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Big data analytics with graphical techniques applied to environmental control

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ABSTRACT

Analysis and processing of large data sets represent a significant challenge. Massive data sets are collected and studied in numerous domains, from engineering sciences to social networks, biomolecular research, commerce, and security. Extracting valuable information from big data requires innovative approaches that efficiently process large amounts of data as well as handle and, moreover, utilize their structure.

Big data can be used to solve a variety of problems with significant cost reduction cost by following the process in figure 1:

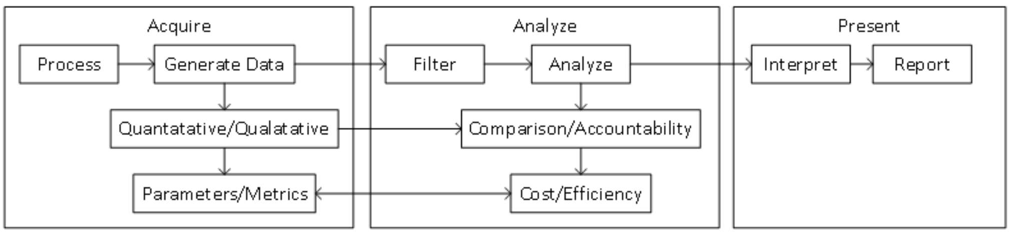

Figure 1. Big data [1]

The term “Big Data” is now a popular way to refer to massive digital information available in both structured and unstructured form integrated from multiple, diverse, dynamic sources of information.

In this research we applyed *big data* analytics with graphical techniques for the study of environmental influence on the human body. The hypothesis we wanted to check is that sounds and especially music have a special effect on human body further on influencing the level of cognition. The provided environment was changed and measurements have been achieved as regards the heart rates by carring out electrocardiograms (ECG) on the subjects. The measurements produced huge amount of data that have to be integrated and analysed considering various parameters. We have choosen to analyse and visualize the data in Labview.

Keywords: big data, analytics, plots, environmental control, Electrocardiogram (ECG)

2. INTRODUCTION

Virtual instrumentation, which combines productive software, modular measurement hardware, and commercial technologies such as the personal computer, has powered scientific and engineering measurement and control systems for over twenty years.

Through virtual instrumentation, engineers can acquire measurements in a test or control application using intuitive software and general-purpose measurement hardware that spans a wide range of frequencies and resolutions. Across nearly every industry and market, from test and measurement to industrial control and automation to monitoring and simulation, real-world measurements are a critical initial step in the process.

However, raw data does not always immediately convey useful information. Often, scientists and engineers must transform the signal, remove noise disturbances, correct for data corrupted by faulty equipment, or compensate for environmental effects, such as temperature and humidity. For that reason, signal processing, which is the analysis, interpretation, and manipulation of signals, is a fundamental need in nearly all engineering applications. In many applications, it is necessary or desirable to perform inline analysis on data as it is collected. However, combining analysis with data acquisition and data presentation into a single application is not possible in most software development environments.

Most software packages are either general purpose programming languages, which do not usually contain any signal processing libraries, or dedicated turn-key software that perform only a single task (i.e. acquisition). Few address all the requirements of a measurement system, including analysis. Unlike software development tools designed only for data acquisition or only signal processing, LabVIEW was developed from the beginning to provide a completely-integrated solution, so that users can simultaneously acquire and analyse data in a single environment.

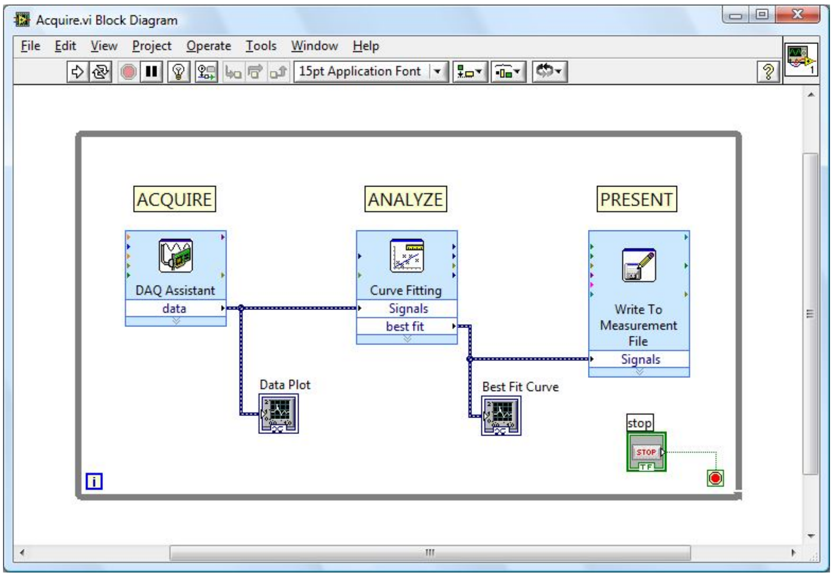

Figure 1. Example of data acquiring and analytics

As an engineering-focused tool, LabVIEW graphical programming and its extensive set of signal processing and measurement functions greatly simplify the development of measurement and inline analysis applications. LabVIEW users can employ these functions right into their applications to make intelligent measurements and obtain results faster.

3. BIG DATA DESCRIPTION

Big data can be used to find solutions for different complex problems through analytics such as:

- Predictive Maintenance (PDM): An application can acquire data from a Unit Under Test (UUT) at regular intervals and constantly analyse to detect an acute failure or degradation of performance over time.
- Performance Analysis: Metrics can be used along with data acquired in real-time to create values representative of performance which can then be used to identify cost. This data could also be used to create a baseline to quantify the effect of process changes.
- Simulation Models: A simple model can be created by playing back acquired data or a more sophisticated model can be created using acquired data to create a statistically similar model. This model can be used to create a control algorithm without hardware and/or avoiding additional edge testing that could be destructive and/or expensive [2].

One of the great strengths of LabVIEW is automatic memory management. This memory management allows the user to easily create strings, arrays, and clusters with none of the worries C/C++ users constantly have. However, this memory management is designed to be safe, so data is copied quite frequently. This normally causes no problems, but when the data size in a wire starts creeping into the megabyte range, copies start causing memory headaches, culminating in an out of memory error. While LabVIEW is not optimized for large data wires, it can be used with large data sets, provided the programmer knows a few tricks and is prepared for large block diagrams [3].

Sometimes, you need to store large data sets in memory. To store large data sets without memory problems, you need a storage mechanism that allows you to save one copy of the data and access the data in chunks, which allows transport of the data without a large memory hit. One common solution to this problem is a functional global. Another solution is a single-element queue [3].

4. METHODOLOGY

Each sensor measures various experimental parameters and the recorded values are stored in Coma Separated Values (CSV) or Excel files. Such kind of files are difficult to be managed because each of them contains millions of data (usually around 1.5 million of values). Also, the research was made in different case study and for different persons. According to this situation, in a period of time a sensor has stored ~44000 records [4]. The average number of values in every file is ~1.5 million; resulting in a very large Excel file (~30-100 MB).

1	KL-75001	Electrocardiogram(ECG)
2	1.520	
3	10.320	
4	11.200	
5	3.680	
6	8.080	
7	4.480	
8	0.240	
9	9.120	
10	6.720	
11	-8.320	
12	-2.080	
13	1.760	
14	-8.320	
15	-5.200	
16	-6.560	
17	-0.560	

18	-8.080
19	-8.320
20	-3.920
21	-5.440
22	-8.320
23	-4.480
24	-6.560
25	-3.360
26	-5.840
27	-1.040
28	0.560
29	5.840
30	6.800
31	11.280
32	-8.320
33	6.560
34	10.720
35	11.280

Figure 2. View of a data sequence in Excel.

To control the evolution process of one sensor in a time span it is difficult because one needs a graphic tool for displaying. Each excel files contain date from one experiment in one situation. Figure 2 shows data stored from the ECG application for a person who is studying with music.

In this paper we propose a method to view and analyse big data in a case study in which the methodology explores the hypothesis that a person's physiological state can be assessed and improved by adequate sensorial stimulation and further on to relate it to its emotional state. In this way it would be possible to infer a person's emotional state by considering physiological measurements, as we know that emotional states are not possible to classify by direct assessment.

We used LabView to design a graphical interface that allows analytics of big data. In figure 3 we present an example of reading data from sensors and the output in graphical form. The programming of this interface is presented in figure 4.

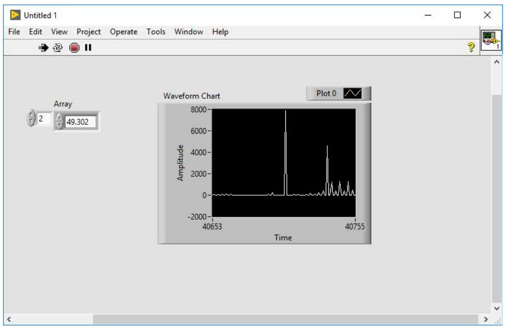

Figure 3. Front end

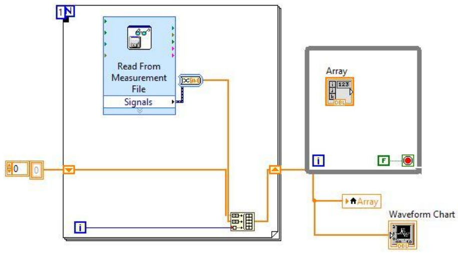

Figure 4. Block Diagram

5. CASE STUDY

LabVIEW with its signal processing capabilities provides a robust and efficient environment for resolving ECG signal processing problems. Labview has powerful tools for denoising, analyzing, and extracting ECG signals easily and conveniently. These tools can be also used in other biomedical signal processing applications such as Magnetic Resonance Imaging (MRI) and Electroencephalography (EEG). Now in LabVIEW Biomedical Toolkit, several VIs is provided for ECG signal analysis. Besides, it also contains an ECG Feature Extraction application to extract ECG features more conveniently [5].

The ECG is created by the electrical impulses of the heart as it progresses through the stages of contraction, the ECG is one of the largest bioelectric signals. Figure 5 shows the components of a typical ECG signal. Our abstraction reads this signal and currently measures two key components: the RR and the QRS complex segments. The heart rate is computed directly from the length of the RR interval, the change in the duration of the RR interval measures the overall heart rate variability (HRV) which has been found to be strongly correlated with emotional stress [6].

The QRS complex can give valuable information on the breathing patterns of the performer without requiring an additional breath sensor, thus it makes it possible to voluntary use breath as a direct controller for sound manipulation as well as to use ancillary breath patterns related to specific instrumental practices (wind instruments and voice).

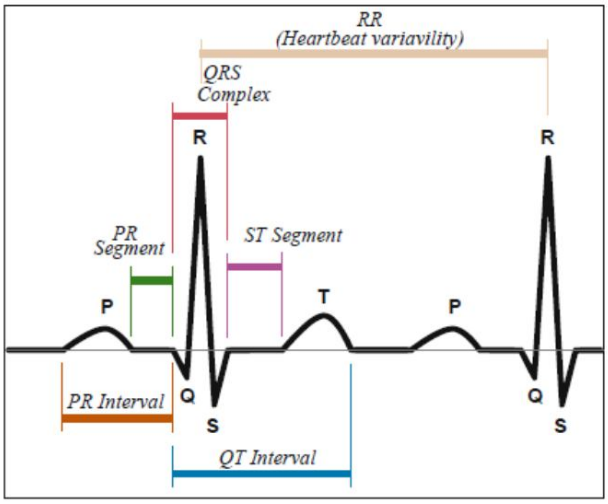

Figure 5. Schematic diagram of normal sinus rhythm for a human heart as seen on ECG [7]

We have conducted physiological measurements on a group of 5 students namely electrocardiography (ECG) to analyse the influence of music on the attention state of the student. LabVIEW [8] with its signal processing capabilities provides a robust and efficient environment for resolving ECG signal processing problems.

Spectral analysis of HRV was contemplated in 5 young male subjects during their engagement in PC based Cognitive Tasks consisting of Auditory Tone Discrimination, Working Memory and Continuous Performance (Vigilance) Tasks, each with two or more levels of memory load/time compression. Manipulation of cognitive demands in these task variants was objectively defined.

Figure 6 shows the view of date from excel files used in LabView. First array *Data 1* contain the ECG data study with music, the second array *Data 2* contain the ECG data study without music and last *Data 3* contain the ECG data in relaxing time.

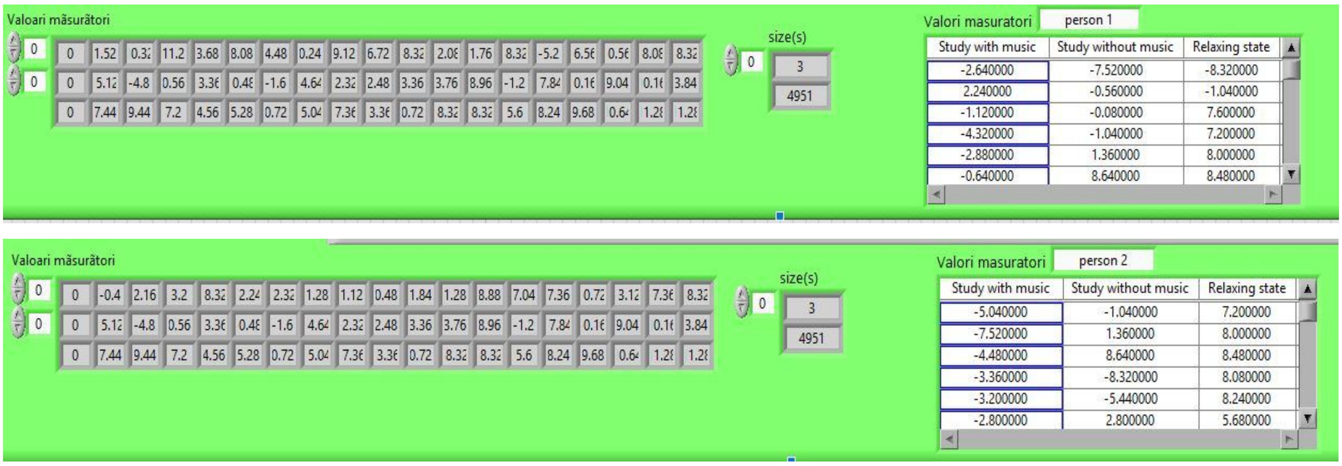

Figure 6. Big Data from Excel files uploaded in LabView

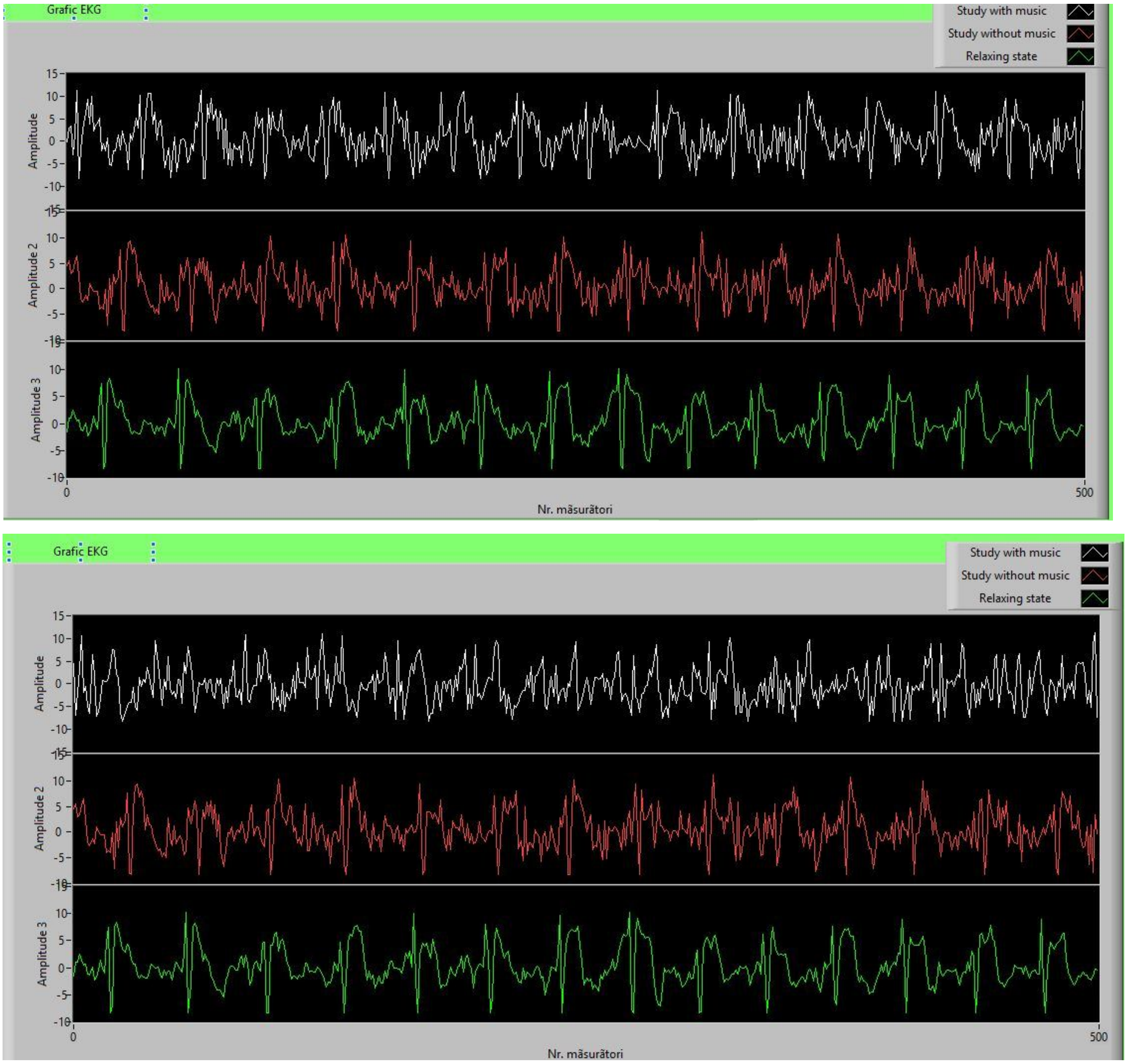

Figure 7. Graphic analyses for each case study (student 1 and student 2)

Figure 7 shows the graphic analysis for each case study. We took into consideration two students, one of the age of 22 and another 33 years old, and we stored ECG date in 3 situations:

- Situation 1 in which the student is studying without music,

- Situation 2, when the student is studying with background music
- Situation 3, when the student is in a relaxing state. We have select 500 representative data for graphical analytics.

The block diagram of this application is presented in figure 8.

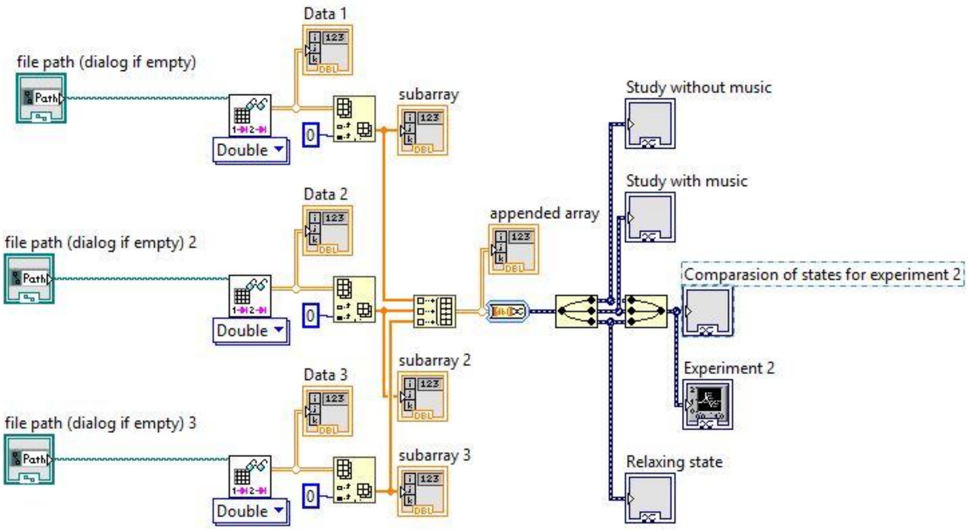

Figure 8. Block diagram

6. RESULTS

Results of the study (Fig. 9) disclosed the susceptibility of certain spectral components of HRV to cognition especially when locus of the load was on working memory. The effect was demonstrably independent of possible entrainment of power spectrum of HRV with the stimulus frequency and/or changes in breathing pattern. Nevertheless, a change was demonstrable only between 'rest' and 'task' conditions and it did not co-vary with a further manipulation of load in the working memory. Modulation of HRV during cognition seemed to be correlational. The ECG signal's amplitude is quite large.

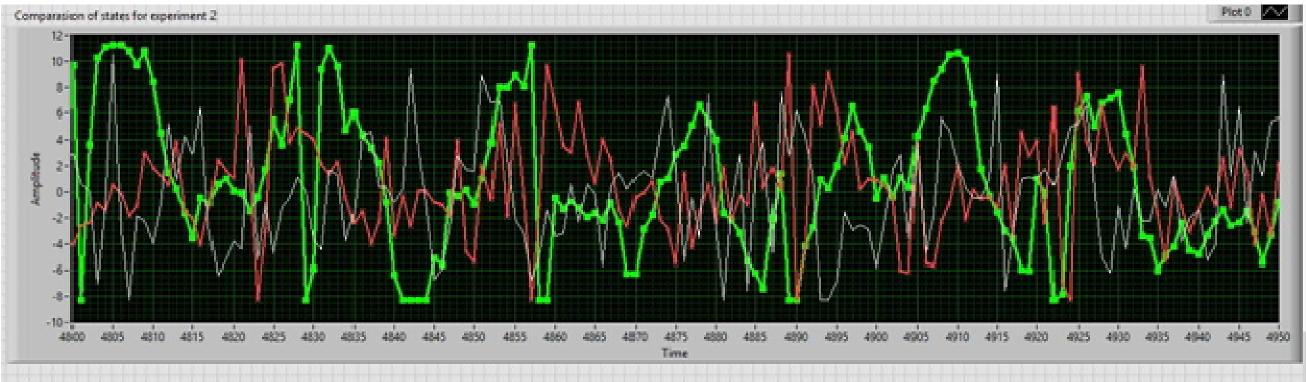

Figure 9. Graphic comparation for all case studies

7. CONCLUSIONS

In this study, we created a graphic tool in LabView for the analyses of ECG signals of five subjects and the influence of the environment on the physiological state of each one. The environmental conditions varied and the varioations in the human body have been assessed in three situations: studying with music, studying without music and in relaxing state. Labview proved to be an efficient tool to analyse and compare the produced signals in various time spans and also to compare the ECG signals for theinvestigated subjects.

Future studies will be focused on including more parameters to the experiments and increasing the number of subjects to validate the hypothesis that music can influence the emotional state and forther on the cognitive capabilites of humans.

ACKNOWLEDGMENTS

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