values.

The heart rate variability is based on the interbeat (RR) interval. We focus on analyzing heart rate variability based on RR intervals. Many studies have been conducted to show that there is a link between emotional state, physiological and physical activities [7, 16, 17].

The RR interval (the time that elapses between each heartbeat) is being recorded for 1 s each time. In the literature, the HRV (hear rate variability) analysis has been analyzed for a short-term duration (less than 3 minutes) and 24h measurements. Our purpose is to bring out several indicators that will be relevant to identify each emotional state during ultra-short-term experimentation.

The digital transformation of healthcare industry, with the help of IoT, has brought about revolutionary changes within patient services. It has made the process of patient care more efficient and transparent than before [18]. The data generated and stored in the cloud systems can be used effectively for treatment purposes. The services of healthcare industry have become "omnipresent" through the development of medical devices, sensors, and the connection of these with smartphones and other wireless technology [18]. The development and advancement in the use of connected devices have made it possible to provide sound health care services through effective patient monitoring and better facilities, regardless of the location of patients. The connected devices have made it possible for patients to have personalized services at the comfort of their home and spend less time at clinics and hospitals. For example, thanks to connected devices, a diabetes patient can receive reminders to take insulin shots and injections on time.

Using connected devices, patients are also able to keep track of their medical records and data [19]. They are enabled to track their health, analyze data and take corrective actions as required, by referring to the appropriate doctor or health professional.

Applying Internet of things technology to connected sensors has made the technology workable and given it the ability to perform important functions as required in healthcare industry. The connected sensors help by capturing data from various sources such as the medical device, the environment and the users [20]. They perform various functions such as monitoring blood pressure, heart rate, glucose levels, body temperature, oxygen in blood, etc.

In recent times, numerous connected devices have been used for treatment of various conditions, such as cancer, diabetes, asthma, and even depression [20]. The technology of IoT is used to monitor the heart's vital signs in order to track alarming symptoms. A patient suffering from CVD needs various categories to be monitored, including blood pressure, glucose levels and heart rate [21].

3. Devices and sensors used for experiments

Experiments have been carried out within INSEAD-Sorbonne Universités. Firstly, the sensor choice was made, secondly, the experimentation questionnaires were tested, validated and implemented on Qualtrices (online system within INSEAD). Finally, the tools for experimentation and analysis were defined. The sensors currently available on the market can support the measurement of three categories of data which provide clues regarding the cardiovascular function. First, the physiological parameters such as activity level. Second, arterial pressure. Third, stress level. The project proposed to build a system capable of detecting stress amongst other emotions and to analyze the relationships with other variables from the two other categories (physiological and arterial pressure). Moreover, the added value of this study was the monitoring of participants and categorization of different kinds of emotions, based on real life and their physical activity.

During this experimentation, we used three wearable sensors. The tension-meter Rossmax is used to measure the blood pressure variability. Six measurements were done per day: three in the morning and three in the evening. Physical activities were measured using the Actigraph sensor (GT9X Link, v1.7.2) worn by participants. This sensor should be worn all day long. In order to measure emoptions under stress, we used the heart rate monitor belt Polar H7 (Fig. 1).

The experiment was conducted in collaboration with the INSEAD Sorbonne University. The concept was to equip participants with wearable sensors in order to measure emotional and physical parameters during their daily life. Before launching the study (Fig. 2), a calibration phase is essential.

As feelings and emotions are very subjective, we found a solution to ensure that we can obtain "objective" data. It is called the calibration phase, during which we simulate feelings in the participants. It is helpful for our technical programming as it is a reference database for each participant. We equip

Fig. 1. Wearable sensors (tension-meter, smartwatch, heart rate monitor belt)

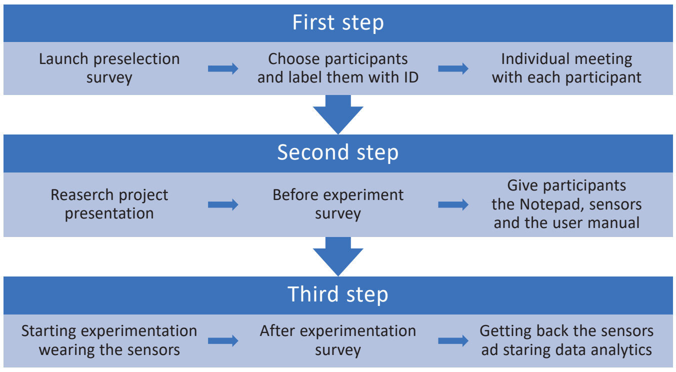

Fig. 2. Study description

the participants with ActiGraph GT9X Link and polar H7 and we record the heart rate data during rest condition.

The calibration phase duration is about 25 minutes, divided into 10 minutes of meditation (calm respiration to calculate the heart rate frequency at rest) and 15 minutes of stress (stressful games like the stroop color test, mental calculation, etc.). The second phase consists in stimulating participants and stressing them. Speed games and cognitive tests are being presented to participants in an interactive way. We implement three games:

- mental calculation, in which one is asked to subtract each time 7 from the figured, while the response speed is recorded;
- stroop color test, in which the participant has to choose based on the color of the ink and not the color described by the word;
- ballon games, in which the participant must answer quickly, counting balls.

4. Problematic and proposed solution

4.1. Problematic. Before analyzing the data, we must ensure data quality (abnormal values, lack of values, etc.). In this paper we will present the complexity of cleaning our database and our customized solution. The data from different wearable sensors contains a lot of incorrect and biased values. We present the methodology proposed to ensure the cleaning and validation of RR interval signal.

In data analysis it is essential to ensure several conditions for a correct data processing. Data consistency is one of the key factors affecting data quality. It allows for an efficient identification of several variables. Respecting the thresholds proposed by a business expert is important to obtain a reliable data. For example, in our case study, a participant's heart rate frequency physiologically cannot be between 30–40 BPM and 200–220 BPM. The raw RR interval data extracted from the monitor belt contains biased data that are distributed randomly in the file system. This issue also concerns other experimental analyses dealing with wearable sensors. This means the problem can be formulated as follows: how can we make sure that this data is incorrect? Should we delete it or replace it? If we do, what procedure shall we use?

Another issue is that our raw data contains missing values. For example, let us consider a problem in data transmission between the smart device and the monitor heart rate belt: we might not find the recording data for about 10–30 seconds. In other fields, like marketing, transactions, etc., we can consider it a technical issue and not a problem, but in the case of physiological data, it is critical to have all the data samples.

Missing values and randomly distributed biased data are the problems to be considered in data cleaning and processing with IoT system.

4.2. Proposed solution. Loss of precision and obtaining biased information are the main risks of missing data. A solution for data imputation is proposed, involving implementation of a procedure to replace missing values. The decision whether to delete, replace or simulate data by approximate values depends on data type and its distribution in the data file system. By implementing the right data imputation procedure, we consider all the constraints discussed above. Below we present different algorithms and methods of data imputation mentioned in other studies.

Data type and its distribution directly impact the choice of method. The distribution of missing values can be univariate, monotonic or non-monotonic.

For example, if we have a database file with 4 variables A, B, C and D, each variable is independent of the other.

In the univariate distribution case, if data is missing in column A, it means that the entire variable A is missing. In the monotonic distribution, if data is missing in variable A, it will impact the other data in variables B, C and D. The non-monotonic way means that missing values are arbitrarily and randomly distributed, which is accurate for our case study. In data imputation there are 3 main types of data:

- MCAR: missing completely at random – when the probability of absence is the same for all observations [22];
- MAR: missing at random – when the probability of having missing data is based on one or more variables [18];
- MNAR: missing not at random – when the fact of obtaining missing data depends on the variable witin the system [19].

The choice between proposed techniques to solve the problems of missing and biased data depends mainly on the type of distribution of missing data in the system. Different methods of data interpolation can be used [23].

Depending on these three categories, a solution is suggested. Some authors proposed the use of Miss Forest [20], others developed a program Amelia II [21], Hastie [24] suggested the use of singular value decomposition (SVD) while other research suggested the use of local regression LOESS [25].

Another solution is to keep working with missing values or just delete them. For example, some algorithms like CART [26] or NIPALS [27] tolerate working with lacking information. For this study we cannot tolerate the last two options as we are analyzing data per second (hear rate variability), so each missing value can impact directly feature value, and consequently increase the error and change the interpretation of data.

5. Methodology

In our study we work with MCAR non-monotonic data. Gelman [17], Little [28] and Glasson [22] propose the deletion of biased values, a calculation of average, median or mode. The idea is to fill the acquiring data with the average value. The disadvantage is that the use of such a method may reduce the standard deviation and therefore we may have more variables with the same value.

In order to set up data cleansing procedure, a data set choice has to be justified. The aim is to choose the best data file with zero mistake or biased data, delete data randomly (RR interval) and then replace it using different algorithms. This allows us to control all the conditions and compare replaced data with real data to obtain the best algorithm. Our methodology includes the following steps.

1. Choose a data set from the calibration phase: this will allow us to have objective data and so to pursue feature variations for each algorithm that will be used to correct biased data.
2. Choose a data file system with no biased or missing data: from the 60 data file system, we choose a correct and reliable file containing correct, non-biased raw data from the calibration phase.
3. Plot the RR interval in both phases (meditation and stress).
4. Calculate and plot LF/HF (low frequency/high frequency) features on raw data (a recognized indicator for the stress).
5. Delete randomly 10% of the raw data. We have computed on our database the maximum percentage of biased data, which is 10%.
6. Simulate the replaced data using different data imputation algorithms.
7. Recalculate LF/HF features on the new file.
8. Compare different algorithms based on the mean square error, the QQ plot, and the standard deviation of variation.

We choose to work with spline, linear, backward and forward interpolation, as well as filling the missing values with the average.

The process of deleting data will be done using three methods. First, data will be deleted randomly from all the data set (that contains raw data). We will follow the methodology described above and thus compute the mean square error.

Second, we will delete randomly data from the data file system, but the deletion will be done by bloc. The suppression will be done successively on each 4 values. The choice of 4 values is purely experimental.

Third, the suppression process will be done using the two methods described above: we will delete 4 values by bloc and one line randomly. The idea is to keep 10% of suppression and try to approximate the dispersion of biased data on a raw data file system.

To resume, the methodology described above is used to help us find the best practice algorithm for data imputation. The best method is one that considers data coherence, the experimental IoT context and data sensitivity. The optimized solution will be testet in the future work on all our data file system.

6. Results and discussion

As shown in Table 1 and Table 2, the difference between the raw RR interval data and the simulated one is not significant. The average of changing is between 0.061 and 0.088.

Table 1
Difference between RR interval raw data and replaced data (raw, average and forward)

Methods	Raw		average		Forward	
	T − 1	T + 1	T − 1	T + 1	T − 1	T + 1
Before meditation	9,9	2,6	1,1	2,3	9,6	2,7
After meditation and before stress	2,6	3,8	1,02	1,98	1,6	3,6
Before stress and during stress	1,4	0,3	1,37	0,23	2,7	0,9

Table 2
Difference between RR interval raw data and replaced data (backward, linear and spline)

Methods	Backward		Linear		Spline	
	T − 1	T + 1	T − 1	T + 1	T − 1	T + 1
Before meditation to meditation	10,6	5,15	12,2	3,2	12,16	3,36
After meditation and before stress	3,09	4,56	2,37	3,7	2,39	3,83
Before stress and stress part	2,3	0,9	3,04	1,08	2,7	1,16

It means that the chosen techniques simulate missing values approximately to real data. We divide our data into three phases:

1. Before meditation (until starting meditation).
2. After meditation and before starting stressful games.
3. Before stress and once stress has started.

We choose T − 1 and T + 1 as measure dates. The main idea was to compare several algorithms while replacing missing data during the 3 transition phases. We used linear, backward, forward and spline interpolation. We compared that to raw data and to "average "data. The last technique aims on calculating the value of missing data on the average of the value before and after. As shown in Table 1, the difference between techniques is not significant. The average of changing did not exceed 1. Threfore, we decided to calculate the LF/HF feature for raw data, average data, linear, spline, backward and forward interpolation. We divided the calibration phase into 4 main parts: before meditation, during meditation, before stress and during stress. As shown in Fig. 3 and Fig. 4, the difference between the LF/HF raw data (marked in blue), LF/HF filled average data (marked in orange) and LF/HF from linear interpolation data (marked in yellow).

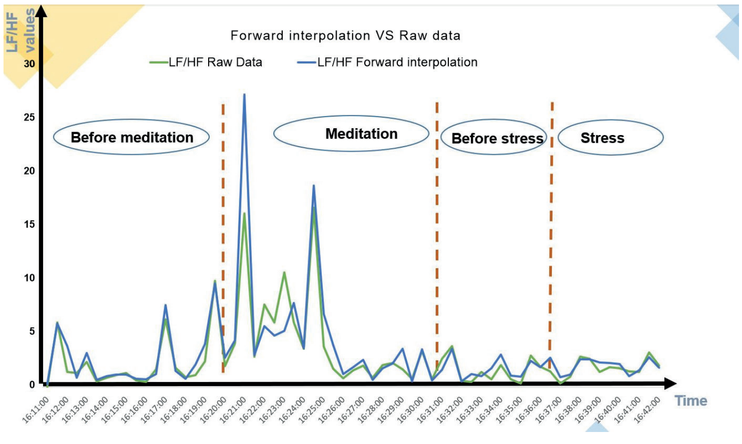

Fig. 3. LF/HF raw data and forward interpolation

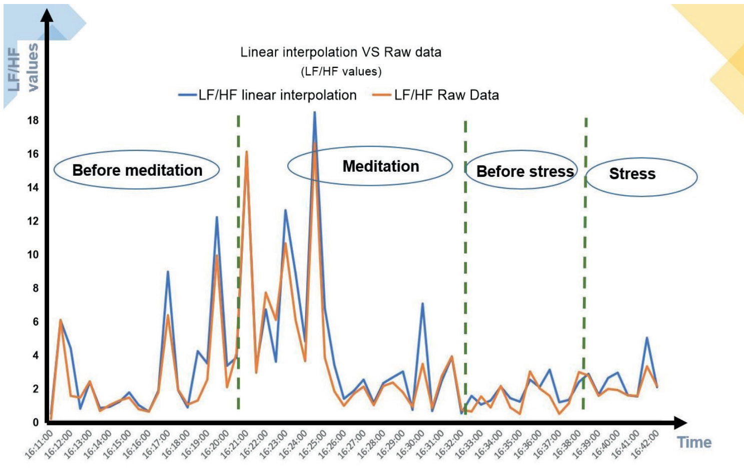

Fig. 4. LF/HF raw data and linear interpolation data

Forward and backward interpolation are those with the highest standard deviation. We calculated the LF/HF for each data file system and compared them.

To make sure that the algorithms that we use do not affect our results, we define "transition phases".

- Transition 1: to detect the peak between before meditation and during meditation.
- Transition 2: to detect the peak between meditation and before stress.
- Transition 3: to detect the peak between before stress and during stress.

The idea is to compare the amplitude of LF/HF raw data during transition with the algorithms used for data imputation (Table 3 and Table 4).

Table 3
LF/HF during different transitions

	Raw	Backward	Forward	Linear	Spline	Average
SD	0.11	0.11	0.12	0.1	0.11	0.11
Means	0.88	0.88	0.88	0.88	0.88	0.88

Table 4
Standard deviation and means of different algorithms

Errors between raw and replaced	average	spline	backward	forward	linear
Average	0.06	0.07	0.09	0.09	0.07
max	0.39	0.70	0.39	0.72	0.63
min	0	0	0	0	0
SD	0.06	0.08	0.08	0.09	0.08

Once filling data was approved, initially there were no significant differences between values of RR raw interval and simulated missing RR values.

The application of algorithms showed that the spline is the best choice to provide approximate values of the raw RR interval.

7. Conclusion

We conducted a study to develop a solution for monitoring people during their daily routine life. The idea was to use the connected sensors available on the market to collect different kinds of data. An experiment with more than 50 participants was conducted in collaboration with INSEAD. Data confidentiality and ethics were respected. A database was created for monitoring each participant for 15 days.

A data cleansing procedure has been implemented (removing duplicates and choosing the best practice algorithm for data imputation). A clustering algorithm was applied to separate two emotional states. In future work, the chosen algorithm will be used for recording, the recognition algorithm will be applied to everyday life and the results will be compared with the physical activity of the individual and their emotional state.

Healthcare industry is being revolutionized with digital transformation and the technology of big data and Internet of things is becoming an integral part of efficient healthcare services. Technologies are being adopted in large scale for the monitoring of patients and better disease management. Connected devices that are based on IoT and data analytics are being used to improve the experience of patients. That ensures timely solutions during emergencies, while also enabling preventive measures based on predictions.

In our future work, we intend to apply the spline interpolation in the entire database and not only for the calibration phase. Quadratic error will also be considered. An optimization algorithm will be applied if needed. Once cleaning and preparing data will have been completed, we will implement the algorithm needed to automatically define classes of stress and meditation.

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