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NATO OTAN

## Emerging Security Challenges Division

# Science for Peace and Security Programme

# Multi-Year Project Progress Report

*insert project title*

# *Smart Patch for Life Support Systems – SP4LIFE*

submit completed report in **Microsoft Word format** to sps.admin@hq.nato.int

| Kickoff Date | Project Duration | Date of this Report |
|---|---|---|
| **10.03.2021** | **36 months** | **10.03.2022** |

## Project Co-Directors


| | Title and Name | Institution | Country | email |
|---|---|---|---|---|
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## Abstract & Current Status

*provide an abstract of the project and its current status (no more than one-half page)*


Abstract:

Wearable real-time systems collecting and smartly analysing information on respiration, heartbeat, SpO2, blood pressure and body temperature could help medical personnel adopting most suitable countermeasure in case of highly stressful situations in military and civil scenarios resulting from terrorist attacks, IEDs' or rescue operations. A system for remote real-time monitoring and analysis of emergency personnel and wounded victim's health status will be designed within the project. The system gives an alert if the health status of a person is changed to prevent overlook of critical health changes. A patch-like device prototypes and methodology enabling continuous evaluation of personnel or victims' vital parameters, using Artificial Intelligence to create software capable of real-time diagnostics and rapid countermeasures' selection will be developed.

Current status:

Graphene on biocompatible material - alginate was produced and working graphene-based sensors that can be used for heartbeats and respiration sensing were prepared and tested. Available sensors for ECG, PPG and breathing were reviewed and suitable modules were analyzed as possible candidates for the use in the smart patch. Basic hardware concept of the patch prototype using selected sensors was proposed.

Software methods for ECG and PPG measurement, processing, and extraction of heart rate (HR) and breathing rate (BR) from ECG and PPG signals were reviewed. Selected methods for HR assessment and for RR estimation based on heart rate variability, peak amplitude variability (PAV), Baseline wander, and low pass filtering of ECG signals were implemented in Python and tested on own signals and signals obtained from public databases. Their performance was evaluated, and a few approaches were recommended for additional research.

Methods for SPO2 prediction from PPG signals using feature extraction functions implemented in HeartPy and Neurokit2 Python libraries were analyzed. Importance of different signal features was investigated when building machine learning models for SPO2 prediction.

Methods for blood pressure (BP) estimation from ECG and PPG signal were investigated. Neural network with a CNN layer for feature extraction, batch normalization layer and two LSTM layers were used. As simplified BP classification seems appropriate for the use in the patch, estimation of only two or three BP classes was experimentally verified therefore the last layer has only two or three neurons representing BP categories.

Databases with larger amounts of data representing measured signals and their features were created and tools for working with big data were being developed.

The AS-IS processes representing activities and roles during intervention on site of mass casualty events were modelled using Business Process Modelling Notation (BPMN) as a base for TO-BE processes using advanced technologies including the smart patch system that is being developed.

## Goals and Obstacles

*summarize the major goals and objectives of the project; highlight any changes from the project plan or previous reports (this is unusual)*

The main project objectives are to:

- Develop wearable monitoring platforms with:

a) sensitive respiration, heartbeat and auditory sensors based on graphene (WP1 – lead member Marko Spasenovic),

b) ECG, SpO2, BP and body temperature sensor modules (WP2 - lead member Carlo Saverio Iorio, WP3 – lead member Milan Tysler),

- Create a biocompatible wearable body-sensing interface hosting electronics, alarm, low-power transmission for lightweight, portable applications (WP2 – lead member Carlo Saverio Iorio),

- Create a software that will generate alert in real time, at the moment of critical physiological parameter changes or changes of the triage medical status according to START algorithm (WP3 – lead member Milan Tysler),

- Use Artificial Intelligence to create unsupervised software capable of real-time diagnostics and rapid countermeasures' selection (WP4 – lead member Ana Madevska Bogdanova),

- Analyze existing (AS-IS) processes and consider their re-design (TO-BE processes) in organization of patient management on the site of accident with respect to wearable monitoring technology being developed (WP4 – lead members Ana Madevska Bogdanova + Oto Masar),

- Create a network of young scientists training in soft and hard skills in the wearable electronics for biomedical applications (WP5 – Milan Tysler).

The main obstacle during the second six-months period still was the limited access to laboratories and limited mobility caused by the COVID pandemics that prohibited some experimental works and influenced the dissemination of results and networking of young scientists. All meetings of the partners and presentations on conferences were only on virtual platforms. There is also some delay in equipment procurement due to the global shortage of microchips and due to disrupted supplier-customer relationships.

## Summary of Accomplishments

*summarize accomplishments under these goals to date, highlighting those that have taken place since the past report*

Accomplishments related to the above objectives:

WP1 – Marko Spasenovic

- Working graphene-based flexible devices were produced in ICTM.

- The devices were tested for acoustic response, as well as for wearable sensing of heartbeats and respiration.
- Graphene was produced on alginate, a biocompatible polymer at VUB.

WP2 – Carlo Severio Iorio

- First steps were taken to produce graphene sensors on a biocompatible polymer material (alginate).
- Available sensor modules for ECG, PPG and breathing were reviewed and selected modules were tested at IMS and ICTM.
- Basic architecture for the smart patch was proposed and alternatives were discussed.

WP3 – Milan Tysler

- Software methods and modules for physiological data (ECG, PPG, breathing) measurement, processing and analysis were reviewed and tested at IMS and FCSE.
- ML models for SPO2 regression were developed at FCSE.
- Methods for RR extraction from ECG signal were compared at IMS.
- Deep Learning models for BP classification were developed at FCSE.

WP4 – Ana Madevska Bogdanova

- Independent cloud-based platform for big data management was set at FCSE to enable various access scenarios (web and script based);
- Python scripts were created and executed at FCSE for downloading data from the Physionet MIMIC 3 database, containing quality ECG+PPG signals, together with ABP and SPO2.
- Data on heartbeats were collected at ICTM and shared with the project partners for further analysis.
- Discussion on existing START triage processes and on including innovative technologies into different stages of the triage continued at FM, IMS and FCSE. Basic and extended sets of monitored vital parameters were set.
- Formal BPMN process model of emergency care in the field was developed at IMS and FM.

WP5 – Milan Tysler

- Communication between all partners, including young scientists, continued mostly through online communication within each partner's institution and among project partners.
- Stipendists were accepted or changed (in ICTM and FCSE) according to the actual needs of the project.
- Project web page was updated and and its content has been expanded.
- Dissemination of the results of research supported by the project continued by conference presentation and preparation of publications.

WP6 – Milan Tysler

- Regular institutional and bilateral meetings (IMS-FCSE, IMS-FM, ICTM-VUB, ICTM-FCSE) were organized mostly on virtual platforms.
- Permanent Zoom platform for on-line meetings of all partners was established and is used.
- Working group on smart patch hardware development was established.
- Within financial management, all partners proposed budget changes to effectively use the funds in the situation caused mainly by the COVID 19 pandemic.

## Accomplishments

*detail accomplishments and progress since the last report for each work package*

**WP1 – Marko Spasenovic**

ICTM:

- Laser-induced graphene (LIG) was selected as the best graphene-based platform for wearable sensors of physiological parameters. LIG was chosen due to the ease of making and handling, as well as excellent first results.
- LIG devices were connected to desktop electronics and a computer and placed at several positions on the human body for monitoring heartbeat. Optimal sensor placement and measurement configurations were found, and heartbeat data were recorded.
- Heartbeat was recorded with various sensors made with different laser induction conditions, and with graphene on Kapton, PDMS, as well as encapsulated between these two materials. All sensors performed well.
- Respiration sensors based on LIG placed on the ribcage were prepared. First results indicate that such sensors can detect respiration in real time.

ULB:

- Graphene was produced on a biocompatible polymer material, alginate. Optimal laser parameters to this purpose were found, as was the particular chemical composition of alginate.

**WP2 – Carlo Severio Iorio**

ULB:

- First steps were taken to directly produce graphene sensors on a biocompatible polymer material - alginate.
- Basic concept of the smart patch with 3 sensors, µP control unit, alarm generator and wireless (Bluetooth) communication port was introduced during the HW working group meeting.

ICTM:

- Possible concept of the smart patch with graphene-based sensor, I2C bus, µP control unit, SD card, local display and alarm and wireless (Bluetooth) communication was presented in the HW working group meeting.

IMS:

- Commercially available PPG and combined PPG/ECG sensors were reviewed. Selected MAX86150 combined PPG/ECG sensor was successfully tested for use with the patch.
- Basic concept of the smart patch using the MAX86150 sensor was proposed. The concept is in agreement with those prepared by other partners.

**WP3 – Milan Tysler**

IMS:

- Methods for estimation of heart rate (HR) and respiratory rate (RR) from ECG and PPG signals were reviewed and their applicability for use with the smart patch was estimated. The study showed that the RR extracted from the PPG is less accurate than the RR extracted from the ECG signal and that the time-domain techniques give better results than the frequency domain techniques. Authors of several studie proposed using fusion techniques that fuse more respiratory modulations of ECG and PPG can improve RR estimation accuracy. Optionally, a signal from a breathing sensor can be directly measured and used in the fusion.
- Several time-domain and frequency domain methods for RR estimation from ECG signal have been implemented and compared: heart rate variability (HRV), peak amplitude variability (PAV), Baseline wander, Baseline wander with averaging the PQRST complex values, filtering for extraction of low frequencies from ECG signal. Methods were tested on measured biosignals dataset from FCSE. Preliminary, the PAV method provided best results (with lowest RMS error). To lower the RMS error,

further work will be focused on the adjustments of the above methods and their testing on larger MIMIC-III databases.

FCSE:

- In collaboration with the ICTM team graphene pulse signal was analysed with HeartPy. We used signal preprocessing and analysis (detection of the signal peaks) and interpretation of the results.
- For SPO2 estimation we proceeded with research of ML prediction of oxygen saturation (SpO2) from photoplethysmogram (PPG) signals. We used classification, then we included regression and we defined three experiments: The first one only uses HeartPy for feature extraction, the second one uses Neurokit2 and the third one uses the combination of both.
- For BP estimation: estimating a blood pressure category from raw ECG and PPG signals. We continued with writing functions for extraction of blood pressure from an arterial blood pressure signal. The data is segmented into signals of the same length. We experimented with different variants of LSTM models, through mainly focusing on the CNN-LSTM variant based on results from similar papers. CNN layer to extract necessary features and LSTM to account for the time dependency of the data. The final model consists of a single CNN layer, 2 bidirectional LSTM layers and 2 dense layers. There is also a batch normalization layer after the CNN one and one dropout layer after the LSTM each. The last layer has a softmax activation containing as many neurons as there are categories (2 and 4).

**WP4 – Ana Madevska Bogdanova**

FCSE:

We continued creation of the needed databases in even larger amounts (currently taking space of 441.4 GB). For the needed space, Python collaborating and sharing environment for collaboration with Partner researchers was defined. Also, several actions were undertaken in order to organize the environment for the big data:

- Setting and management of cloud storage server (ownCloud), setting the server properties and its management.
- Virtual machine setting and management with virtual resources to enable execution of long Python scripts.
- Creation of Python environment on the virtual machine.
- Creating documents with instructions on how to use the virtual machine for the team members.
- Modifying the Python scripts for downloading from Mimic III quality data, to put the data on the ownCloud server. Due to the large available amount of data, the scripts were modified to process only part of the data, in chunks.

ICTM:

Heartbeat data were recorded at ICTM and sent to project partners in FCSE for processing with the HeartPy module. The processing was successful, and a first joint publication is in preparation.

IMS and FM:

- Existing rescue and triage processes were analysed.
- Selection of formal methods for process modelling and representation was done.
- The AS-IS process was modelled in BPMN for explicit representation of activities and roles during intervention on site of mass casualty events.
- Validation of the formal processes model was done in cooperation with FM.
- Analysis of extensions to process model enabling modelling decision criteria was done using DMN.

**WP5 – Milan Tysler**

Communication between all partners, including young scientists, continued mostly through online communication within each partner's institution and among project partners. See more details in WP6.

To communicate the project and its results web page at at https://www.um.sav.sk/SP4LIFE was updated and its content has been expanded. In a newly created private section of the web page also recordings of project meetings and selected working documents prepared in the project are also accessible.

Dissemination of the results of research supported by the project continued by conference presentations and preparation of publications as shown in the "Products & Dissemination" section.

During the evaluated 6-months period one new student - stipendiary was accepted in ICTM according to actual needs of the project.

**WP6 – Milan Tysler**

The work in the project was organized using regular institutional and bilateral meetings (IMS-FCSE, IMS-FM, ICTM-VUB, ICTM-FCSE), mostly on virtual platforms:

- Permanent Zoom platform for on-line meetings of all partners was established and is used. The ZOOM link managed by IMS is: https://zoom.us/j/98096100711?pwd=UStLV0tpbUJyaVVUK3FHb3Y5WXJoQT09.
- At IMS and FM regular meetings and discussions with project members are organized on Google Meet or SKYPE every Tuesday.
- ICTM organizes regular meetings in the lab to discuss progress and plan further steps.
- At ULB, we have organized monthly meetings about the activities' progress.
- Within the FCSE institution, regular meetings and discussions with project members to follow up progress and discuss next steps are organized in two weeks' terms. Sometimes separate meetings are held with different working groups. Meetings are organized via internal Moodle plug-in BBB and Google Meet.

During the evaluated period virtual common meetings took place on 28 September 2021, 8 November 2021, 1 December 2021, 22 December 2021, 17 February 2022 and 2 March 2022.

The in-person meeting of partners involved in the development of software methods scheduled in Bratislava on December 7-11, 2021, had to be cancelled because of the COVID lock-down. The goal of the meeting was to investigate usage of biosensors for measuring vital parameters and possibilities of biosensors hardware integration. Also, a meeting with the National Centre of Telemedicine Services was scheduled. The meeting was provisionally postponed to September or October 2022.

Working group on smart patch hardware development (HW group) was established during the meeting on March 2, 2022. Its task is to coordinate the works mainly within WP2. It is managed by ULB (Christophe Mainetti).

Within financial management, all partners propose budget changes to effectively use the funds in the situation caused by the COVID 19 pandemic. In most cases, reallocation of travel costs not used during the COVID pandemic is proposed to equipment or for newly recruited young researchers (in ICTM).

## Obstacles

*detail any obstacles, technical, administrative, or other encountered since the last report and how they were or are being dealt with; highlight ongoing issues*

The continuing main obstacle was the limited possibility of in-person meetings and limited or prohibited access to laboratories. Many coworkers were on home-office or in quarantine and only electronic communication was possible

Since the second half of 2021 we have encountered problems in the procurement of equipment and materials due to the disruption of supplier-customer relationships and the global microchip shortage. Several deliveries have been postponed or cancelled. For example, the ICTM team is experiencing long delays in delivery of a microscope camera that will allow high-resolution high-quality observation of graphene samples. To mitigate this delay, the team is using a camera from an older microscope, which has weaker performance and is not permanently attached to the Olympus microscope but rather shared with other groups.

The N. Macedonia team tried to visit Slovakia during the scheduled meeting in December 2021 (purchased 3 plane tickets) but the total COVID lock-down occurred in Slovakia at the supposed time of arrival, so the meeting was cancelled. The teams from Belgium and Serbia tried to arrange meetings on several occasions, but meetings were impossible to schedule due to COVID restrictions. All meetings thus far are online. First general in-person project meeting is proposed for May or June in Serbia, if conditions permit.

## Collaboration

*detail the collaboration and consultation among co-directors and their groups since the last report*

As mentioned within the WP5 accomplishments description, most consultations among co-directors were organised via emails. Due to the COVID situation during the evaluated six-months period it wasn't possible to organize in-person meetings. Audio-visual meetings of the project co-directors with possible participation of all project coworkers were organised using the project ZOOM link:

https://zoom.us/j/98096100711?pwd=UStLV0tpbUJyaVVUK3FHb3Y5WXJoQT09.

Email communication and the online ZOOM meetings were focused on project management issues, stipends payments and organising interactions between research groups from each partner.

Bilateral and trilateral collaboration is in place on behalf of ICTM. Namely, ICTM collaborates with ULB on developing the biocompatible patch, via sample exchange by post. Also, ICTM, FCSE, and FM collaborate on analysis of physiological data measured with graphene sensors. The collaboration occurs through online meetings and data sharing.

The network of young researchers is building among the partners during the on-line meetings with all the partners and several bilateral ones among the young researchers from different partner teams.

Recently, collaboration on patch hardware development is supported by the creation of a working group headed by ULB and with members from all project partners.

## Milestones & Deliverables

*list milestones and deliverables due since the last report and their current status; if they are not complete, explain and detail plans and timelines for their completion*

Two deliverables (D1.2 and D2.1 within the WP1 and WP2) were planned for the second 6-month period and Milestone 2. The deliverables are included in the corresponding WP reports.
Below are shown the project tasks that were scheduled and performed during the second 6 months and achieved results.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP1: Flexible Capacitive and Strain Sensors with Biocompatible, Wearable Interface** | | | |
| T1.1 Design and Materials choice | | | |
| T1.2 Sensing element manufacturing, assembling and functional testing | | | |
| T1.3 Biocompatible materials choice | | | |
| T1.4 Mechanical properties assessment | | | |

**Deliverables**

D1.2 (M12) Report on the biocompatible interface protocol, including mechanical characterization

**Milestone**

M1 creation of a working prototype of graphene-based sensors with biocompatible interface complying with the mechanical requirement of stretchability, light invasiveness and robustness.

ICTM (T1.1, T1.2, T1.3):

Testing of various graphene materials for use as wearable sensors of physiological parameters was completed. Homemade liquid phase exfoliated graphene was gauged against commercially obtained electrochemically exfoliated graphene and laser-induced graphene (LIG). It was quickly found that LIG is the most reliable, sensitive, and easy to use solution of the three. A report on the results is being produced.

We tested several potential sensor substrates for mechanical performance and biocompatibility. The substrates considered were commercial plastic sensing substrates with transparent ITO contacts, PDMS, and Kapton tape. The commercial substrates did not show satisfactory mechanical robustness. Namely, the substrates were found to be too rigid and thick for the desired application, with sensors reacting poorly to mild actuation such as by a pulsing vein. Also, the commercial plastic substrates were found to be of weak durability, enduring only several cycles of flexing before the electrical contacts break down. As such, the commercial plastic substrates were selected as unusable for the current application. PDMS was found to be biocompatible, with literature suggesting that it is a common material for wearable patch technology. Laboratory tests revealed that the material is a good substrate for depositing graphene, with excellent adhesion, especially when pre-treated in an ozone atmosphere. Nevertheless, producing thin films of PDMS is a difficult task, requiring polymer expertise and a sequence of physico-chemical steps. Finally, Kapton proved to be the most optimal substrate of the three considered. The material is widely available at low cost and producing graphene directly on top of it with laser induction is a reliable and reproducible process. Furthermore, the mechanical properties are excellent, including flexibility, durability, and adhesion of graphene. Biocompatibility is good, although long-term effects such as skin irritation at the place of binding will need to be considered.

Laser induced graphene has been pursued and tested in various configurations. The LIG sensors showed enormous promise as flexible wearable strain gauges which, when attached to the median cubital vein registered heartbeat through changes in graphene film resistance upon vein pulsing. The signal was used to measure heartbeat on three subjects and with various configurations of LIG, such as directly on Kapton uncovered, on Kapton but covered with a thin PDMS layer, and completely transferred and encapsulated in PDMS. It was found that signal quality is dominated by positioning on the body and quality of the electrical contacts, and not on the actual sensing element configuration. Hence, in most use case scenarios, LIG directly on Kapton or covered with a layer of PDMS can be used. The obtained measurements were forwarded to FCSE for analysis with the HeartPy module, which showed excellent compatibility with our homebuilt sensors. Meanwhile we started to consider options for miniaturizing the measurement electronics for wearable use.

We obtained samples of alginate from ULB, for the purpose of making LIG directly on that material and using it as a sensor. Alginate is an extremely biocompatible material that is often used in on-skin applications such as wound healing. We succeeded in making the world's first LIG on alginate, which is a promising option as a potential sensor for project SP4LIFE.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP2: Smart Patch HW Definition, Integration, Testing and Evaluation** | | | |
| T2.1 Definition of the sensor modules for physiological data acquisition and analysis | | | |
| T2.2 Data processing, transmission protocols and network management | | | |
| T2.3 Assessment of power requirements for sensing, processing and transmission | | | |
| T2.4 Integrated platform assembly and testing | | | |

**Deliverables**

D2.1 (M12) Report on tested sensor modules and their performance.

**Milestone**

M2 Tested and operational wearable HW platform for physiological data acquisition and analysis

IMS (T2.1, T2.2):

## Review of available options for PPG and ECG sensing and proposed concept of a patch for monitoring vital functions

Different methods have been developed for the monitoring of vital functions of human subjects and correspondingly a large number of different types of sensors were designed. Some of them are designed for sensing a single biological parameter, but today it is also possible to find sensors (integrated circuits) on the market that incorporate the possibility of sensing two or more types of biological parameters. Typical examples could be combined temperature, heart rate, blood oxygen saturation (SPO2) sensors.

Particularly interesting are non-invasive types of sensors for Photoplethysmogram (PPG). They are based on a simple and inexpensive optical method for sensing the heart rate and blood oxygen saturation. Current research in the field of PPG signal analysis focuses on the second derivative of the PPG signal wave which contains important health information and can contribute to the early diagnosis of various cardiovascular disorders. PPG sensors are available in different designs. There are two main types of PPG sensors that directly affect the way of their attachment to the body, namely transmissive and reflective. Transmissive sensors are commonly used in medicine, with the option of attaching to the earlobe or finger. Reflex type sensors offer the possibility of fixing them practically anywhere on the human body. The simpler sensors provide an analogue output signal [1] (mostly transmissive). More complex types of PPG sensors (mostly reflective), in addition to more functionality, provide a digital output signal [2-11]. Manufacturers provide development kits for almost all sensors. They consist of a development board and software [12-21]. Almost all sensors operate with supply voltages in the range of 1.8V to

3.3V, with a separate LED supply in the range of 3.3V to 5V. This makes them suitable for battery-powered mobile applications. Most digital output sensors support the I2C communication interface [2 - 4,6 - 10], the more complex ones also support interfaces such as UART and SPI [5] in addition to I2C. In the case of the sensors [3, 6 - 11], the light emitting diode (LED) and the sensor are part of a single package. Reflex sensors [3, 6-11] such as the MAXM86161 [3] integrate 3 precision LED DAC current drivers, along with three types of LEDs (namely infrared, red and green) that modulate LED pulses for various optical measurements. These high integration sensors [3, 6-11] have good ambient light suppression. Due to their low power consumption, compact size, simplicity (no need for large number of external components) and good ambient light suppression, reflective sensors appear to be an ideal choice for a wide range of optical sensing applications, such as heart rate detection and pulse oximetry. From the above mentioned, sensors mentioned in [3, 6-11] are an ideal choice for the purpose of a kind of „smart patch“ for sensing vital functions. In addition to development kits, some PPG sensor manufacturers also supply ready-made compact, wearable devices, such as the "Health Sensor Band" [22]. Since no in-depth analysis of biosignals is required in case of accidents the only relevant parameters of sensors for use "in a smart patch" are the size of the sensor itself, a small number of external components, low power consumption, good resistance to interference from ambient light and finally, their price. Table 2.1 compares the properties of some PPG sensors, partially combined also with ECG sensors.

After analysis of available products, the combined PPG/ECG sensor MAX86150 was selected and tested as a candidate for the use in the smart patch. (Figure 2.1). This sensor allows PPG sensing in two segments of the spectrum, namely red and infrared. The integrated ECG sensor is optimized for use with dry electrodes. For the first testing, the MAX86150EVSYS development kit was used. ECG sensing was performed using gel carbon and Ag-AgCl chest electrodes.

Table 2.1. Comparison of selected commercial PPG and combined PPG/ECG sensors

| Product Info: | | | | | | | |
|---|---|---|---|---|---|---|---|
| Image: |  |  |  |  |  |  |  |
| Mouser Part No: | 700-MAX30102EFD+T | 700-MAX86916EFD+ | 700-MAX86150EFF+T | 584-ADPD144RIACEZRL7 | 964-OB1203SD-C4V | 700-MAX86160EFN+ | 700-MAXM86161EFD+T |
| Mfr.'s Part No: | MAX30102EFD+T | MAX86916EFD+ | MAX86150EFF+T | ADPD144RI-ACEZ-RL7 | OB1203SD-C4V | MAX86160EFN+ | MAXM86161EFD+T |
| Manufacturer: | Maxim Integrated | Maxim Integrated | Maxim Integrated | Analog Devices Inc. | Renesas Electronics | Maxim Integrated | Maxim Integrated |
| Description: | Biometric Sensors Integrated Optical Sensor | Biometric Sensors Heart-Rate and Blood Oxygen Bio-Sensor | Biometric Sensors 3rd Gen High-Accuracy Pulse Oximetry and Heart Rate Bio Sensor ,SPO2,UVA+B,Temp, EKG, GSR,BioZ, General | Optical Sensor Modules Optical Biometric Trans Red & Infrared | Multiple Function Sensor Modules LGA / 14 / 2X4MM-TRAY | Biometric Sensors An integrated Bio Sensor System supporting PPG, EKG, Bio Z, Non Contact Temp and UV | Biometric Sensors Optical Bio Sensor Module Optimized for Wearables |
| **Specifications** | | | | | | | |
| Brand: | Maxim Integrated | Maxim Integrated | Maxim Integrated | Analog Devices | Renesas / IDT | Maxim Integrated | Maxim Integrated |
| Maximum Operating Temperature: | + 85 C | + 85 C | + 85 C | + 85 C | + 85 C | + 85 C | - |
| Minimum Operating Temperature: | - 40 C | - 40 C | - 40 C | - 40 C | - 40 C | - 40 C | - |
| Moisture Sensitive: | Yes | Yes | - | Yes | Yes | Yes | - |
| Mounting Style: | SMD/SMT | SMD/SMT | SMD/SMT | SMD/SMT | SMD/SMT | SMD/SMT | - |
| Operating Supply Current: | 600 uA | 450 uA | 400 uA | 9.3 mA | 2 uA | 400 uA | - |
| Operating Supply Voltage: | 1.8 V | 1.8 V | 1.8 V | 1.8 V | 1.7 V to 3.6 V | 1.8 V | - |
| Package/Case: | OLG-14 | OLGA-14 | OLGA-22 | - | - | LGA-18 | - |
| Packaging: | ReelCut TapeMouseReel | Cut Tape | ReelCut TapeMouseReel | ReelCut TapeMouseReel | Tray | Tray | ReelCut TapeMouseReel |
| Product: | Sensors | Optical Sensors | ECG Sensors | Optical Sensor Modules | Sensor Modules | Heart-Rate Sensors | Optical Bio Sensors |
| Product Type: | Biomedical Sensors | Biomedical Sensors | Biomedical Sensors | Optical Sensor Modules | Multiple Function Sensor Modules | Biomedical Sensors | Biomedical Sensors |
| Series: | MAX30102 | MAX86916 | MAX86150 | ADPD144RI | OB1203 | MAX86160 | MAXM86161 |
| Standard Pack Qty: | 5000 | 2500 | 5000 | 1000 | 490 | 490 | 2500 |
| Subcategory: | Sensors | Sensors | Sensors | Sensor Modules | Sensor Modules | Sensors | Sensors |
| Supply Voltage - Max: | 2 V | 2 V | 2 V | - | - | 2 V | - |
| Supply Voltage - Min: | 1.7 V | 1.7 V | 1.7 V | - | - | 1.7 V | - |
| Part # Aliases: | - | - | - | - | - | - | - |
| Maximum Input Resistance: | - | - | 100 MOhms | - | - | - | - |
| Height: | - | - | - | 1.36 mm | 1.2 mm | - | - |
| Interface Type: | - | - | - | I2C | I2C | - | - |
| Length: | - | - | - | 5 mm | 2 mm | - | - |
| Resolution: | - | - | - | 14 bit | - | - | - |
| Type: | - | - | - | PPG | Health Sensor | - | - |
| Width: | - | - | - | 2.8 mm | 4.2 mm | - | - |

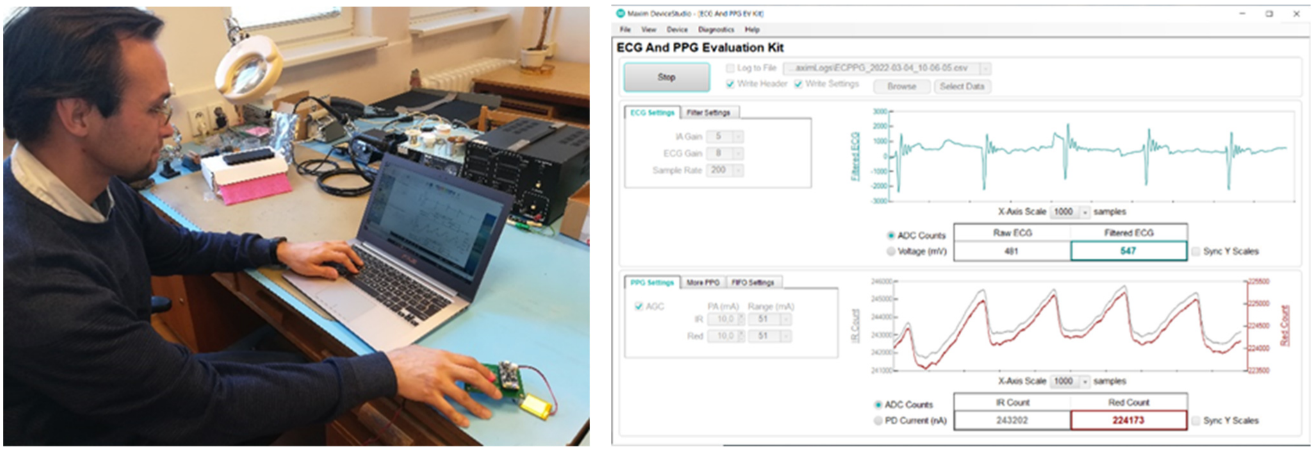


Figure 2.1: The image on the left shows the control program from Maxim integrated sensor with the measured PPG and ECG signal waveforms.

The measured data from the first tests look satisfactory. In the case of PPG signals, an increase of noise in the red spectrum was observed when room lights were switched on. The testing demonstrated the possibility to get PPG and ECG signals of acceptable quality for heart rate monitoring.

Based on successful initial testing, the basic concept of the smart patch using the MAX86150 sensor was proposed. Figure 2.2 shows the 3D sketch of the patch.

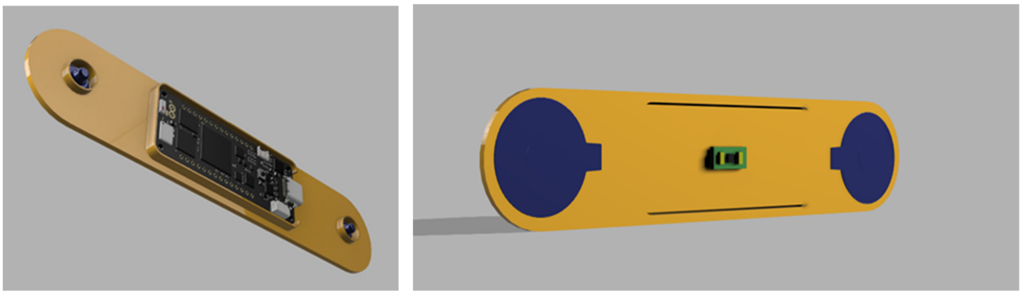

Figure 2.2. On top of the patch (left image) is a microprocessor unit with opto-acoustic signalization. On the underside (right image) there is one pair of ECG sensing electrodes with a PPG sensor placed between them.

The concept of the patch (Figure 2.3) consists of the selected PPG sensor combined with an ECG sensor and optional respiratory sensor. The device could be further equipped with a connector for connecting additional external sensors. The sensors are connected to a microprocessor unit that provides basic data processing, light and sound alarms in case of pathological manifestations in the sensed biosignals. Additional optional features of the patch concept are the possibilities of logging of the measured data to a local SD card and sending the measured data and communication with external devices (smart phones, tablets, …) via wireless communication (WiFi or BlueTooth).

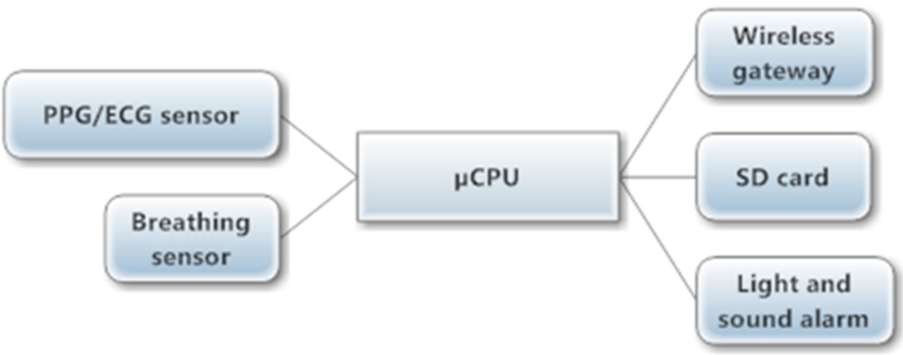


Figure 2.3. Basic concept of the proposed patch.

[1] https://pulsesensor.com/products/pulse-sensor-amped
[2] https://www.mouser.sk/new/maxim-integrated/maxim-maxm86146-biosensing-module/
[3] https://www.mouser.sk/ProductDetail/Maxim-Integrated/MAXM86161EFD%2bT?qs=sGAEpiMZZMv0NwlthflBiyFxF6z2E0nFJOCBMkMGkZU%3D
[4] https://www.mouser.sk/ProductDetail/Analog-Devices/ADPD1080WBCPZR7?qs=sGAEpiMZZMv0NwlthflBi6MKNLxIkeqscHQoNcD6onk%3D
[5] https://www.mouser.sk/ProductDetail/Analog-Devices/ADPD4000BCBZR7?qs=sGAEpiMZZMv0NwlthflBi4gWp4FwIpc6ZYovs1YX9IM%3D
[6] https://www.mouser.sk/ProductDetail/Maxim-Integrated/MAX86160EFN%2b?qs=sGAEpiMZZMueQxo7L%2FBPyPbkhe0VnJyGWbFUpAzRNG0%3D
[7] https://www.mouser.sk/ProductDetail/Renesas-IDT/OB1203SD-C4V?qs=sGAEpiMZZMv0NwlthflBiwzVl1EvpkOZT6qEGB07dN4%3D
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[18] https://www.mouser.sk/ProductDetail/Analog-Devices/EVAL-ADPD144RIZ-SF?qs=sGAEpiMZZMv0NwlthflBi8f06NFfD58DXL056%252BqxO3I%3D
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[21] https://www.dennisxl.com/products/max30102-heartbeat-frequency-tester-heart-rate-sensor-module-pulse-detection-blood-oxygen-concentration-test_1354772?utm_source=google&utm_medium=cpc&utm_campaign=gss&gclid=CjwKCAiAo4OQBhBBEiwA5KWu_2yj1f8wugeJkX2r4fcuGPAPP1k3FL8ALgVHwIIOXFGn9OfnZ0gVVxoCA00QAvD_BwE
[22] https://sk.farnell.com/maxim-integrated-products/maxrefdes103/health-sensor-band-ppg-biosensor/dp/3364875?st=ppg%20sensors

ICTM (T2.1, T2.2):

## Wearable breathing sensors for respiratory rate monitoring overview

This is a report on the state of the art of both research and commercial solutions for respiration monitoring. It is found that there are few solutions in either sector. The research solutions are generally complex, whereas commercial solutions are all in development and are not available for purchase, except one which costs ~ 2,000 EUR.

### I Research progress

1. **Respiration rate and volume measurements using wearable strain sensors**
   npj Digital Medicine **2**, 8 (2019) (https://pubmed.ncbi.nlm.nih.gov/31304358 /)

Here we introduce a wearable sensor capable of simultaneously measuring both respiration rate and volume with high fidelity. Our disposable respiration sensor with a Band-Aid© like form factor can measure *both respiration* *rate and volume by simply measuring the local strain* of the ribcage and abdomen during breathing. We demonstrate that both metrics are highly correlated to measurements from a medical grade continuous spirometer on participants at rest. Additionally, we also show that the system can detect respiration under various ambulatory conditions. Because these low-powered piezo-resistive sensors can be integrated with wireless Bluetooth units, they can be useful in monitoring patients with chronic respiratory diseases in everyday settings.

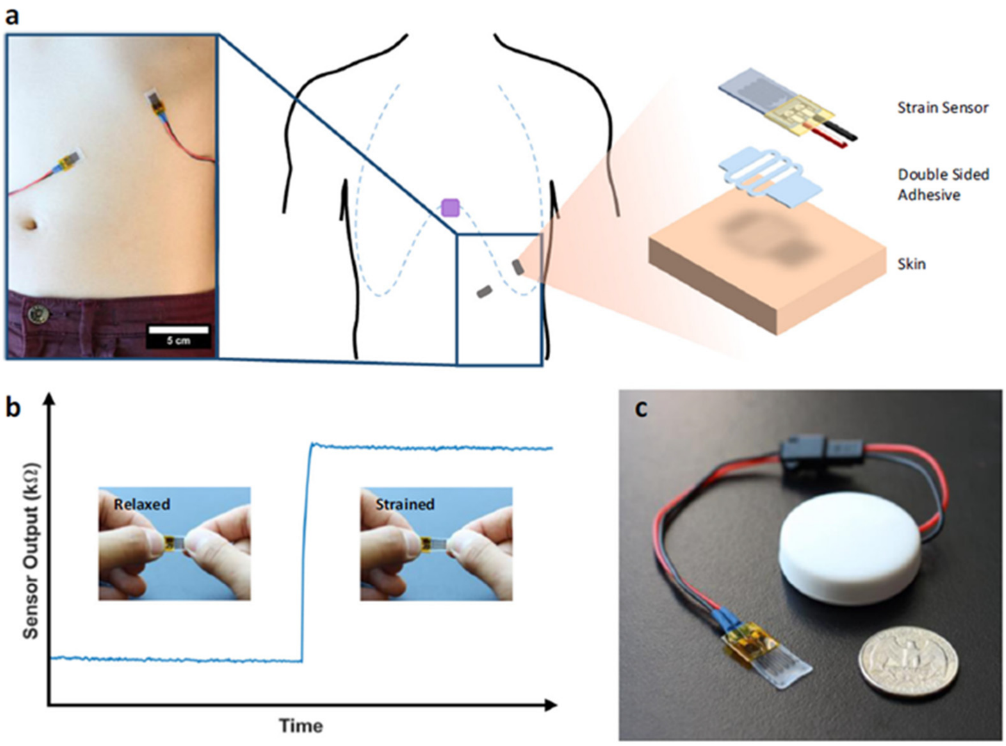



**Fig. 1** **a** The left image shows the strain sensors on the ribcage and abdomen. The middle schematics shows the placement of the accelerometer (purple square) in addition to the strain sensors (gray rectangles). The exploded schematic on the right shows the strain sensor and double-sided tape in order of attachment on the skin. All subject test was conducted using a wired data acquisition unit (Supplementary Figure 1). **b** Change in resistance of the sensor, under strain, measured using the wireless Bluetooth unit. **c** Image of the wireless Bluetooth unit with a single strain sensor attached

Advantages:

- Compact
- Bluetooth integrated

Disadvantages:

- Complex fabrication

**2. Waist-wearable wireless respiration sensor based on triboelectric effect**
([https://www.sciencedirect.com/science/article/abs/pii/S2211285519300837](https://www.sciencedirect.com/science/article/abs/pii/S2211285519300837))

Obstructive sleep apnea syndrome (OASA) is a respiratory disease caused by upper airway obstruction that is harmful to sleep quality and human health. Real-time monitoring of the respiration status may help to detect the symptoms of apnea and provide accordance to early warning, diagnosis, and proper treatment. As a solution, we here propose a waist-wearable wireless respiration monitoring device *based on triboelectric nanogenerator* (TENG) that is designed to monitor the breathing status by sensing the variation of the abdomen circumference. The breathing information is transmitted to a mobile phone via a wireless transmission chip. A theoretical electromechanical analysis is performed to predict the output performance of the TENG with two different sizes. The results agree very well with measured data, thus addressing the feasibility of the TENG sensor for monitoring respiration of different modes (thoracic and abdominal respiration) and various daily activities (lying, standing and sitting). A series of real-time tests on two volunteers with different waistlines and various breathing rhythms have been carried out. It is demonstrated that the current TENG sensor have high accuracy and sensitivity in real-time monitoring of respiratory status. The results may provide a new alternative for real-time monitoring respiration related diseases especially the obstructive sleep apnea syndrome.

A waist-wearable wireless respiration sensor based on contact mode triboelectric nanogenerator (TENG) is proposed to monitor the real-time respiratory rates by detecting the variation of use's abdominal cavity *and display the electric signals on a mobile phone via a wireless transmission system*.

*H. Zhang, et al.* *Nano Energy 59 (2019) 75–83*

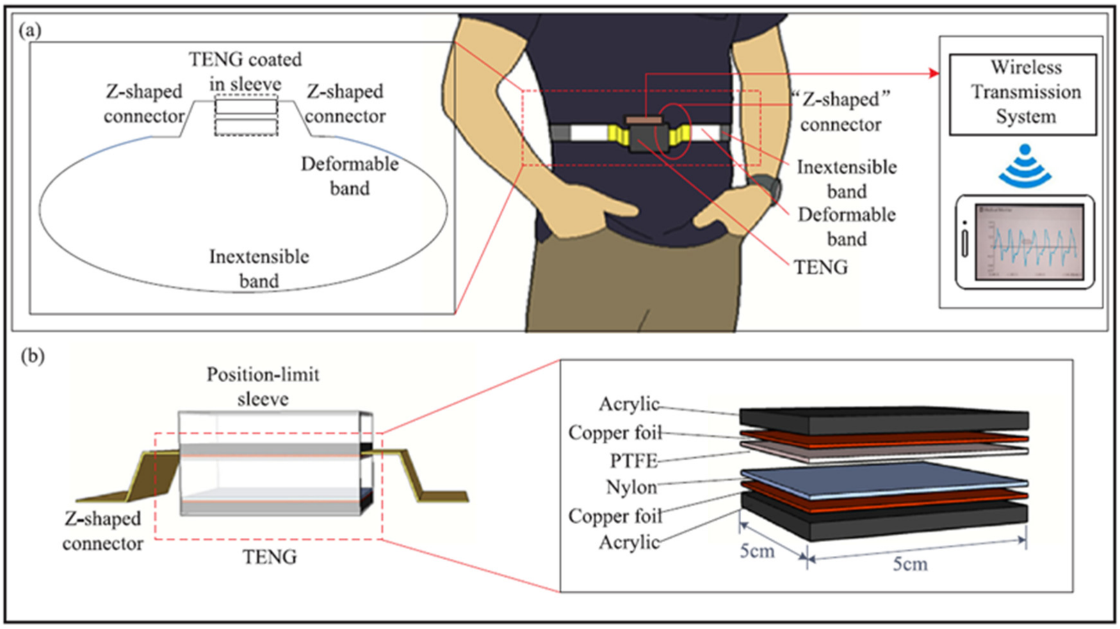



**Fig. 1.** Waist-wearable respiration sensor and wireless transmission chip. (a) Schematic design of the respiration sensor with a wireless transmission chip, (b) schematic structure of the contact mode TENG.

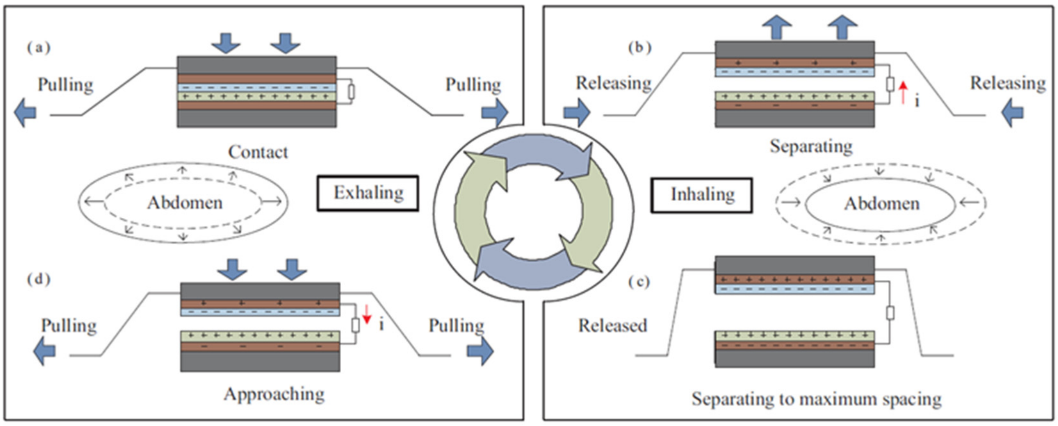



**Fig. 2.** Working mechanism diagram of the respiration sensor and its four working processes: contact, separating, separated to maximum spacing and approaching. (a) "Contact" process: user is exhaling and the dielectric materials are in full contact. (b) "Separating" process: user is inhaling and the dielectric materials are separating. (c) "Separated to maximum spacing" process: user is inhaling and the dielectric materials separated to the maximum extent. (d) "Approaching" process: user is exhaling and the dielectric materials are approaching.

Advantages:

- Self-powered
- Relatively simple to make

Disadvantages:

- Bulky and probably not very comfortable

## II Commercial systems

### 3. RESPA: World's 1st breathing sensor for fitness

(https://www.zansors.com/respa)

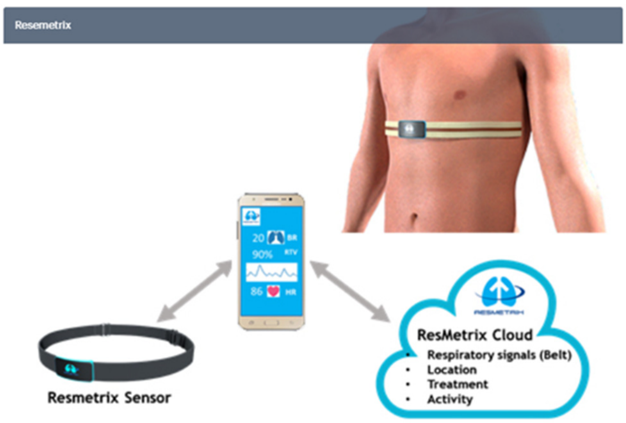
RESPA™ is an easy-to-use wearable sensor that tracks your breathing for the duration of your workout. With the RESPA™ companion app, you can train smarter and practice better as you get real-time alerts for staying in optimal breathing zones. The algorithm interprets breathing data collected by sensors to notify in real-time when you should push harder, stay in your sweet spot, or slow down for optimal performance.


Neither the app, nor the hardware solution are available (crowdfunding in place).

### 4. Resmetrix Medical – Wearable Respiratory Monitoring System

(http://www.resmetrix-medical.com/)
https://www.israel21c.org/wearable-monitor-could-prevent-rehospitalization-for-copd/
https://finder.startupnationcentral.org/company_page/resmetrix-medical)

Resmetrix Medical has developed a wearable technology designed to monitor patients with asthma and COPD in order to provide early warning of episodes. The company's solution also immediately notifies clinicians if the patient's condition worsens, enabling rapid medical intervention with the aim of preventing hospitalization. The Resmetrix wearable respiratory monitoring system consists of a sensor integrated into a comfortable chest strap or patch that continuously and accurately monitors the patient's respiratory patterns, regardless of the individual's location or activity. The device wirelessly connects to a smartphone app that displays the patient's respiratory parameters and vital signs in real time and can communicate exacerbations early, ensuring rapid attention and clinician response. The Resmetrix system utilizes an AI-powered algorithm that assesses disease progression based on the patient's breathing patterns and trends. The device is seamless to the patient, requiring no interaction or management to enable its continuous monitoring of lung performance and other related health indicators.




The sensor is not available for purchase.

**5. FLOW™ - The First Consumer Wearable To Master The Art Of Breathing**
(https://www.prnewswire.com/news-releases/flow---the-first-consumer-wearable-to-master-the-art-of-breathing-300605830.html#:~:text=FLOW%20is%20an%20affordable%20breathing,almost%20any%20sport%20or%20activity.&text=This%20knowledge%20of%20breathing%20combined,improving%20athletic%20stamina%20and%20performance.
https://www.sweetzpot.com/ )

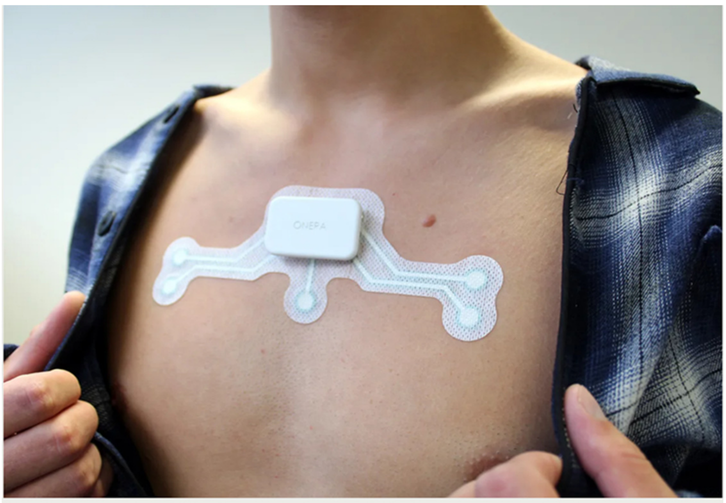
Sweetzpot, an athletic wearables company, unveiled a combined breathing sensor and heart rate monitor named FLOW, a comfortable chest band that can help improve athletic stamina and performance. Set for release in the second half of 2018 for $299 USD, FLOW will support both Garmin Connect and STRAVA. Compatible with an ecosystem of mobile devices and smartwatches, the FLOW companion app will be available on iOS and Android.

FLOW is the First Affordable Sensor Combining Breathing and Heart Rate that Helps Athletes Train in their Elusive Sweet Spot

Still not commercially available.

**6. Onera Health – Wearable Patch Uses Machine Learning to Detect Sleep Apnea**
(https://spectrum.ieee.org/prototype-wearable-monitor-sleep-apnea-news )

Getting screened for sleep apnea often means spending a night in a special clinic hooked up to sensors that measure your brain activity, eye movement, and blood oxygen levels. But for long-term, more convenient monitoring of sleep apnea, a team of researchers has developed a wearable device that tracks a user's breathing. The device, described in a study published 20 January 2020 in the IEEE Journal of Biomedical and Health Informatics, uses a unique combination of bioimpedance (a measurement of electrical signals passing through the body) and machine learning algorithms.


This prototype patch by Onera Health relies on machine learning and bioimpedence measurements to detect sleep apnea. PHOTO: ONERA HEALTH INC

Solution is in development, not available on the market.

**7. iBreve – Wearable helping you to relax, tracks stress and monitor your breathing** (https://www.innovationworldcup.com/ibreve-wearable-helping-you-to-relax-tracks-stress-monitor-your-breathing/ )

We set out to create a solution that motivates people to use their breathing to reduce stress, feel better and would also help them to measure their progress. The brand iBreve is a word play around the word "I breathe" and 'Eve' – as we focus initially on women's health & well-being. From very early on, we focused on talking to potential customers, started building a network and developed the first proof of concept prototypes. That helped to catch the interest of some university professors, who supported us to bring the project to the next level. We are a company since September 2017.


Not commercially available.

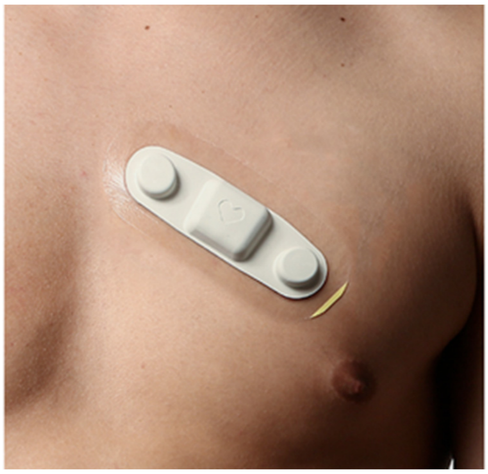
**8. respiBAN Professional** (https://plux.info/biosignalsplux-wearables/313-respiban-professional-820202407.html

High-performance wearable for real-time acquisition of respiration and motion data, consisting of an adjustable chest strap with integrated inductive respiration sensor and accelerometer for real-time acquisition of respiration and motion data even in dynamic conditions. This system comes with data-logging capabilities, allowing out-of-the-lab signal acquisitions without the need for a permanent Bluetooth connection with a computer. It allows data acquisitions with up to 16-bit resolution at up to 3000Hz sampling rate and continuous data streaming via Bluetooth for up to ~10h. Our proven Bluetooth USB dongle is included in this kit to ensure a reliable communication between the respiBAN Professional and your computer. This device includes the Respiration Analysis add-on for our OpenSignals (r)evolution software to provide useful information about the breathing dynamics such as temporal and statistical parameters associated with respiratory cycles.


This is the only commercially available solution. The above price is with software and ports for additional sensors, the below price is for the "researcher" variant that does not include software.

**9. VivaLINK's Tiny Reusable and Wearable ECG Cleared in Europe**
(https://www.medgadget.com/2019/12/vivalnks-tiny-reusable-and-wearable-ecg-cleared-in-europe.html )

VivaLNK, a Silicon Valley company, won the European CE Mark for its VivaLNK multi-vital medical wearable sensor and accompanying software development kit. The reusable device sticks to the patient's chest and can record ECG waveforms, the respiratory rate, heart rate, *RR interval,* as well as movement based on a three-axis accelerometer. It weighs only .26 ounces (7.5 grams) and can be used repeatedly. It may have significant impact for helping to diagnose difficult to detect cardiac arrhythmias such as atrial fibrillation (AFib).

The reusability of the device should help with the economics of introducing such technology into clinical practice. Most wireless, wearable monitors that have similar capabilities to the VivaLNK product are single-use devices.

Not commercially available.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP3: Methods and Software for Acquisition, Processing and Evaluation of Physiological Signals** | | | |
| T3.1 Specification, development and implementation of software modules for physiological data measurement, processing and analysis | | | |
| T3.2 Method, and software development and testing for cuffless blood pressure measurements | | | |
| T3.3 Methods and software for processing of acoustic signals | | | |
| T3.4 Fast and secured transfer of physiological data | | | |

**Deliverables**

-

**Milestone**

M3 Software modules for acquisition, local processing and possible transfer of physiological data.

IMS (T3.1):

## Estimation of the Heart Rate from the ECG and PPG Signal

The heart rate (HR) provides information about the function of the heart and is expressed as the number of heart beats in one minute. The normal value of the HR is individual and differ between subjects. However, the HR for a healthy adult range from 60 to 100 beats per minute [1]. The value of the HR depends on the physiological and psychological state of the subject. A deviation from the normal HR may indicate a deterioration in health [2]. The simplest method for determining the HR is to count the number of pulses at the wrist. A more sophisticated method uses the recording of the heart's electrical activity by electrodes placed on the skin. This recording, called an electrocardiogram (ECG), can be written on paper or displayed on the monitor. Several rules are used to estimate the HR from the ECG curve written on the paper such as the sequence method, the six-second method, the 300 method or the 1 500 method [3]. At present, devices with automatic processing of a digital signal are used in clinical practice. The ECG device continuously monitors the patient's heart's electrical activity and displays the measured ECG in real-time together with the information about basic cardiac parameters.

In addition to the ECG signal, a photoplethysmography (PPG) signal can be used to determine the HR. The PPG method measures the changes in the intensity of the light emitted by the LED diode that is passing through the tissue. During the heart contractions, blood is pumped by the heart into the blood circulation system and thus the volume of the blood in the arteries changes. The changes in the intensity of the light captured by the photodetector of the PPG device corresponds to the blood volume changes and thus the PPG signal can be used to determine the HR [4]. In the following paragraphs, the methods for the estimation of the HR from ECG and PPG signals are described.

**Methods for the Estimation of the HR from the ECG**

The methods used to estimate the HR from the digital ECG signal are based on the detection of the peaks in the ECG signal. The most distinctive peak in the ECG signal, called the R peak, can be found within the QRS complex as shown in Figure 3.1. The QRS complex represents the contraction of the heart ventricles. The HR is then estimated from the time distance between the two following R peaks [3].

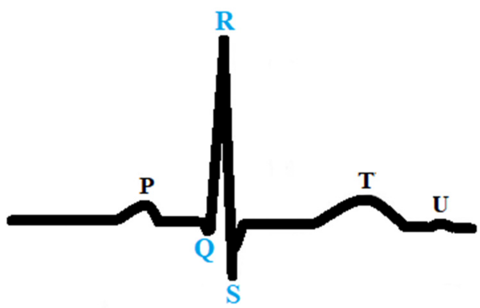



Figure 3.1. The ECG curve.

First, it is important to pre-process the measured ECG signal to eliminate any noise and suppress all necessary parts of the ECG signal, such as P or T wave to detect the QRS complex accurately. A frequently used algorithm for the QRS detection is Pan-Tompkins's algorithm proposed in 1985 for real-time QRS detection. This algorithm consists of band-pass filtering, derivative filtering, signal squaring, integration, and implementation of the decision rule [5]. Further, Hamilton-Tompkins's algorithm can be used for the QRS detection. This algorithm differs from the Pan-Tompkins algorithm in implementing the decision stage based on optimization of the decision rules [6]. Both algorithms have low computation demands and good results in the case of noisy signals and are still used in practice [7].

Another frequently used method for the QRS detection is the zero-crossing method. This method counts the number of zero crossings within the segment. First, the QRS complex is extracted from the ECG signal. The frequency content of the QRS is up to 40 Hz while the frequency content of other features of the ECG signal is lower.

Therefore, these features can be suppressed by the appropriate filtration technique with the linear phase response. Then, the high-frequency sequence is added to the signal to obtain a higher number of zero crossings outside the QRS complex and a lower number of zero crossings within the QRS complex. The beginning of the time interval for the search of the R peak is detected when the number of zero crossings falls below the adaptive threshold. The end of this time interval is detected when the number of zero crossings exceeds the adaptive threshold. Last, the R wave is localized within the time interval. The zero-crossing methods are highly reliable in cases when the ECG signal is contaminated with noise. Further, these methods have a low computational demand [8][9].

The wavelet transform is used to detect the QRS complexes thanks to its robustness for the detection from noisy signals. The waveform that is similar to the shape of the QRS complex is chosen for the ECG signal analysis. The variations of the waveform, such as changes in scale, are compared using convolution with the course of the analysed signal [10][11] [12][13].

Currently, neural networks such as multilayer perceptron (MLP)[14][15], radial basis function (RBF)[15] are used for the QRS detection. The purpose of these methods is to predict the current value of the signal based on its previous values. The neuronal networks are able to attenuate the low-frequency components of the signal and highlight the QRS complexes. The weight values and the threshold change during the learning phase so that the desired output is obtained.

Further, the HR from the ECG signal can be estimated in a frequency domain. The methods are based on the detection of the peaks in spectrum e.g., in the energy signal envelope [16]. Other methods that can be used for the QRS detection are the maximum a posteriori estimation method [17], Hilbert transform [16], and others.

**Methods for the Estimation of the HR from the PPG**

The procedure for estimating the HR from the PPG signal is similar to the procedure for estimating the HR from the ECG signal. The procedure involves the pre-processing of signals, detection of peaks, and tracking of peaks. The HR from the PPG signal is determined by the analysis of the peaks in the PPG signal that corresponds to the heart beats as shown in Figure 3.2.

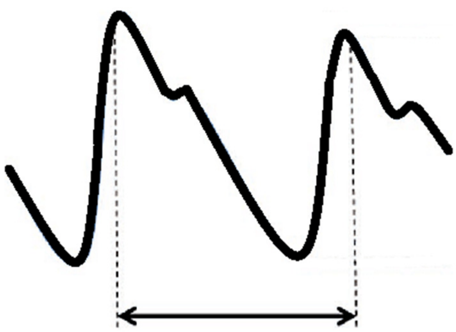



Figure 3.2. The PPG curve.

However, the PPG signal is often disturbed by the artifacts caused by the patient's movement or superimposed noise. These motion artifacts need to be removed from the PPG signal to estimate the HR accurately. Current research studies various algorithms for the removal of motion artifacts from the PPG signal. The good results in the estimation of the HR from the noisy PPG signal are achieved using the signal decomposition techniques [18], adaptive filters [19][20], Kalman filtering [21] [22], Wiener filtering [23][24], denoising using wavelets [25] and other. Further, the research explores the use of deep learning methods such as a Multi-Layer Perceptron (MLP) [26] or Deep Neural Network (DNL) composed of the Convolutional Neural Network (CNN) and the Long Short-Term Memory (LSTM) network [27], in order to remove the motion artifacts from the PPG signal and consequently estimate the HR. Further, data obtained from the accelerometer can be used in order to sufficiently remove the motion artifacts from the measured PPG signal [28][29].

When the artifacts and noise are attenuated in the PPG signal, the algorithms for the HR detection can be implemented. In this case, the methods do not need to preserve the signal shape because the goal is to detect the HR that is estimated from the peaks in the PPG signal. The HR from the PPG signal can be estimated in the time or frequency domain. In the time domain, the peaks in the PPG signal are detected and the time distance between them is calculated. To enhance the peaks, the derivation of the signal or squaring of the signal can be used. The peaks are detected when the threshold is exceeded. Further, the envelope analysis [30], Hilbert transform [31], and others can be used. In the frequency domain, the most prominent peak in a spectrum corresponds to the HR. For continuous monitoring, the Short Time Fourier Transform [32] or other methods can be used.

**Conclusion**

The HR reflects the psychological state of the measured subject. Therefore, information about the HR is needed for the monitoring of the patient's health mainly for patients with some cardiovascular diseases. The small, light, wearable devices are used for long-term monitoring. In this case, the ECG or PPG signal is acquired by the wearable device attached to the body of the measured subject. Therefore, the computational load of the selected algorithms for the processing of the measured signals and the estimation of the HR should be low because batteries often drive those devices. The low-computational demanding algorithms such as the derivation of the signal, band-pass filtering, signal integration, moving average filters or others are used. The studies show that adaptive thresholding methods have good accuracy in estimating the HR and can be implemented in wearable systems thanks to its low computational demands [33][34]. However, the comparison of the efficiency and the accuracy of the proposed methods is ambiguous because the authors use different metrics for the evaluation and the evaluation is done on different datasets. There are no straightforward results of the accuracy of the estimation of the HR from the ECG compared to the accuracy of the estimation of the HR from the PPG. Some studies show that the estimation of the HR from the ECG signal is more precise than from the PPG signal [35] and others report similar performance between the estimation from the ECG and PPG signal [36].

## Estimation of the Respiratory Rate from the ECG and PPG Signal

The respiratory rate (RR) is another vital parameter that contains information about the subject's health status. The changes in RR can point to the deterioration of health. The RR is calculated as the number of breaths taken per minute by the measured subject. The physiological values of RR of a healthy adult are between 12 to 15 breaths per minute. The simplest method for the estimation of the RR is by the visual counting of breaths [37]. As studies show, this technique can be inaccurate [38]. More advanced methods are impedance pneumography, capnography, strain gauge and others. However, those methods can be uncomfortable if the RR of the subject should be monitored for a longer time.

The ECG and PPG signal contains information about the cardiovascular system but also it contains information about the respiratory system. Thus, various algorithms for the detection of the RR from ECG or PPG signal have been proposed. However, the estimation of RR from ECG and PPG signals is not straightforward. There are three respiratory modulations shown in Figure 3.3 than can be observed in ECG or PPG signal:

- baseline wander,
- the modulation in signal amplitude,
- the frequency modulation[39] [40].

Unfortunately, those modulations are individual and do not occur to the same extent among subjects. Therefore, the combinations of these modulations should be inspected if we would like to estimate the RR from ECG or PPG signal [41].

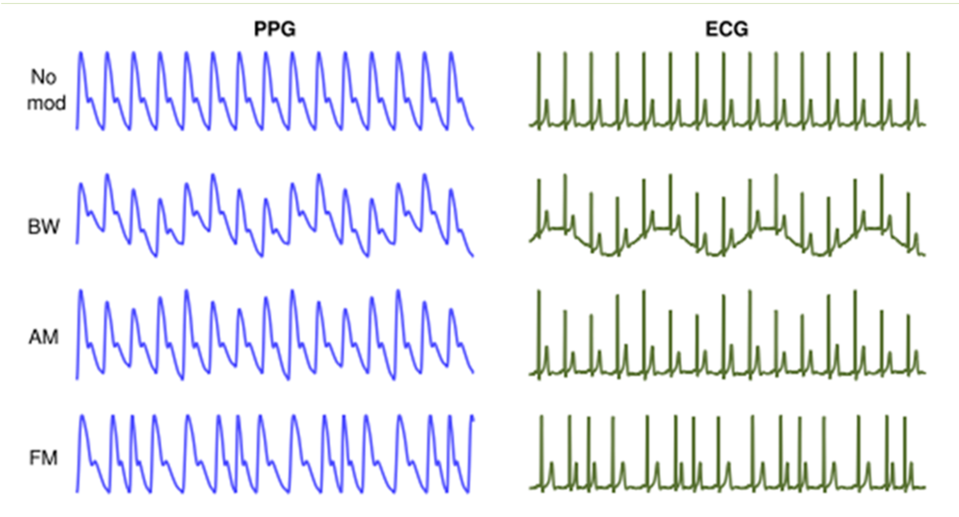



Figure 3.3. The respiratory modulations in PPG and ECG signal. From the top: signal with no modulation, signal with baseline wander, signal with amplitude modulation and signal with frequency modulation [40].

**Methods for the Estimation of the RR from the ECG and PPG**

The main information in ECG and PPG signals is the information about the cardiac source. The information about respiration is present to a lesser extent in those signals. Therefore, the respiratory signal should be extracted if we would like to estimate the RR from ECG or PPG signal. In the following paragraphs, methods for the respiratory signal extraction from the ECG and PPG signal will be described without its division because the methods described below can be used for both signals in some modifications.

The extraction of the respiratory signal is preceded by the attenuation of the low frequencies (0.03-0.05 Hz) using filtration techniques such as high pass filter, median filter and others [40]. Various methods are used to extract the respiratory signal from the ECG or PPG signal such as the filtration techniques that suppress the frequencies that do not correspond to the expected respiratory frequencies. The simplest method is band-pass filtering [42][43]. Frequently used methods for the extraction of the RR from the ECG and PPG signal are based on the Discrete Wavelet Transform (DWT) that decomposes the signal by a set of basis functions. The method uses a series of filters (high and low pass filters). Using DWT, the signal is decomposed up to the $9^{th}$ or $10^{th}$ level in order to obtain a signal that corresponds to the respiratory modulations [44]. In comparison to the DWT, the more robust method for the extraction of the RR from the ECG or PPG signal is the Empirical Mode Decomposition (EMD). Here, the basis functions are extracted from the data itself and thus can adapt over time to the oscillating patterns of the signals [30]. The Ensemble Empirical Mode Decomposition (EEMD) can be used in presence of motion artifacts and noise in the original signal such as signals obtained by the wearable sensors [45]. The difference between EMD and EEMD is that the EEMD adds to the original signal white noise. In addition, methods such as Hilbert transform [46], centered correntropy function [47], multiscale principal component analysis [48] can be used for the extraction of respiratory signal from ECG or PPG signal.

The feature-based methods can be used for the extraction of the respiratory signal. For example, the variability in the duration of the RR intervals that depends on the respiratory cycle can be observed in the ECG signal. The duration of RR intervals is shortened (HR increases) during inspiration and it lengthens (HR decreases) during the expiration. This is called respiratory sinus arrythmia (RSA). Therefore, in this method, the QRS complexes are detected, and the duration between RR intervals are investigated in order to calculate Instantaneous Heart Rate (IHR). However, the accuracy of this method depends on the age of the subject. Further, the accuracy of the method can be influenced by the medical treatment of the subject [49][50].

During the respiratory cycle, the chest of the subject is moving. Therefore, the QRS axis shift can be detected in the ECG signal. This shift is caused by the changes in cardiac vector projections on the changing position of electrodes. The algorithms for the respiratory signal extraction incorporate the detection of the QRS and then the total magnitude of the deviation in the QRS complex is analysed. The deviations that meet the criteria for the respiratory signal are used to compute the continuous respiratory signal by interpolation e.g., cubic spline interpolation. This method can also be used to extract the respiratory signal from PPG. The peaks of the pulse wave are detected either using band-pass filters or by other techniques. The method based on the QRS axis shift can be used to detect central apnea episodes thanks to the good correlation with tidal volume. On the contrary, the episodes of obstructive apnea may not be detected in the case of chest movement without airflow present [50]. To increase the accuracy of the methods for the RR detection, the fusion of extracted respiratory signals using e.g., spectral averaging can be used [51].

Once the respiratory signal is extracted and the non-respiratory signals are eliminated, the RR rate can be detected either in the time or frequency domain. In the time domain, a zero-crossing detector or peak detector can be used to detect individual breaths [52]. The RR is computed from the duration of the breath. In a frequency domain, the dominant frequency within the respiratory signal is estimated e.g., using spectral analysis [39][53]. Further, the multiple autoregressive models of different orders can be used for determining the dominant respiratory frequency [54].

**Conclusion**

The RR is a parameter that reflects the health status of the measured subject. Therefore, it is used to monitor the health of the patients in the hospital and outside the hospital. With the development of microelectronics, there is a great opportunity to monitor the RR by small and wearable devices that the subject could wear for a longer time. However, there are some difficulties. The measured signals, either ECG or PPG, are often contaminated by the motion artifacts and noise of different sources. Thus, specific attention must be put on the proper elimination of those unwanted components of the measured signal to accurately estimate the RR. In case the device measures the ECG and PPG signal, the fusion techniques can be used to increase the accuracy of the RR estimates [45]. Further, the accelerometric data, which contains information about the movement of the subject's chest, can be used together with ECG or PPG signal to estimate the RR [55][56].

Unfortunately, it is difficult to assess the accuracy of each method proposed so far for the RR estimation for further comparison of those methods. As described in the chapter above, this is mainly because the authors of the studies used different datasets and different statistics to evaluate the accuracy of the proposed method. In the comprehensive study that compared 314 algorithms for the RR estimation from the ECG or PPG curve it was shown that the RR extracted from the PPG is less accurate than the RR extracted from the ECG signal. This is mainly due to the clear morphology of the ECG signal and thanks to the more robust algorithms for the detection of the R peak that works well in the presence of the motion artifacts. Further, this study showed that the time-domain techniques give better results than the frequency domain techniques. The authors proposed using fusion techniques that fuse all respiratory modulations such as smart fusion to improve estimation accuracy [57].

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IMS (T3.1):

## Extraction of respiratory rate (RR) from ECG signal

We used Python libraries (Neurokit2, Pandas, Scipy) for implementation and testing of the following methods on datasets from FCSE:

The first method uses heart variability (HRV) of the signal. Distance between two consequent R-peaks in ECG signal changes while breathing. This phenomenon is called Respiratory Sinus Arrhythmia. Respiratory signal can be derived by cubic spline interpolation of distances of every two consequent R-peaks. After this, RR can be calculated. This method is one of the most common methods as it is described in many papers. Advantage of this method is that only R-peaks are needed. It was relatively easy to detect R-peaks in ECG signal. One of the drawbacks is that this method loses its accuracy in the cases when there is some pathologic arrhythmia or some movement of the patient present while measuring the signal

Method based on peak amplitude variation (PAV). Except for distances between R-peaks, also amplitudes of R-peaks vary during Respiration. This is caused by different pressure and angle between electrodes and chest when lungs are filled up with air. Cubic spline interpolation can be done through all these amplitudes (differences in signal between R-peaks and S-peaks). We found that the advantage of this method is relatively resistance to muscle artefacts. However, it may be less accurate in case of obstructive apnea, when the chest moves, but air is not filling the lungs.

We have also implemented a slightly different approach based on interpolation through all the R-peaks. This method uses baseline wander. Individual values of the signal regularly shift up and down while breathing. This is also because of the chest movement. Interpolation through average signal values of whole PQRST-complexes can be also a good option since it may be resistant to some artefacts in the signal.

We found that the advantage of interpolation only through the R-peaks can be the same as in the HRV method. It is relatively easy to detect R-peaks. As in the PAV method, loss of accuracy can raise in case of obstructive apnea. While processing the signals, we applied a bandpass Butterworth filter on them to reduce noise. For the Filter method, we set the lowcut of 0,1 Hz and high cut of 0,35 Hz. We used these boundaries for filtering derived respiratory signals in all the methods, too. This means that we were expecting RR values between 6 to 21 breaths per minute.

We used a set of 90 recordings of ECG and RR for testing the implementation (dataset was created by FCSE). ECG and RR were measured simultaneously by the Zephyr BioHarnes biosensor. We calculated RR from the ECG signal using above mentioned individual methods. After that, we calculated Pearson's and Spearman's correlation coefficients and root mean square error between calculated and measured values of RR. The results are shown in table 3.1.

Table 3.1. Comparison of different methods for RR extraction

| Method | Pearson's coefficient | Spearman's coefficient | RMSE |
|---|---|---|---|
| HRV | 0.368 | 0.358 | 2.899 |
| PAV | 0.550 | 0.590 | 2.333 |
| BW | 0.438 | 0.509 | 2.573 |
| BW_Mean | 0.400 | 0.438 | 2.622 |
| Filter | 0.442 | 0.479 | 2.503 |

The PAV method seems to be the best, having RMSE of 2.33. In Figure 3.4 is shown a correlation diagram between measured and calculated  RR using the PAV method:

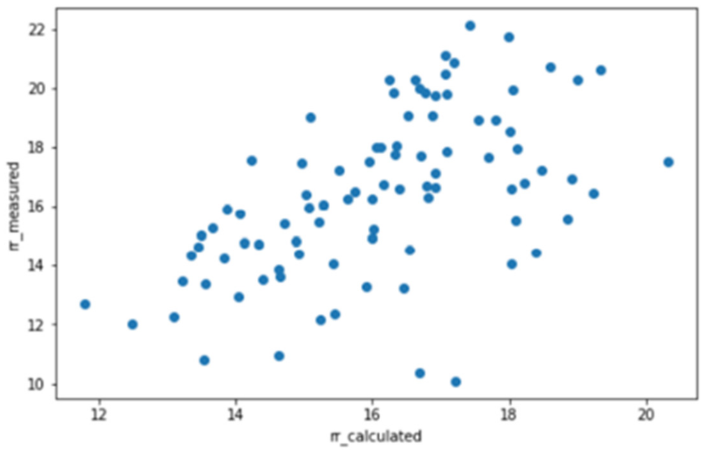


Figure 3.4. Correlation diagram between measured and calculated  RR using the PAV method

FCSE (T3.1, T3.2):

In FCSE papers related to processing the ECG and PPG for estimation of, SPO2 and BP were analysed. Papers were selected from online databases IEEE Xplore, Elsevier, PubMed, and by keywords from Google search, also by exploring github projects.

**SPO2 determination from PPG signal.**

We used two Python libraries (HeartPy and Neurokit2) for PPG signal feature extraction. First we used SpO2 classification (we have 1  if the SpO2 is between 96 and 100 and 0 if the SpO2 level is below 96).

For the signal features extraction two different signal processing Python libraries were used: HeartPy and Neurokit2. Specifically, we used the HeartPy process and Neurokit2 ppg analyze functions. A pool of features was created from the outputs of these functions when applied to the PPG signals. HeartPy process function returns 13 different features: BPM - the amount of heart beats per minute; IBI - inter-beat interval, the mean distance of intervals between heartbeats; SDNN - the standard deviation of intervals between heartbeats; SDSD - the standard deviation of successive differences between adjacent R-R intervals; RMSSD - the root mean square of successive differences between adjacent R-R intervals; pNN50/pNN20 - the proportion of differences greater than 50ms/20ms; MAD - median absolute deviation; SD1, SD2, S, SD1/SD2 - Poincare analysis and breathing rate. Neurokit2 ppg analyse function returns 78 heart rate variability (HRV) features: MadNN, MeanNN, MedianNN, MCVNN, RMSSD, SDANN, SDNN, etc., PPG Rate Mean - the mean heart rate and HRV DFA alpha1, HRV DFA alpha2 - detrended fluctuation analysis.

In order to select the features that will be used for building ML models, we investigated four different experiments:

• First experiment: considering only the HeartPy features;

• Second experiment: considering only the Neurokit2 features;

• Third experiment: considering the union of all features extracted from both HeartPy and Neurokit2 libraries;

• Fourth experiment: considering selected features from both HeartPy and Neurokit2 libraries according their correlation to the target value.

In the Second, Third and Fourth experiment, the Neurokit2 features that had a large percentage of NaN values, when extracted from PPG signals from the BIDMC database, were filtered out. For example, the features HRV SDANN5, HRV SDNNI5, HRV ULF and HRV VLF have NaN values for all input PPG signals, while the features HRV DFA alpha1 ExpRange, HRV DFA alpha1 ExpMean, HRV DFA alpha1 DimRange and HRV DFA alpha1 DimMean have NaN values for 30 out of 53 rows from the BIDMC database. There were no NaN values in the case of HeartPy. To summarize, there were 13 features in the First experiment, 70 features in the Second one and 72 in the Third one (union of the features from both libraries). The details for the Fourth experiment are provided below. After the feature merging in the Third experiment, the correlation coefficients of each feature to the target value, in our case SpO2, were calculated. Since only two features (HRV DFA alpha1, HRV DFA alpha2) had correlation with SpO2 greater than 0.2, we consider them as moderate/ high correlated features. All other features with correlation coefficient below 0.2 were considered as low correlated features. In order to fulfill the task of SpO2 prediction, the Machine Learning models were built utilizing the supervised approach, i.e. regression. Different models were built for each combination of the chosen 7 features and for each model we calculated the following statistical evaluation metrics, defined in Section III-D: Mean Squared Error (MSE), Mean absolute error (MAE), Root Mean Squared Error (RMSE) and Root Mean Squared Logarithmic Error (RMSLE).

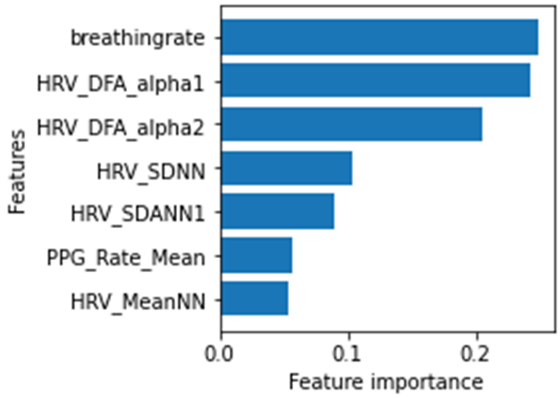


Figure 3.5. Diagram of feature importances

We performed feature importance analysis (Figure 3.5) on the model that stood out as the most successful, in order to conclude which of the features had the biggest impact on the process of model decision. This analysis helps in dimensionality reduction and proper feature selection, in order to get the results using smaller processing powers but still getting more accurate results. Using a deep learning approach on the database of extracted features from HeartPy and Neurokit. The implementations used for building deep learning models included: Keras – MLP Regressor with 100 hidden layers and 200 epochs, Tensorflow with 3 hidden layers and 100 epochs and Convolutional Neural Networks with 3 hidden layers and one hidden Convolutional 1D layer. In order to achieve more accurate scores, another approach is considered for experimenting: Extracting PPG signal samples of 125Hz from every patient and building a database of PPG signal chunks with the SpO2 value that suits the according chunk. Approach 2: extracting PPG signal of 5 chunks in order to extract features using HeartPy and Neurokit. Approach 3: Using an extended version of BIDMC database (BigData) with data collected from more patients and longer PPG signals, more appropriate for extracting PPG chunks. After preprocessing the PPG data collected, the next step involves extracting features from the PPG signal using HeartPy and Neurokit and building models based on Deep Neural Networks.

**Cuffles BP estimation from ECG and PPG signal.**

The preprocessing includes standardization of the data, filtering the signals to reduce noise and segmentation of the signals. Several different filters have been tried, such as Butterworth and Chebyshev for PPG and Butterworth and Notch for ECG. The attempts show that a Butterworth filter of order 4 for PPG, and Butterworth filter of order 5 perform the best. However, that claim needs to be verified when a new dataset will be available. Functions for extraction of blood pressure from an arterial blood pressure signal were written. The data is segmented into signals of the same length. Actively experimenting with different variants of LSTM models, through mainly focusing on the CNN-LSTM variant based on results from similar papers. CNN layer to extract necessary features and LSTM to account for the time dependency of the data. The final model selected consists of a single CNN layer, 2 bidirectional LSTM layers and 2 dense layers. There is also a batch normalization layer after the CNN one and one dropout layer after the LSTM each. The last layer has a softmax activation and contains as many neurons as there are categories, since there were some experiments with the class boundaries the number was usually between 2 and 4. A few vizualizations made with the neurokit package, a python library for processing biological signals, were added to better explain the used data type (Figure 3.6).

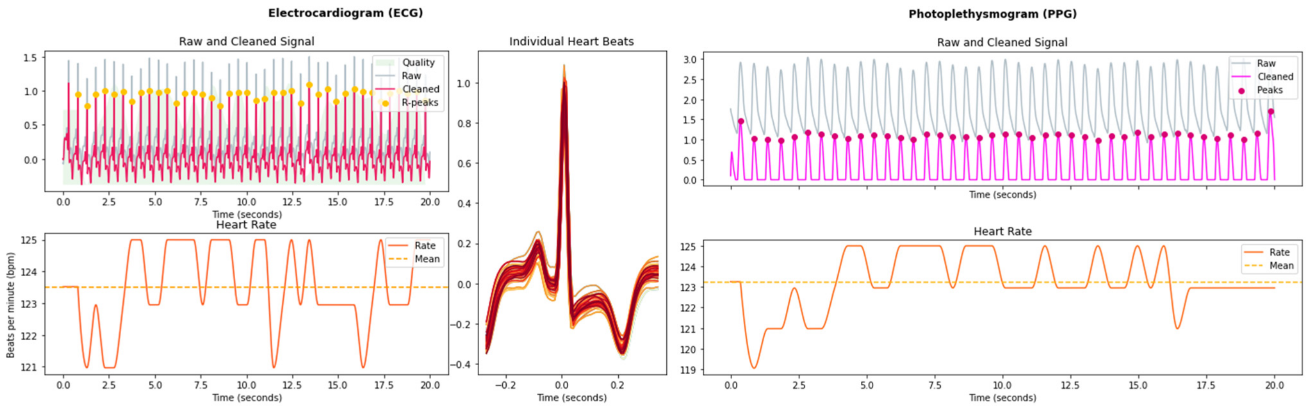


Figure 3.6. Vizualiation of the HR extraction form ECG and PPG signal

In this research, two approaches of data division into classes are undertaken - three BP classes (First Experiment) and two BP classes (Second Experiment). A CNN-LSTM architecture combines CNN layers for extraction of features from input data with LSTM for sequence prediction [25]. CNN-LSTM contains both CNN and LSTM layers. The first layer is CNN that receives the input vectors. As aforementioned, the instances are 8 seconds long, so there are 1000 data points from ECG and PPG, each. The CNN layer is used for feature selection. The next layer is a batch normalization layer, that normalizes the inputs before they are fed to the LSTM layers. It is used to allow every layer to learn independently. Next part are two bidirectional LSTM layers. After each LSTM layer, there is a dropout layer meant to prevent overfitting. These layers attempt to follow the temporal connections between the data. The last layers of the networks are dense with the last one having only:

- First experiment: 3 neurons representing the blood pressure categories (0: Normal, 1: Prehypertension, 2: Hypertension).

- Second experiment: 2 neurons representing the blood pressure categories (0: Hypotension, 1: Nothypotension).

In the First experiment, the Normal pressure is recognized very well( f1=0,76; Precision=0,81; Recall 0,71), but the recognition of the other two classes was not successful. The Second experiment gives better results (f1=0,76; Precision: 0.75 and 0.77; Recall: 0.77 and 0.74) for both of the classes.

We believe that this simplified classification for BP is more suitable for the patch device in the future development, since it can help in the recognition of the sudden BP drop as the first sign of possible internal bleeding.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP4: Predictive Tools and Alerting System** | | | |
| T4.1 Exploiting existing and building own databases of collected vital parameters | | | |
| T4.2 Big Data in support of the sensing platform | | | |
| T4.3 Training of the analysis software to understand correctly how to evaluate specific event | | | |
| T4.4 Development of mathematical models for health status changes | | | |
| T4.5 Analysis of AS-IS processes and definition of TO-BE processes of medical response to massive incidents | | | |

**Deliverables**

-

**Milestone**

M4 Software platform to analyse in real time physiological data including the cardiac and respiratory rhythm, and create mathematical models based on Big Data, AI and Deep Learning to connect them with known disorders, for assessment of person's health status change from YtoG and GtoY, and corresponding alarm generation.

FCSE (T4.1, T4.2):

Within T4.1 task existing databases were explored with the vital signals of interest, several improved Python scripts for data quality filtering were developed with ECG+PPG signals for SPO2 and BP estimation.

Physionet database Mimic3 was further checked for high quality PPG signal with developed Python scripts, and those that satisfied the criteria were downloaded in 510 distinct chunks, 441.4 GB total (opposed to 13 chunks in 7.5GB in the previous M1 report). Due to data storage optimization the database is stored using pickle format.

Within task T4.2 Independent platform for Big data management is created where the latest database is set. The platform is cloud based and ownCloud platform is used to enable various access scenarios (web and script based) of the local team as well as the other members in the project. To be able to create a storage environment for Big data management, several activities were undertaken:

- Setting and management of cloud storage server.
- Installing ownCloud server that will be used for file sharing and Big data storage.
- Setting server properties and management.
- Creating a mail that will be used by the server.
- Creating and sharing user credentials for team members.
- prepraing virtual machine setting and management and virtual resources to enable execution of long Python scripts for our team.
- Virtual machine setup and management.
- Creating and sharing public and private keys for virtual machine access for all the members of the team
- Creating a Python environment on the virtual machine.

IMS, FM (T4.5):

**Description of the AS-IS field process**

After a mass accident, an ambulance, police and fire service are sent to the scene of the accident. The police service's primary responsibility is to direct traffic and then handle riots as they arise. The commander of the whole intervention is a member of the Fire and Rescue Service and their main responsibility during the whole intervention is mainly to ensure safety. The first paramedic on the scene will become the medical department commander. Its role is to assess the overall situation, determine the number of injured, then inform the operations center, which then activates other services. This is followed by two parallel processes, one of which is to create a list of all the injured in order to prevent a situation where someone will be missing. The second is the process of assessing the health of the injured, when the commander of the emergency medical service makes a classification of the injured into 4 categories based on the START (Simply Triage And Rapid Treatment) classification algorithm. It provides the same chance of survival to each of the injured. It is important to note that children under the age of 8 are classified into categories according to the JumpSTART algorithm, which is appropriate for them due to their physiological parameters.

- Priority 1 - red label. Indicates a critical condition in which assistance must be given within a few minutes. This category includes disorders of respiration, circulation, unconsciousness or bleeding.

- Priority 2 - yellow label. Indicates an urgent condition in which help is necessary within 1-2 hours. This class includes, in particular, burns, polytraumas, abdominal or chest injuries.

- Priority 3 - green label. Indicates non-urgent injuries, where help is needed within 4-6 hours. This category includes minor injuries, minor burns, and limb fractures. Patients are characterized by the fact that they are mostly able to walk.

- Priority 4 - black label. Indicates people who are incurably injured or dead. This category includes injuries whose injuries are incompatible with life, burns over 60%, injuries of the skull, brain, polytraumas with hemorrhagic shock in the terminal phase.

**START classification algorithm**

According to the START system algorithm, it is first necessary to classify the injured according to whether they are able to walk or not. Based on this, they can identify people with priority 3 (green label). If the injured person is unable to walk, the medic observes his breathing. When the injured person is not breathing, he checks the position of the airways. Open airways mean classification of the injured into a group with priority 1 (red label). When the airway is closed, the injured person has the lowest priority, priority 4, and is marked with a black label. On the other hand, if he is able to breathe on his own, the medic determines the respiratory rate. If the value is more than 30 per minute, it is automatically classified as the highest priority injury. If it is less than 30 per minute, the medic observes perfusion (blood flow). At this point, it monitors its radial pulse or capillary filling. If a radial pulse is absent or capillary refilling is greater than 2 seconds, the injured person is marked with a red label. If a radial pulse is present or capillary refilling is less than 2 seconds, the patient's mental status is further monitored. When the injured person is unable to respond to a simple question, the medic assigns him a red label as an indication of the highest priority. When he can answer the question, he is classified in the group with priority 2 (marked with a yellow label).

**JumpSTART classification algorithm.**

According to the JumpSTART classification algorithm, which is intended for small children up to the age of 8, it is necessary in the first place to classify the injured person according to their ability or inability to walk. If the injured person is able to walk, he is assigned a green label, which indicates priority 3. If he is unable to walk, the doctor continues to observe his breathing. When the injured person is not breathing, but his airways are open, he gives him the highest possible priority. However, when the airways are closed, it checks whether the pulse is palpable or not. If the pulse is not palpable by a medic, he automatically assigns a black label to the injured person, which indicates the lowest priority. When the pulse is palpable, it performs 5 rescue breaths. He then observes whether the injured person can breathe spontaneously or not. Based on this, the healthcare professional classifies the injured person into priority 1 (if he can breathe spontaneously) or into priority 4 if apnea (respiratory arrest) has occurred. On the other hand, if the injured person is breathing, the healthcare professional determines the respiratory rate. If the value is less than 15 per minute or more than 45 per minute, the injured is classified in the group with the highest priority. If the value is between 15 and 45 per minute, it further checks the pulse. When the pulse is not palpable, the injured person also gets into the group with the red label. However, if the pulse is palpable, a neurological examination is continued, which is also the last point to be examined when sorting children. If the injured person reacts inappropriately to painful stimuli or does not respond at all, he is classified with a red label. On the other hand, if it is only on standby, it responds to verbal stimuli or responds appropriately to painful stimuli, it is marked with a yellow label and therefore belongs to priority 2.

This triage itself should not take long, no more than 1 minute per injured, and the goal is not to treat the wounded, but to administer only the necessary action (e.g. airway clearance).

Then depending on which category an injured person falls into; it is time to transport them to hospitals or transfer them to assembly points. The wounded marked with a red label are transported immediately to hospitals, the injured with yellow and green labels are placed at assembly points according to the categories where other paramedics are present. People with a black label are transferred to the assembly points of the dead. At the yellow and green assembly points, healthcare professionals perform the necessary examinations to determine the patient's health status and thus know about his deterioration or improvement.

The injuries with the red mark are the first to be transported to the hospital. After the transport of all the injured with the red label, the injuries with the yellow marking follow, and subsequently all those who have a green label, which indicates a non-urgent condition.

Based on this process analyses we think that Smart patch might be used as part of the initial triage and will stay with the victim during all time until him/her will be provided proper healthcare in a hospital. This will require process redesign as part of TO-BE process analyses and will be done in close collaboration with the experts from the Medical Faculty in the upcoming project periods.

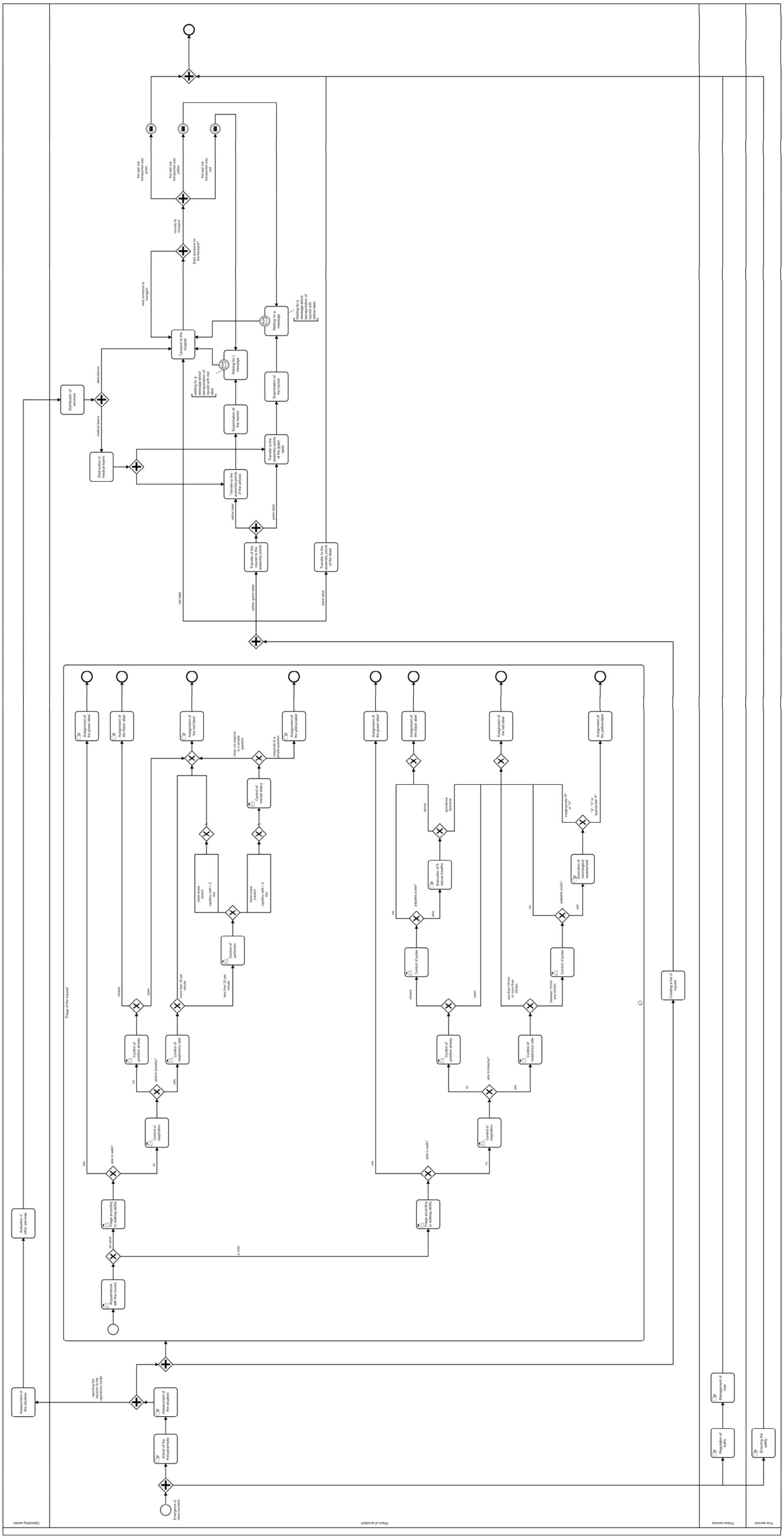

Figure 4.1. BPMN model of AS-IS rescue process

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP5: Dissemination, Communication and Exploitation** | | | |
| T5.1 Development of the Communication plan | | | |
| T5.2 Dissemination | | | |
| T5.3 Exploitation of the results | | | |

**Deliverables**

D5.1 (M12) Annual report on Communication activities including Recruitment of young researchers
D5.2 (M12) Annual report on Dissemination and Communication activities
D5.3 (M12) Annual report on Exploitation activities

**Milestone**

M5 Organization of the events foreseen for the dissemination and communication campaigns in due time

Within WP5 the established communication continued mostly through online communication within partners' institutions and among project partners as described in section "Accomplishments".

During the second 6-months period, the project web page was updated, and dissemination of the results of research supported by the project continued by conference presentations and preparation of publications as shown in the "Products & Dissemination" section. Dissemination was again influenced by the pandemic measures.

Since November 2021 one new young researcher - stipendiary was accepted in ICTM according to actual needs of the project.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP6: Management** | | | |
| T6.1 Financial and administrative management | | | |
| T6.2 Technical Management of the whole project | | | |
| T6.3 Quality Management | | | |
| | | | |

**Deliverables**

D6.1 (M12) Progress activity reports, including dissemination, communication and exploitation plans and timeline updates
D6.2 (M12) Annual progress reports incl. financial reports

**Milestone**

M6 Annual report in due time and correctly filled

Within this WP the current progress report and financial report were prepared. Detailed project managing activities and measures are shown in the WP6 part of the Accomplishments section.

## Training & Professional Development

*detail training and professional development activities since the last report*

During the evaluated period the planned training stays could not take place because of the pandemic. One meeting had to be cancelled because of the lockdown, despite the travel costs were already paid.

## Impact

*describe the impact of the project on the scientific community or the public since the last report; if nothing significant to report, write None*

- In IMS, two students were involved with their bachelor theses in the development of software for HR and RR extraction from ECG signals.
- In FCSE one diploma work is in preparation and diploma work on BP estimation was defended). Another MSc thesis on SPO2 estimation is in preparation.

## Looking forward

*detail your plans for advancing project goals in the next reporting period including upcoming milestones and deliverables*

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP1: Flexible Capacitive and Strain Sensors with Biocompatible, Wearable Interface** | | | |
| T1.1 Design and Materials choice | | | |
| T1.2 Sensing element manufacturing, assembling and functional testing | | | |
| T1.3 Biocompatible materials choice | | | |
| T1.4 Mechanical properties assessment | | | |

**Deliverables**

D1.1 (M18) Report on the development and testing of the sensing elements

D1.3 (M18) White paper on biocompatible materials and their applications in the wearable electronics domain

D1.4 (M20) Prototype of the sensing elements with body interface

**Milestone**

M1 creation of a working prototype of graphene-based sensors with biocompatible interface complying with the mechanical requirement of stretchability, light invasiveness and robustness.

Plan for the next 12 months (ICTM and ULB):

- Finalise development and testing of graphene-based sensing elements for heartbeat and respiration monitoring.
- Produce a comprehensive report on development and testing.
- Work closely with project partners to raise technology readiness level of the sensors, in particular through integration with biocompatible materials on a wearable patch, through development of accompanying wearable electronics, and through developing data processing algorithms.
- Close in on a working prototype.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP2: Smart Patch HW Definition, Integration, Testing and Evaluation** | | | |
| T2.1 Definition of the sensor modules for physiological data acquisition and analysis | | | |
| T2.2 Data processing, transmission protocols and network management | | | |
| T2.3 Assessment of power requirements for sensing, processing and transmission | | | |
| T2.4 Integrated platform assembly and testing | | | |

**Deliverables**

D2.2 (M24) Report on possible solutions for computational electronics, transmission protocols and power delivery.

**Milestone**

M2 Tested and operational wearable HW platform for physiological data acquisition and analysis

Plan for the next 12 months:

- Based on the previous reviews within T2.1, optimal set of selected sensors will be integrated with the data processing part of the patch prototype. Development of at least two variants of the patch prototype with different level of network communication and for different applications (use cases) is foreseen.
- Network communication part of the patch prototype will be developed, preferably as an optional patch module.
- Required power supply for the patch will be analyzed and appropriate power sources will be proposed.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP3: Methods and Software for Acquisition, Processing and Evaluation of Physiological Signals** | | | |
| T3.1 Specification, development and implementation of software modules for physiological data measurement, processing and analysis | | | |
| T3.2 Method, and software development and testing for cuffless blood pressure measurements | | | |
| T3.3 Methods and software for processing of acoustic signals | | | |
| T3.4 Fast and secured transfer of physiological data | | | |

**Deliverables**

D3.1 (M18) Software modules for measurement and local processing of ECG, SpO2 and breathing signals.
D3.2 (M24) Software module for cuffless blood pressure measurement based on measured ECG signal

**Milestone**

M3 Software modules for acquisition, local processing and possible transfer of physiological data.

Plan for the next 12 months (IMS and FCSE):

- In IMS and FCSE we will continue developing, testing, and implementing SW modules for extraction of physiological parameters, namely improving methods for HR and RR extraction from ECG and PPG. The software modules for measurement, processing and analysis should be implemented in the suggested hardware and software platform (selected sensor types and processing unit of the patch prototype).
- Under the FCSE leadership, development of AI methods for cuffless BP estimation based on ML will continue. So far, we have succeeded to build Neural network models for BP classification, in the following period we will investigate the DNN approach for BP regression, i. e. estimation of the real victim's BP.
- Processing of acoustic signals will be done in collaboration with all partners. Potentially, algorithms for HR and RR extraction from signals from graphene sensors will be proposed.

| SP4LIFE | Year 1 | | | | | | Year 2 | | | | | | Year 3 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **WP4: Predictive Tools and Alerting System** | | | | | | | | | | | | | | | | | | |
| T4.1 Exploiting existing and building own databases of collected vital parameters | | | | | | | | | | | | | | | | | | |
| T4.2 Big Data in support of the sensing platform | | | | | | | | | | | | | | | | | | |
| T4.3 Training of the analysis software to understand correctly how to evaluate specific event | | | | | | | | | | | | | | | | | | |
| T4.4 Development of mathematical models for health status changes | | | | | | | | | | | | | | | | | | |
| T4.5 Analysis of AS-IS processes and definition of TO-BE processes of medical response to massive incidents | | | | | | | | | | | | | | | | | | |

**Deliverables**

D4.1 (M18) Database of vital signs from ECG, SpO2, body temperature.
D4.3 (M24) Software platform to be used as analytical tool for pattern recognition in sensing data
D4.4 (M24) Software implementation of the mathematical models for detection of changes in victims health status

**Milestone**

M4 Software platform to analyse in real time physiological data including the cardiac and respiratory rhythm, and create mathematical models based on Big Data, AI and Deep Learning to connect them with known disorders, for assessment of person's health status change from YtoG and GtoY, and corresponding alarm generation.

Plan for the next 12 months (FCSE and IMS):

- Continuation of building own databases and filtering and gathering high quality data mainly from Physionet database. We need further research of using this Big data for developing more successful models for SPO2 and BP estimation, based on PPG and ECG signals, adopted for the prototype sensor.
- The Big data databases will be fully functional by the end of M3, since more SSD drives are expected to be purchased in FCSE.
- The training of the analysis software to understand correctly how to evaluate specific events is about finding the precise parameters that would define the optimum performances of the chosen models, considering their future incorporation in the patch prototype.
- Development of mathematical models for health status changes will incorporate developing an algorithm that will trigger the alarm in the patch prototype.
- Analysis of AS-IS processes and definition of TO-BE processes of medical response to massive incidents has already begun in cooperation with FM. In the following period we will start with the TO-BE part of the possibilities according to the patch prototype.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP5: Dissemination, Communication and Exploitation** | | | |
| T5.1 Development of the Communication plan | | | |
| T5.2 Dissemination | | | |
| T5.3 Exploitation of the results | | | |

**Deliverables**

D5.1 (M24) Annual report on Communication activities including Recruitment of young researchers
D5.2 (M24) Annual report on Dissemination and Communication activities
D5.3 (M24) Annual report on Exploitation activities

**Milestone**

M5 Organization of the events foreseen for the dissemination and communication campaigns in due time

Plan for the next 12 months:
If the situation will come back to normal, at least 3 in-person project meetings are foreseen:
- Project meeting in May or beginning of June (possibly in Belgrade) that should summarize results of the first year, introduce the two deliverables of the first year of the project and discuss the current status of the project.
- Project meeting in September or October (possibly in Bratislava) devoted to presentation of 4 deliverables due at that time (in M18) and update the tasks for the rest of the second year of the project,
- Project meeting in March 2023 summarizing results of the second year, presenting 5 deliverables due in M24 and updating the tasks for the next 6-months period.

Besides these meetings, workshops and training stays will be organized as needed.

Dissemination of project results is also expected in journal papers and at conferences (in the near future in the 19th International Conference for Informatics and Information Technologies – CIIT 2022 which will be held on May 5-6, 2022, in Mavrovo) from all the partners.

FCSE is planning to submit papers to the 6th International Conference on Biomedical Engineering and Bioinformatics, September 18-20, 2022, Berlin, Germany and 14th ICT Innovations conference, September 29 – October 1, 2022, Skopje, N. Macedonia.

ICTM will submit a research paper to the IEEE Access journal, on the topic of heartbeat monitoring with laser induced graphene and HeartPy.

| SP4LIFE | Year 1 | Year 2 | Year 3 |
|---|---|---|---|
| **WP6: Management** | | | |
| T6.1 Financial and administrative management | | | |
| T6.2 Technical Management of the whole project | | | |
| T6.3 Quality Management | | | |
| | | | |

**Deliverables**

D6.1 (M24) Progress activity reports, including dissemination, communication and exploitation plans and timeline updates

D6.2 (M24) Annual progress reports incl. financial reports

**Milestone**

M6 Annual report in due time and correctly filled

Plan for the next 12 months:

Within this WP the second Annual report and corresponding financial report will be prepared. There are 9 deliverables expected in month 18, 20 and 24 in WP1, WP2, WP3 and WP4:
- D1.1 (M18) Report on the development and testing of the sensing elements.
- D1.3 (M18) White paper on biocompatible materials and their applications in the wearable electronics domain.
- D1.4 (M20) Prototype of the sensing elements with body interface.
- D2.2 (M24) Report on possible solutions for computational electronics, transmission protocols and power delivery.

- D3.1 (M18) Software modules for measurement and local processing of ECG, SpO2 and breathing signals.
- D3.2 (M24) Software module for cuffless blood pressure measurement based on measured ECG signal
- D4.1 (M18) Database of vital signs from ECG, SpO2, body temperature.
- D4.3 (M24) Software platform to be used as analytical tool for pattern recognition in sensing data.
- D4.4 (M24) Software implementation of the mathematical models for detection of changes in victims' health status.

## Project Participants and Roles

*list the participants in the project and the rough fraction of their time spent on it since the last report; describe briefly how each person contributed to the project; add or subtract rows as needed*

| Name | Affiliation | Position/Title | % Time | Role |
|---|---|---|---|---|
| Milan Tyšler | Institute of Measurement Science, Slovak Academy of Sciences (IMS) | Senior Researcher | 30% | WP2: Consultations to the sensor modules for physiological data acquisition and analysis with D.Gogola.<br>WP3: Consultations with B. Ondrušová on specification and development of software modules for physiological data measurement<br>WP5: Updates of the Communication plan. Dissemination of knowledge.<br>WP6: Project management: meetings with co-directors and partners. |
| Marko Spasenović | **Institute for Chemistry, Technology and Metallurgy, Centre for Microelectronic Technologies (ICTM)** | Associate Research Professor | 20% | WP1: Graphene sensor design, manufacturing and material choice. Biocompatible material choice and mechanical property assessment. Taking and assessing measurement data.<br>WP5: Dissemination of knowledge. Exploitation of the results.<br>WP6: Management. |
| Carlo Saverio Iorio | Universitè libre de Bruxelles (ULB) | Senior Researcher | 20% | WP1: Graphene-based sensing element manufacturing, assembling and functional testing<br>WP2: Assessment of power requirements for sensing, processing and transmission. Integrated platform assembly and testing<br>WP3: Methods and software for processing of acoustic signals to extract information on heart beating and breathing.<br>WP5: Dissemination of knowledge. Exploitation of the results.<br>WP6: Management. |
| Ana Madevska Bogdanova | Faculty of Computer Sciences and Engineering, Sts Cyril and | Full Professor | 30% | WP3, WP4: Papers on SPO2 and BP estimation, Big data preparation<br>WP5: Dissemination of knowledge.<br>Organization of the WS1, 28.09.2021. |

| | | | | |
|---|---|---|---|---|
| | Methodius (FCSE) | | | Exploitation of the results.<br>WP6: Coordination of the stipend group, Financial Management |
| Oto Masár | Faculty of Medicine in Bratislava, Comenius University in Bratislava (FM) | Full Professor | 30% | WP3 and WP5: Assessment of results from RR and HR extraction from selected biosignals. Design and validation of AS-IS process models. |
| Fedor Lehocki | IMS | Senior Researcher | 30% | WP3: Analyses and implementation of methods for RR extraction from ECG. WP5: Development of formal models for AS-IS processes for emergency care. |
| Ján Zelinka | IMS | Senior Researcher | 20% | WP2, WP3: Consultations on hardware and software modules for physiological data measurement, processing, and analysis. |
| Daniel Gogola | IMS | PhD. Student (young scientist) | 100% | WP2: Review and testing of sensor modules for smart patch HW, their comparison and evaluation<br>WP5: Dissemination of knowledge |
| Beáta Ondrušová | IMS | PhD. Student (young scientist) | 100% | WP3: Review of software modules for physiological data measurement, processing and analysis.<br>WP5: Dissemination of knowledge |
| Teodora Vićentić | ICTM | PhD. Student (young scientist) | 30% | WP1: Graphene sensor design, manufacturing, and material choice. Biocompatible material choice and mechanical property assessment. Taking and assessing measurement data |
| Immacolata Grieco | ULB | PhD Student (young scientist) | 60% | WP1: Biocompatible, Wearable Interface materials choice. Mechanical properties assessment. |
| Vanja Miskovic | ULB | PhD Student (young scientist) | 15% | WP1: Biocompatible, Wearable Interface materials choice. Mechanical properties assessment. |
| Stefan Ilić | ICTM | PhD. Student (young scientist) | 20% | WP1: Creating measurement protocol. Developing first-stage electronics. Taking and assessing measurement data |
| Vladimir Trajkovik | FCSE | Senior Researcher | 10% | WS1 organization/participation |
| Nevena Ackovska | FCSE | Senior Researcher | 20% | WS1 organization/participation, preparation of a research paper |
| Magdalena Kostoska Gjorcevska | FCSE | Postdoc (young scientist) | 100% | WP4: Management of cloud storage server and maintenance, maintenance of owncloud server due to overfilling storage with data, preparation of a journal paper for BP estimation<br>WP5, participation in WS1 |
| Bojana Koteska | FCSE | Postdoc (young scientist) | 100% | WP3: Defining MU and deep learning model for predicting SpO2 from PPG, |

| | | | | |
|---|---|---|---|---|
| | | | | Python scripts, processing of Serbian data from graphene, preparation of a journal paper for SPO2 estimation from PPG signal<br>WP5: participation in WS1 |
| Hristina Mitrova, from 10.06.2021 | FCSE | BSc. (young scientist) | 50% | WP3: Using a deep learning approach on the database of extracted features from HeartPy and Neurokit. Working with created database with features extracted using HeartPy and Neurokit on the PPG data signals from the BIDMC database,<br>preparation of a conference paper |
| Ivan Kuzmanov from 10.06.2021 | FCSE | BSc. (young scientist) | 50% | WP4: Functions and modules in Python, different variants of LSTM models-the CNN-LSTM variant. CNN layer to extract necessary features and LSTM to account for the time dependency of the data, preparation of a conference paper |

## Criteria for Success

*list the Criteria for Success established in the Project Plan and your estimate as to their current state of completion*

| Criterion | Relative Weight | Complete | Comments |
|---|---|---|---|
| Creation of a working prototype of graphene-based sensors with biocompatible interface complying with the mechanical requirement of stretchability, light invasiveness and robustness. | **20 %** | **30 %** | No obstacles, progress according to project plan (timetable of WP). |
| Fully tested and operational HW platform for physiological data acquisition and analysis | **20 %** | **10 %** | No obstacles, progress according to project plan (timetable of WP). |
| Software modules for acquisition, local processing and possible transfer of physiological data | **20 %** | **15 %** | No obstacles, progress according to project plan (timetable of WP). |
| Software platform to analyse in real time physiological data including the cardiac and respiratory rhythm, and create mathematical models based on Big Data, AI and Deep Learning to connect them with known disorders, for assessment of person's health status change from YtoR and GtoY, and corresponding alarm generation | **30 %** | **30 %** | No obstacles, developed some modules for SPO2 estimation from the PPG signal, and BP estimation (classification) from ECG+PPG signals Experimentation about YtoR and GtoY is scheduled for M3 |
| Organization of the events foreseen for the dissemination and communication campaigns in due time | **10 %** | **15 %** | Due to the COVID 19 pandemic no in-person meetings were organized or had to be cancelled. Until now, also all conference presentations were also on virtual platforms. |

## Products & Dissemination

*please list all products and outcomes of the project since the last report*

### Journal articles, conference papers, book chapters, and other publications (please do not attach copies)

Two journal articles are in preparation:

- Heartbeat monitor based on laser-induced graphene and HeartPy
- SPO2 prediction with DNN approach

### Submitted conference papers:

1. H. Mitrova, B. Koteska, A.Madevska Bodganova, F. Lehocki, "Machine learning based SpO2 prediction from PPG signal's characteristics features", 17th edition of IEEE International Symposium on Medical Measurements and Applications, June 22-24, 2022 // Giardini Naxos - Taormina , Messina, Italy.
2. I. Kuzmanov, A. Madevska Bogdanova, M. Kostoska, N. Ackovska, "Cuffless Blood Pressure Classification with ECG and PPG signals using CNN-LSTM Models in urgent medicine", IEEE conference, 45-thMIPRO, 23-27 May, 2022, Opatija, Croatia.
3. K. Zdravkova, A. Madevska Bogdanova, " Smart patches in mass-casualty incidents", Ethicomp 2022, 26-28th July, 2022, Turku, Finland.

### Conference presentations and public lectures

- Poster or oral presentation for each WP leader and young scientists during the SP4LIFE Wokshop in the scope of the ICT Innovations Conference 2021, 27-29 September 2021. http://ictinnovations.org/workshops

  (Two presented papers of young scientists were prepared during the previous period and are shown in section "Journal articles, conference papers, book chapters, and other publications" of the previous Progress report..

### Inventions, Patents, & Licenses

None

### Other products such as web sites, databases, etc. released to the scientific community or the public

The project web page is published and updated at https://www.um.sav.sk/SP4LIFE.

### Project publicity (please attach copies of articles or reports about the project)

Information on the project is available also on the web pages of partners Institutions:

IMS web page:
https://www.um.sav.sk/en/research/projects/?age=live&project_type=international&program_name=7cd8e4bf&solver=all

ICTM web page:
https://ihtm.bg.ac.rs/en/novosti-eng/2066-ictm-participates-in-project-sp4life-of-the-program-%E2%80%9Cnato-science-for-peace%E2%80%9D

FCSE web page:
https://www.finki.ukim.mk/mk/content/%D0%BF%D1%80%D0%BE%D0%B5%D0%BA%D1%82-nato-mutli-year-science-pease-project-nato-sps-project-g5825-%E2%80%93-%E2%80%9Csmart-patch-life

## Schedule

*provide a revised project schedule, including an updated Gantt or other suitable chart, indicating the current position and highlighting changes to the original schedule in the Project Plan*

No changes of the working plan are expected. The plans within individual work-packages were introduced above.

Due to the COVID pandemic in-person meetings and training of young researchers had to be cancelled or postponed. If the situation permits, the first in-person meeting connected with young researcher training could be prepared in May or June 2022 (possibly in Belgrade). Another meeting is preliminary scheduled for September or October 2022 in Bratislava.

## Budget

*ensure that the budget table (Excel) is included and up to date*

Please ensure that the MYP Detailed Budget for your project is up to date and attached to this report (in the same email). In particular, ensure that information in the following tabs is correct:

- **Financial Record**: should contain one entry for each payment from SPS funds spent both by the NPD and by other co-directors. A single line stating a bulk transfer to a co-director is not sufficient.
- **Milestone X**: contains the budget spent to date based on entries in the Financial Record. Please fill in budget predictions for subsequent milestones through the end of the project.
- **Property**: ensure that the property record is up to date with all durable equipment purchased for over €2,500.

During the first 12 months only 121,997.00 € was spent from the total budget of 258,200.00 €. This was mainly because of the very limited possibilities of travelling and young researcher training during the pandemic situation. During this period also some equipment deliveries were cancelled or postponed, and some bidding procedures are still not finished. Therefore, we ask to transfer these funds to the next milestone period.

To effectively use the available NATO funds, all partners propose some budget reallocations, namely:

IMS: wants to use the funds saved on traveling (-4210 €) for equipment (+2480 €) and communication and publications (+1730 €). The use of a part of the budget in most categories is postponed to a later milestone.

ICTM: wants to use one part of the funds for equipment that was not procured (-6000 €) for stipends in the next milestone (+6000 €) so the successful stipendiaries can keep working without change and to move the unused travel budget to the next milestone.

ULB: wants to transfer the unused funds for equipment (-23020 €), training (-1500 €), travel (-1000 €), consumables (-500 €) and stipends (-3000 €) to the next milestone period.

FCSE: limited the budget for other (-1500), consumables (-500 €), publications (-2000 €) and the budget for stipends (-14200 €) so that it agrees with the limits shown in SPS MYP Handbook. These funds should be used for equipment (+10500 €), training (+4500 €), and travel (+3200 €). At the same time, purchase of SSD drives for database storages (2000 €, approved by NPD instead of a 3D printer) will be delayed as the bidding procedure is still not finished.

FM: wishes to transfer the unused funds for training (-2000 €) and travel (-1800 €) to equipment (+3800) and to spend the funds in the future milestone periods.