



## Personal Health System architecture for stress monitoring and support to clinical decisions

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### ABSTRACT

Developments in computational techniques including clinical decision support systems, information processing, wireless communication and data mining hold new premises in Personal Health Systems. Pervasive Healthcare system architecture finds today an effective application and represents in perspective a real technological breakthrough promoting a paradigm shift from diagnosis and treatment of patients based on symptoms to diagnosis and treatment based on risk assessment. Such architectures must be able to collect and manage a large quantity of data supporting the physicians in their decision process through a continuous pervasive remote monitoring model aimed to enhance the understanding of the dynamic disease evolution and personal risk. In this work an automatic simple, compact, wireless, personalized and cost efficient pervasive architecture for the evaluation of the stress state of individual subjects suitable for prolonged stress monitoring during normal activity is described. A novel integrated processing approach based on an autoregressive model, artificial neural networks and fuzzy logic modeling allows stress conditions to be automatically identified with a mobile setting analysing features of the electrocardiographic signals and human motion. The performances of the reported architecture were assessed in terms of classification of stress conditions.

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### 1. Introduction

The medical knowledge is frequently updated and re-evaluated comprising new risk factors identification, new drugs and diagnostic tests, new evidences from clinical studies [1]. The challenges faced today are to incorporate the most recent and evidence-based knowledge into Personal Health Systems [2,3] and to transform collected information into valuable knowledge and intelligence to support the decision making process [4,5]. Several expert systems tailored to specific diseases are nowadays available in clinical research [6–11], often covering the topics addressed by European priorities [12]. Technology can play a key role to gain the continuity of care and a person-centric model, focusing on a knowledge-based approach integrating past and current data of each patient together with statistical evidences. In currently applied care practices, the

emergence of clinical symptoms allows a disease to be discovered. Only then, a diagnosis is obtained and a treatment is provided. Currently, different healthcare practice models are used [12–14]. In some models, the Hospitals is the core of the care and any level of technology available at the patient site may help in providing information useful for both monitoring, early diagnosis and preventive treatments. In other models dedicated call centers or point of care act as an intermediary between hospital/health care professional and patients. Many of the solutions available today on the market follow the above-mentioned model and call center services or point of care are used by the patients just as a complement to the hospital-centered healthcare services [12–15]. In the more advanced Personal Health Systems [16–20] model focused on the empowerment, the ownership of the care service is fully taken by the individual. This model is suitable for any of the stages of an individual's care cycle, providing prevention, early diagnosis services and personalized chronic disease management. Under this model, the technological innovations can help each person to self engage and manage his/her own health status, minimizing any interaction with other health care actors. Solutions fully led by the patients are the overwhelming majority of those developed by research efforts

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covering chronic disease management, lifestyle management and independent living. Even if, in the clinical practice this model has not been yet implemented, it can be considered as a target to be reached achieving at the same time the empowerment of the users and the reduction of workload and costs, preserving the quality and safety of care.

The main reasons for the lack of effective implementations of Personal Health Systems range from legal and societal obstacles, issues related to the real application of wearable devices, inappropriate use of decision support systems and the skepticism of many healthcare professionals. Wearable devices need to be non-intrusive, easy to use, and comfortable to wear, efficient in power consumption, privacy compliant, with very low failure rates and high accuracy in triggering alarms, especially if used for diagnostic purposes [18–21]. The decision support system must infuse clinical knowledge into methodology and technology, thus enhancing the reliability of high-level processing systems customized to his/her personal needs represents the next critical step. The currently used approaches are based on values of health-related parameters, often monitored instantaneously during a check-up [21,22]. Moreover, the correlations across physiological, psycho-emotional, environmental and behavioral parameters, such as a patient's physical activities or stress levels, are difficult to explore. Refer to this, the experience sampling method approach, i.e. a naturalistic observation technique that allows capturing participants' thoughts, feelings, and behaviors at multiple times across a range of situations as they occur in the natural environment, can be adopted in research and clinic [23,24], especially for psychological stress [25].

The stress system represents an essential alarm system that is activated whenever a discrepancy occurs between the expectation of an organism and the reality it encounters. Lack of information, loss of control, unpredictability or psychosocial demands can all produce stress responses. Allostasis, i.e. the adaptive response of the organism to a stressful agent, is produced by the joint activity of the central nervous system, the hypothalamus–pituitary–adrenal axis and the immune/proinflammatory system [26]. It appears clear that stress as it relates to illness has been studied by a variety of disciplines with differing research traditions. Each medical sub-specialty emphasized the capability of stress in participating in the pathogenetic process of disease of competence. It resulted a varied plethora of detailed physiologic models in which psychological stress can intervene in regulation of different organ system activity (for example variation of blood pressure and heart rate, platelet activation, immune and inflammatory response under mental stress), but are not included in an integrative model to outline the coordinated individualized biological response of the entire body response to current challenging circumstances, which is the primary means of connecting experience with resilience or risk of the disease.

Presently, distributed wireless systems for stress monitoring consisting of biomimetic wearable suits for the unobtrusive monitoring of physiological and behavioral signals and decision support systems are continuously improving [19,27–30]. Such systems integrate sensors together with on-body signal conditioning and pre-elaboration, as well as the management of the energy consumption and wireless communication systems. Previous interesting results indicate a correlation between physiological cues and stress levels [27–31]. Some works demonstrate the feasibility of detecting stress acquiring physiological measurements, but using complex sensor architectures during the experiments and complex labeling methods often based on judgement of human coders [27,28]. Other simpler approaches indicate that HRV may represent an inexpensive methodology for the objective assessment of human reactions under stress, but the results are only preliminary and stress is detected just by means of a manual post-processing method [29,31].

In this work an automatic simple, compact and efficient pervasive architecture for the evaluation of the stress state of individual subjects in a natural environment with a minimal discomfort for the subject is reported. Differently from the state-of-the-art, our system is suitable for prolonged stress monitoring during normal activity. The innovative contribution of the paper relies on the processing approach able to automatically identify stress conditions of the patient from physiological and behavioral information. Moreover, our architecture and method is able to remotely (anytime and anywhere) acquire and analyse heterogeneous medical data originating from historic data, medical knowledge sources, collection of vital sign data by wearable sensors and handheld devices, as well as it is able to control all modules of the elaboration chain, including clinical protocol management and the sensor interfaces, and to support clinical decisions. The architecture is modular, flexible and simple, and has the potentiality to empower the user to take a more proactive role in prevention of stress, guided by data coming from sensor networks and personal health profile.

## 2. Mobile pervasive architecture for patient-centered systems

From a general point of view, a mobile pervasive architecture consists of different wireless modules cooperating in order to perform data acquisition from multiple sensors, data analysis and decision through several techniques and data redirection and feedbacks. The architecture here proposed addresses the design of a flexible instrument for data acquisition, management, elaboration and decision suitable for those systems which are equipped with distributed remote wearable devices, where a particular attention is paid to the heterogeneous medical information flow and inter-process communication (Fig. 1). Moreover, the possibility to operate in real time imposes critical efficiency requirements to each single module.

The core of the architecture is the Personal Digital Assistant (PDA), which collects data from the Personal Mobile Sensing Platform using a configurable time resolution and dedicated Bluetooth communication channels. A data pre-processing step is performed on the sensor electronic board, so that the wireless communication with the PDA is significantly reduced.

The PDA is able to integrate the time-aligned wearable sensor information and to store relevant data in its own local DataBase (DB). The PDA performs a provisional analysis of device-mediated responses (Lite Processing), being able to take into account context information (GPS, motion activity) and physiological data (e.g. hearth rate, heart rate variability, breath rate) to obtain a provisional score (Mobile Reasoning Module). The provisional score triggers a more accurate analysis in order to perform the local feedback strategy and allows the user to get as feedback the output of the analysis.

In the case of a provisional score higher than a fixed (configurable) threshold, the PDA is able to establish a connection with the remote central DB and to upload the collected data for further and more accurate analysis. The remote central DB I/O communication layer is implemented through a Web Services Description Language (WSDL) interface. The WSDL interface design pays attention to the management and the synchronization of data and processes. Pattern recognition algorithms, knowledge-based and rule-based models are defined as running processes inside the analysis module.

In the PDA a data fusion approach is implemented in order to act as a buffer for the flow of information coming in from different sensors. With this strategy sensor data fusion is gained enabling an abstraction with respect to the specific technology of the transducers. Signals coming from the sensors are gathered in parallel and encoded according to a dedicated protocol. A specific filter for each

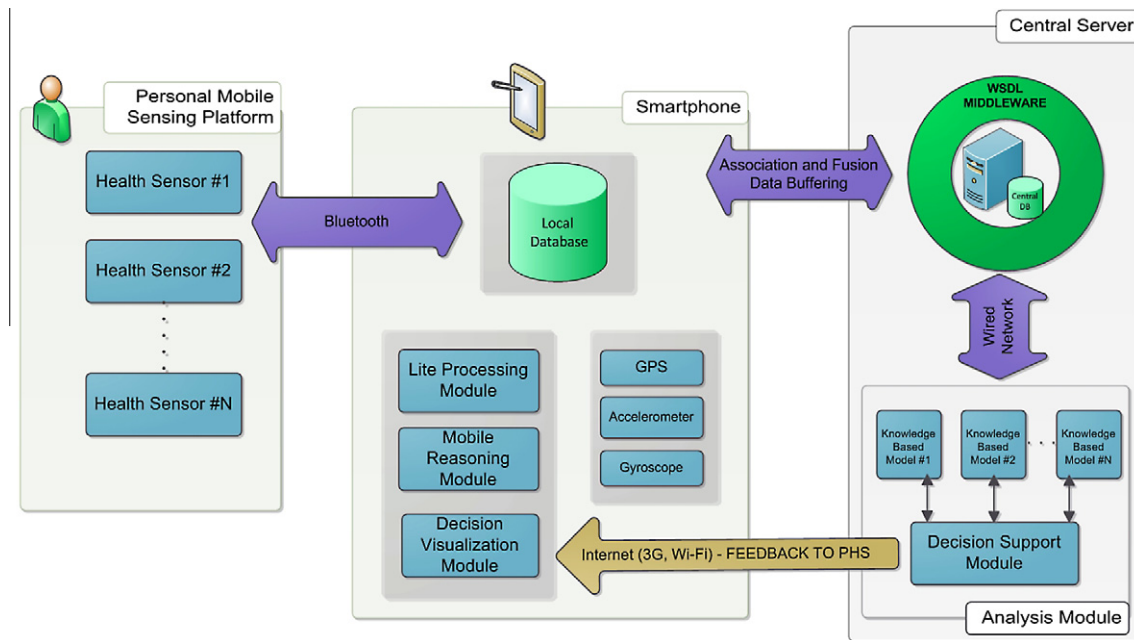


Fig. 1. The mobile pervasive architecture.

sensor receives the encoded information. The information available in the PDA data fusion module is encoded in order to set up a common communication language between the sensor interfaces and the analysis module. This guarantees an increased flexibility thanks to the presence of interfaces performing the function of interpreters for the specific hardware and filters which specify the way the communication framework senses and communicates the information.

Analysis and decision modules run asynchronously in respect of the PDA. The server analysis module is realized on modular knowledge basis enabling an objective and quantitative assessment of physiological data and the decision support provides warnings and motivating feedback. At fixed (configurable) time steps or following the request of the user, the modules will: (i) retrieve relevant data from the remote central DB; (ii) apply the analysis algorithms; (iii) store the analysis results in a specific report within the remote central DB. The PDA can be configured to poll the analysis report at fixed time steps or at the request of the user. In this way the PDA always works as client system in respect of the server analysis modules.

Portable devices compliant with the following features are adopted: (i) High level operating system (Windows Mobile, iOS, Android); (ii) Large screen for user-interface (3–9 inches); (iii) Touch screen; (iv) Internal memory + SD card (2 GBs); (v) Powerful internal CPU (400–600 MHz); (vi) WiFi/3G connection for communication with remote servers; (vii) Bluetooth/Zigbee connection for communication with wearable sensors; (viii) Long-life Battery (1 day autonomy at least); (ix) Ergonomics.

The PDA will communicate with the server in the following situations:

- Time-based connection: All data needed by the remote analysis modules should be uploaded. Data compression is essential to limit the upload time. Moreover, encryption is mandatory to grant privacy of sensible/personal data. Continuous authentication may be avoided using authorized certificates.
- Emergency connection: During sensor monitoring, if the mobile reasoning module detects an unphysiological condition the PDA sends the collected data to the central server, in order to receive clinical assessment and treatment planning.

- (Event awareness) connection on-demand: During the report polling process, the PDA uploads the amount of data requested by the remote analysis modules.

### 3. Personal Mobile Sensing Platform

The Personal Mobile Sensing Platform (PMSP) is a small-form-factor wearable device designed for bio-monitoring applications. Biosignals such as biopotentials and daily activity motion states are acquired by wireless multimodal devices attached to a patient's body and/or worn and sent to the PDA for processing and/or relaying to a remote terminal. Each sensor acquires the signal, performs low-level, real-time signal preprocessing, and wirelessly communicates with the PDA, which in turn connects to a remote server for further signal processing and storage. The use case here proposed integrates physiological and behavioral sensors in the PMSP.

The PMSP integrates one ECG acquisition board in an ergonomic unobtrusive, soft-textile chest strap with an integrated tri-axial accelerometer. The acquisition board includes a low-power Class 2 Bluetooth® Module (RN-42, Roving Network), transduction, amplification and signal pre-processing blocks. The chest strap is mainly made of flexible biocompatible elastomer, cotton and elastan; it is fully washable and guarantees an optimal and comfortable contact between the strap and the thorax adapting itself to the body shape. The three-axial accelerometer is employed to monitor the user activity and to contextualize the features extracted from the physiological sensor. The wearable chest strap integrates smart sensors together with on-body signal conditioning and pre-elaboration, as well as the management of the energy consumption and wireless communication systems. Both signals are analogue-to-digital converted with 12-bit accuracy in the  $\pm 3$  V range. For ECG and accelerometer sensors, the firmware of the microcontroller adopts a sampling rate of 100 Hz. It uses an appropriate interrupt management to avoid possible loss or overwrite of data transmission. The data are acquired in real-time and analyzed under Lite Processing on a PDA using Bluetooth connection. All the data are managed and collected with a software realized in Visual C# running in the PDA, which collects digital ECG and accelerometer signals and provides (i) data synchronization, (ii) data storage, and (iii) data communication to the WSDL

**Table 1**  
device description.

Features	Description
Wearable sensing components	ECG + Accelerometer integrated in chest strap
Sensor electronic board	SHIMMER <sup>®</sup> platform: ECG lead with four electrodes and triaxial accelerometer integrated. Processing unit is based on MSP430F1611.
Dimension	53 × 32 × 23 mm of electronic board
Power supply	3.6 V, rechargeable battery
Battery life	8 h
Communication channel	Bluetooth
Communication protocol	Serial
Internal sampling rate	100 Hz
External coding	ECG + Accelerometer signal
External output type	Byte
External output range	0–255

interface. Additional devices for recording other parameters can also be added. In Table 1 a description of the device is reported.

A set of parameters and functions are available to the PDA developers to change the relevant device options and to control the data acquisition process. The communication protocol is realized through a serial communication using the packet format reported in Fig. 2, very powerful for detecting byte or packet losses because it is check summed and sequenced.

The interactions among the different components are reported in Fig. 3. As it can be noticed, the user interaction does not require further workload than the use of the sensors in contact on the body and the calibration, whereas the system performs a multiple step interaction involving three logical entities: PMSP, bio-monitoring application installed on PDA, remote Central server connected to the analysis module. The user is asked to calibrate the sensors at the beginning of each new acquisition session.

The available functions are reported in Table 2.

#### 4. The analysis module and the clinical decision support system for stress monitoring

The analysis module is based on Knowledge-Based Models (KBM) [13–16]. The module receives the features extracted from the acquired signals as input data. Inside the analysis module, the clinical decision support system (CDSS), taking into account the response of the knowledge based models, provides a feedback to the patients in terms of four momentary stress levels (low, medium, moderate, high), in order to empower her/him to take a more proactive role in prevention of stress, and a feedback to the physician in terms of physiological and behavioral information to be used for individual treatment planning aimed to improve compliance and long-term outcome, i.e. momentary stress level, activities and autonomic nervous system information. The analysis module infers the physiological arousal within subjects' typical daily environments and activities, focusing on the analysis of the autonomic nervous system as shown in Fig. 4. In the next future any warnings and motivating feedback could be easily included in the remote central DB and integrated with medical records and clinical reports in order to support the clinician in the analysis of clinical variables and in the decision making process, as well as to prevent medical errors and improve patient safety.

The autonomic nervous system is a control system functioning largely below the level of consciousness, to predict autonomic reactivity to emotional stress. It is classically divided into two subsystems: the Parasympathetic Nervous System (PSNS) and Sympathetic Nervous System (SNS) [32]. In particular it is accepted that conditions such as mental stress and anxiety are associated with an increase in sympathetic tone (SNS) and in contrast with a decrease in vagal tone (PSNS), during resting and relaxing conditions [33,34]. The “sympathovagal balance” refers to a reciprocal functional relationship, implying that when one

of the two subsystem of the autonomic outflow is excited, the other is inhibited, according to a central push-pull pattern of organization [35].

For each individual, both sympathetic and parasympathetic tones fluctuate throughout the day. The state-of-the-art reports the following evidences [36–38]: (1) the heart period variability defined as the High Frequency (HF, range between 0.15–0.50 Hz) spectral component, is a marker of vagal modulation; (2) the heart period variability defined as the low-frequency (LF, range between 0.04–0.15 Hz) component is a marker of sympathetic modulation and (3) the reciprocal relation existing in the heart period variability spectrum between power LF band and power HF band is a marker of the state of the sympathovagal balance modulating sinus node pacemaker activity. The architecture is identified to help each person to manage stress by his/her own, minimizing any interaction with other health care actors.

#### 5. Methods

Dedicated algorithms are implemented in the PDA to filter, process and extract relevant features from the three lead ECG and three-axis accelerometer signals. The features are the input of the analysis module, which consists of two sub-systems. The former is devoted to the analysis of the ECG signals, while the latter to the analysis of the three-axis accelerometer signals. The ECG signals are filtered through a 35 Hz low-pass filter in order to remove artifacts, and processed through the automatic algorithm developed by Pan-Tompkins [39] to detect the QRS complex and to extract the Heart Rate (HR) and Heart Rate Variability (HRV), i.e. time series sequence of non-uniform R–R intervals. An auto-regressive model is dedicated to the extraction of frequency-domain features from HRV using an estimation of the <sup>1</sup> Power Spectral density (PSD) according to the Yule–Walker algorithm [40]. The model quantifies the sympathetic and Parasympathetic Nervous System activities associated with different frequency bands of the power distribution. The energy of High Frequencies (HF) and Low Frequencies (LF) components of the HRV, and the LF/HF ratio, allow cardiac vagal and sympathetic activities as markers of the autonomic interaction to be estimated. In order to reduce the variability of the LF/HF ratio during activity, the sympathetic and Parasympathetic Nervous System activities are evaluated during the resting conditions. The Signal Magnitude Area (SMA) [40] is extracted from the three-axis accelerometer in order to reveal the resting condition of the user and trigger the analysis module to process the HRV. SMA is evaluated by the following equation:

<sup>1</sup> The power spectral density (PSD) is a positive real function of a frequency variable associated which describes how the power of a signal or time series is distributed with frequency. Moreover following the Wiener–Khinchin theorem the PSD is the Fourier transform of the autocorrelation function of the signal if the signal is treated as a wide-sense stationary random process.



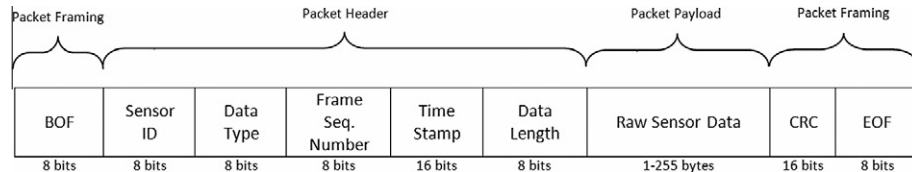


Fig. 2. Packet format.

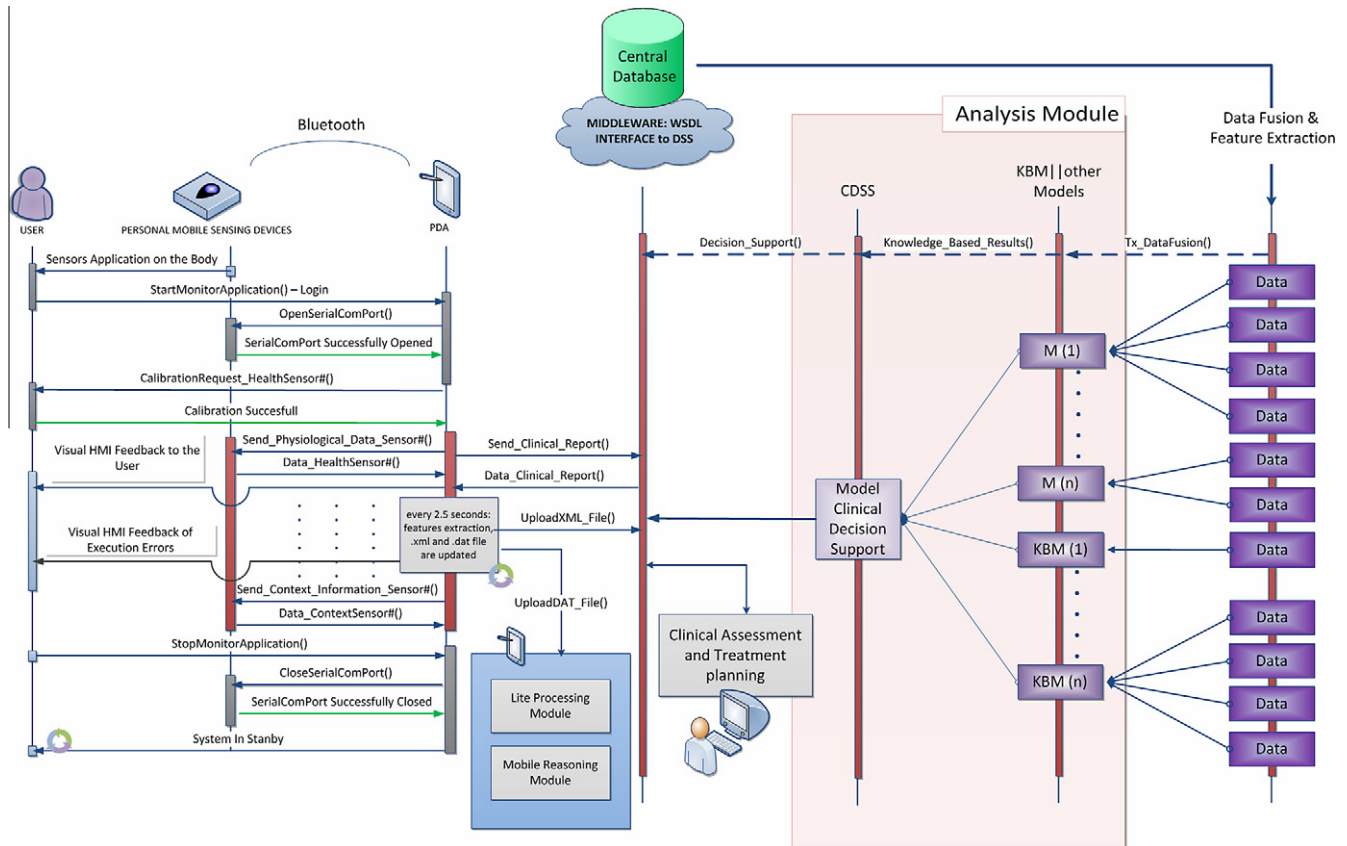


Fig. 3. Interactions among the different components of the pervasive architecture.

Table 2  
Device functions.

Function	Description	Flow
StartMonitorApplication(); OpenSerialComPort();	The PDA issues the start of sensor data acquisition and open serial communication	User ->PDA -> devices
StopMonitorApplication(); CloseSerialComPort();	The PDA issues the device to stop data acquisition and streaming.	User ->PDA -> devices
StartDataAcquisition(); Req Physiological Data Sensor#();	Data streaming will start at the specified frame time interval. The PDA ask the device (request) to send Physiological Signals from the specific sensor#	Device -> PDA PDA -> devices
Data_HealthSensor#() Req Context Information Sensor#()	The device sends to the PDA the data from the specific sensor#. The PDA ask the device (request) to send motion localization signals from the specific sensor#	Device -> PDA PDA -> devices
Data_ContextSensor#() Req_Clinical_Report() Data_Clinical_Report() Tx_DataFusion()	The device sends to the PDA the data from the specific motion localization sensor#. The PDA sends a request of clinical reports to central database The central database responses to the request of PDA Fusion of sensor data coming from PDA	Devices -> PDA PDA -> remote Central DB Remote Central DB -> PDA Remote server -> PDA -> devices
Knowledge_based_results()	Interpretation of features using knowledge based models	Remote server -> PDA -> devices
Decision_Support()	Extraction of feedback to the user	Remote server -> PDA -> devices
CalibrationRequest_HealthSensor#()	The PDA ask the device to calibrate the sensor	Remote server -> PDA -> devices

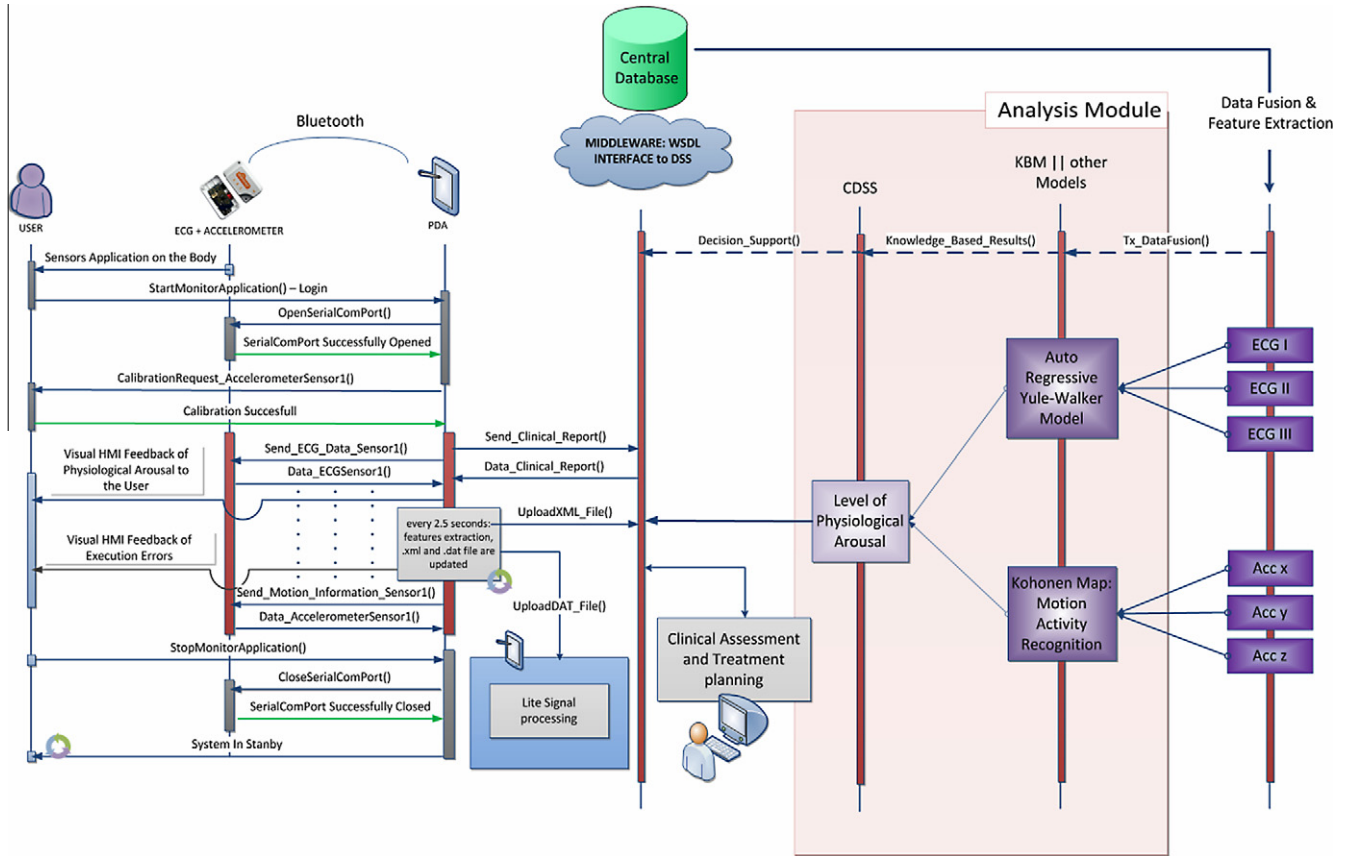


Fig. 4. Use case application.

$$SMA = \frac{1}{w} \left( \sum_{i=1}^w |x_i| + \sum_{i=1}^w |y_i| + \sum_{i=1}^w |z_i| \right) \quad (1)$$

where  $w$  is the window length, while  $x_i$ ,  $y_i$  and  $z_i$  refer to the body components of the  $x$ -,  $y$ -, and  $z$ -axis samples in a window, respectively. The resting condition is identified if SMA is below a fixed threshold. During activities, the three-axis accelerometer signals are analyzed through a KBM for the recognition of the motion activity information. KBM consists in a self-organizing Kohonen map (KSOM) [41]. The KSOM [41,42] is composed of an input layer and an output layer. Each neuron in the input layer is linked with each neuron in the output layer by weights. Let  $X$  represents the input vector,  $W$  the matrix of weights, and  $Y$  is the output neurons. During the training of the model, at time  $t$ , for each output neuron  $j$ , the activation is evaluated by the Euclidean distance, i.e.  $Y_j = \|W_j(t) - X(t)\|$ . The neuron with the minimum activation is the winning neuron. The weights  $w_{ij}$  of the winning neuron  $i$  and of its neighbourhood neurons at the time  $t$ , for the input vector  $X$ , are modified according to the following equation:  $w_{ij}(t) = w_{ij}(t-1) + \alpha(t)[X(t) - w_{ij}(t-1)]$ , where the gain coefficient  $\alpha(t)$  is in the range  $(0, 1)$ . At the end of the training process, a supervised labeling step is performed.

The CDSS is implemented by means of a fuzzy-logic rule-based algorithm. The CDSS receives as input the features extracted by the sub-systems of the analysis module and provides as output the level of stress (SL). The fuzzy-logic rule-based algorithm consists of three steps: fuzzification, inference and defuzzification. In the former, the inputs are transformed from continuous values to linguistic variables through the definition of membership functions. In the second, the linguistic variables, in function of rules in turn generate other linguistic values as output. In the latter, the

linguistic variables are converted to continuous values (real outputs of the system). The output of the CDSS could be merged with other personal and historical clinical, physiological and behavioral data in the central clinical DB guaranteeing a continuous and cyclic clinical assessment and treatment planning, while providing a feedback to the subject dedicated to enhance his/her motivation and empowerment.

## 6. Experimental results

Six healthy volunteers were enrolled age  $22 \pm 3$  (3 males and 3 females) in the study. The parameters of the CDSS, i.e. the mean HR and the LF/HF ratio after spectral analysis from HRV at rest conditions, were tailored to each subject in function of the individual psychological profile (intrinsic motivation, self determined extrinsic motivation, demotivation) assessed by expert psychologists. Yule-Walker algorithm is implemented to estimate the PSD of the RR interval by fitting an autoregressive (AR) prediction model to the windowed input data by minimizing the forward prediction error in the least squares sense. The order 5 of the model is selected using Akaike's Information Criterion [43]. PSD estimation was adopted to assess the LF/HF ratio at rest conditions. An example of 5 min ECG monitoring is reported in Fig. 5; the domination of parasympathetic activity (graphics on the left) and sympathetic activity (graphics on the right) can be observed.

As regard the activity classification, a  $10 \times 10$  neurons KSOM with the parameters  $\alpha(T) = 0.9$  and a training phase of 2000 epochs, which allow to obtain the best performance of the model, were adopted. The volunteers were asked to usually act during their daily life, while wearing the pervasive architecture. Five target classes were defined: standing, sitting, lying down, walking and running.

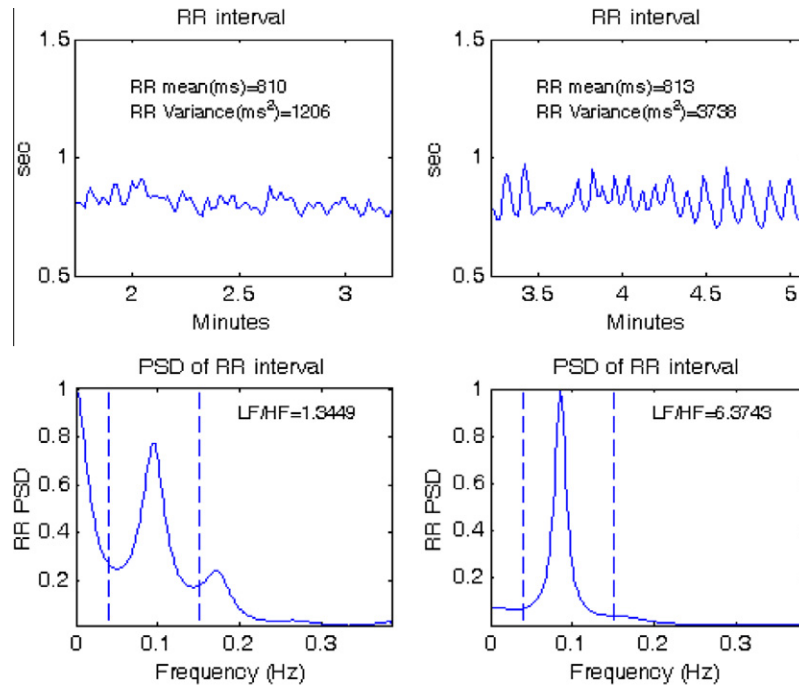


Fig. 5. RR-Time Series and PSD estimation using Yule-Walker model after five minutes of ECG monitoring at rest condition.

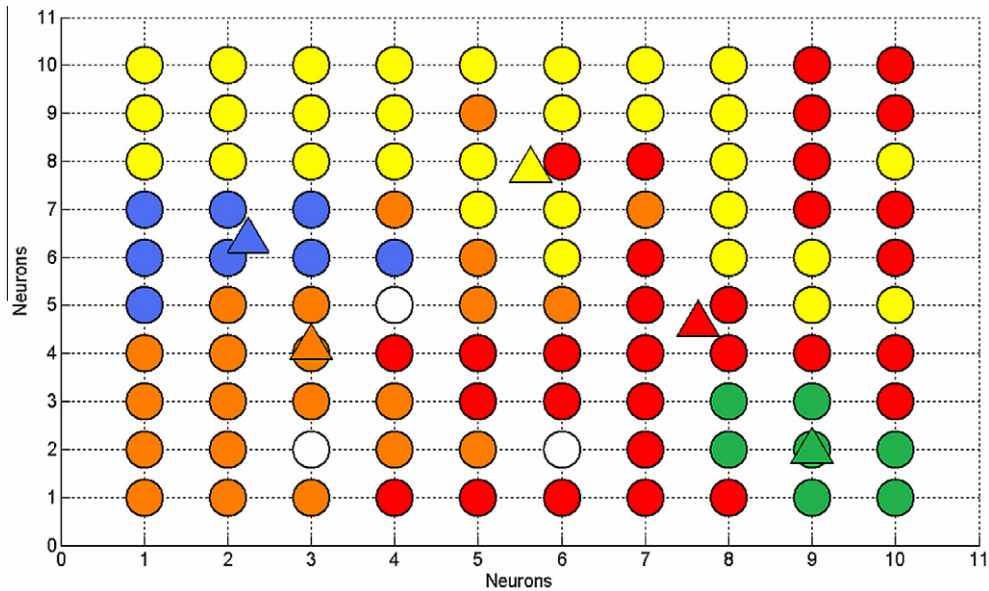


Fig. 6. Activation of the KSOM after training and labeling steps. (blue = standing; yellow = walking; red = running; orange = sitting; green = lying). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3  
Confusion matrix for all the subjects.

	Standing	Walking	Running	Sitting	Lying
Standing	<b>92.72 ± 0.19</b>	1.45 ± 0.13	1.83 ± 0.8	3.22 ± 0.19	0.78 ± 0.21
Walking	1.32 ± 0.15	<b>86.36 ± 0.08</b>	8.09 ± 0.21	1.75 ± 0.23	2.48 ± 0.26
Running	1.44 ± 0.24	5.41 ± 0.13	<b>89.55 ± 0.24</b>	2.49 ± 0.16	1.12 ± 0.11
Sitting	0.53 ± 0.18	1.59 ± 0.12	2.68 ± 0.18	<b>92.79 ± 0.25</b>	2.41 ± 0.17
Lying	1.21 ± 0.5	0.17 ± 0.13	1.22 ± 0.8	2.89 ± 0.21	<b>94.51 ± 0.14</b>

The mean, energy and variance [44] as input for the KSOM were extracted during a sliding 5 s window from each component of

the acceleration data (for a total of 9 features). The performance of the classification task is evaluated using the confusion matrix,

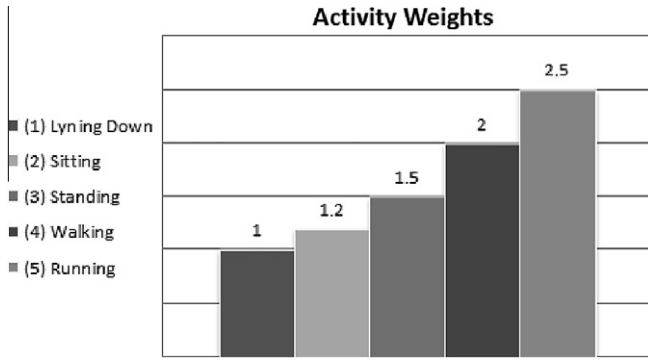


Fig. 7. Weights of each activity.

Table 4 Activity in function of the AI and the psychological profile.

Psychological profiles				
Activity index	Intrinsic motivation	Self determined extrinsic motivation	Non self determined extrinsic motivation	Amotivation
>1.8	Active	High	High	High
1.6 < AI ≤ 1.8	Moderate	Active	Active	High
1.4 < AI ≤ 1.6	Moderate	Moderate	Moderate	Active
1.2 < AI ≤ 1.4	Sedentary	Sedentary	Moderate	Moderate
1 < AI ≤ 1.2	Sedentary	Sedentary	Sedentary	Sedentary

Table 5 Input and output of the fuzzy-logic rule-based algorithm.

Description	
<i>Inputs</i>	
LF/HF ratio	Sympatovagal ratio
HR	Heart Rate
AI	Activity index
<i>Output</i>	
SL	Stress Level: LOW MEDIUM MODERATE HIGH

which the generic elements  $i, j$  indicate how many times in mean percentage  $\pm$  standard deviation a pattern belonging to the class  $i$  was classified as belonging to the class  $j$  [41]. In order to check the generalization capability of KSOM, a 10-fold cross-validation process was carried out; each fold consists of randomly selected samples, at least one for each category index was included in each fold. In Fig. 6 the visual representation of the KSOM model with clusters and centroids are reported. In Table 3 the confusion matrix is reported. It is worth mentioning the high discrimination performance of the model.

Following the activity discrimination step, the Activity Index (AI) is assessed according to the following equation in agreement with expert psychologists:

$$AI = \frac{\sum_{i=1}^5 K_i \cdot \Delta T_i}{\sum_{i=1}^5 \Delta T_i} \cdot \xi \quad (2)$$

where  $i$  is the number of each action (standing, sitting, lying down, walking and running) and  $K_i$  is the weight of each action, as

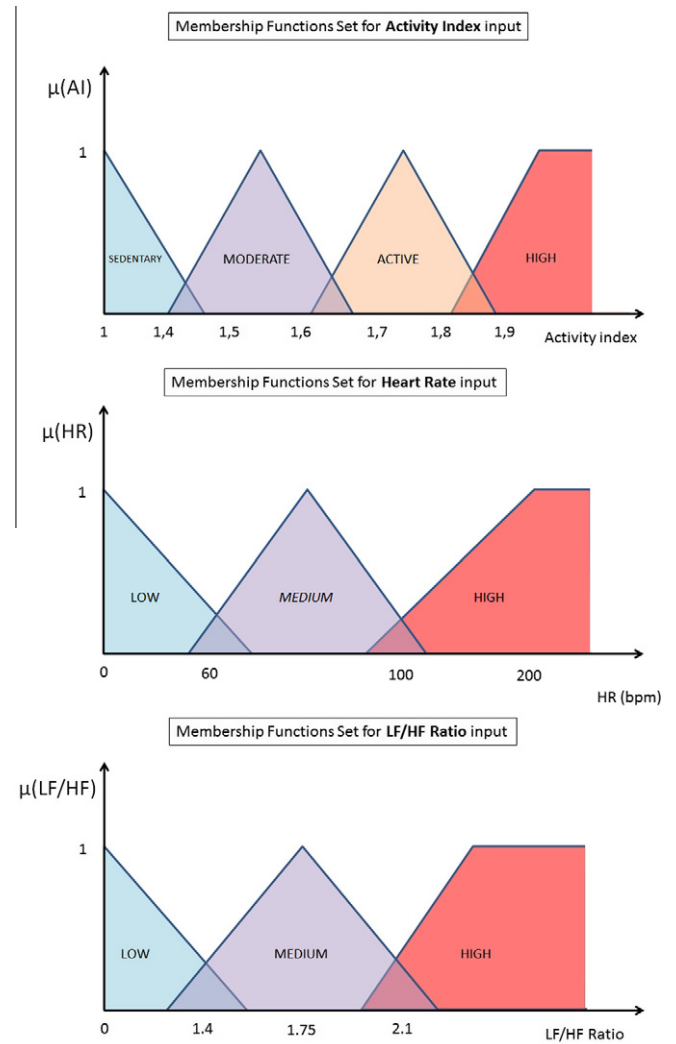


Fig. 8. Membership functions and fuzzy sets.

reported in Fig. 7, while  $\Delta T_i$  is the duration of each action and  $\xi$  is the sleep efficiency. In this study, considering healthy young volunteers  $\xi = 1$ . The activity in function of the AI and the psychological profile is reported in Table 4.

In summary, the input and the output of the fuzzy-logic rule-based algorithm are reported in Table 5.

According to expert physicians and psychologists, and in agreement with the activity in function of the AI and the psychological profile reported in Table 4, the fuzzyfication step was performed according to membership functions ( $\mu$ ) and fuzzy sets shown in Fig. 8. The membership functions of the AI shown in Fig. 8 are related to the intrinsic motivation psychological profile.

The adopted fuzzy rules of the fuzzy-logic rule-based algorithm for the inference step, in agreement with expert psychologists, are:

If (LF/HF Ratio is HIGH) And (HR is HIGH) And (AI is HIGH)	Then (SL is MEDIUM)
If (LF/HF Ratio is HIGH) And (HR is HIGH) And (AI is ACTIVE)	Then (SL is MODERATE)
If (LF/HF Ratio is HIGH) And (HR is HIGH) And (AI is MODERATE)	Then (SL is HIGH)
If (LF/HF Ratio is HIGH) And (HR is HIGH) And (AI is SEDENTARY)	Then (SL is HIGH)

(continued on next page)



If (LF/HF Ratio is MEDIUM) And (HR is HIGH) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is MEDIUM) And (HR is HIGH) And (AI is ACTIVE)	Then (SL is MEDIUM)
If (LF/HF Ratio is MEDIUM) And (HR is HIGH) And (AI is MODERATE)	Then (SL is MODERATE)
If (LF/HF Ratio is MEDIUM) And (HR is HIGH) And (AI is SEDENTARY)	Then (SL is MODERATE)
If (LF/HF Ratio is LOW) And (HR is HIGH) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is HIGH) And (AI is ACTIVE)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is HIGH) And (AI is MODERATE)	Then (SL is MEDIUM)
If (LF/HF Ratio is LOW) And (HR is HIGH) And (AI is SEDENTARY)	Then (SL is MODERATE)
If (LF/HF Ratio is HIGH) And (HR is MEDIUM) And (AI is HIGH)	Then (SL is MODERATE)
If (LF/HF Ratio is HIGH) And (HR is MEDIUM) And (AI is ACTIVE)	Then (SL is MODERATE)
If (LF/HF Ratio is HIGH) And (HR is MEDIUM) And (AI is MODERATE)	Then (SL is HIGH)
If (LF/HF Ratio is HIGH) And (HR is MEDIUM) And (AI is SEDENTARY)	Then (SL is HIGH)
If (LF/HF Ratio is MEDIUM) And (HR is MEDIUM) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is MEDIUM) And (HR is MEDIUM) And (AI is ACTIVE)	Then (SL is LOW)
If (LF/HF Ratio is MEDIUM) And (HR is MEDIUM) And (AI is MODERATE)	Then (SL is MEDIUM)
If (LF/HF Ratio is MEDIUM) And (HR is MEDIUM) And (AI is SEDENTARY)	Then (SL is MEDIUM)
If (LF/HF Ratio is LOW) And (HR is MEDIUM) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is MEDIUM) And (AI is ACTIVE)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is MEDIUM) And (AI is MODERATE)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is MEDIUM) And (AI is SEDENTARY)	Then (SL is MEDIUM)
If (LF/HF Ratio is HIGH) And (HR is LOW) And (AI is HIGH)	Then (SL is MEDIUM)
If (LF/HF Ratio is HIGH) And (HR is LOW) And (AI is ACTIVE)	Then (SL is MEDIUM)
If (LF/HF Ratio is HIGH) And (HR is LOW) And (AI is MODERATE)	Then (SL is MODERATE)
If (LF/HF Ratio is HIGH) And (HR is LOW) And (AI is SEDENTARY)	Then (SL is MODERATE)
If (LF/HF Ratio is MEDIUM) And (HR is LOW) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is MEDIUM) And (HR is LOW) And (AI is ACTIVE)	Then (SL is LOW)
If (LF/HF Ratio is MEDIUM) And (HR is LOW) And (AI is MODERATE)	Then (SL is MEDIUM)
If (LF/HF Ratio is MEDIUM) And (HR is LOW) And (AI is SEDENTARY)	Then (SL is MEDIUM)
If (LF/HF Ratio is LOW) And (HR is LOW) And (AI is HIGH)	Then (SL is LOW)
If (LF/HF Ratio is LOW) And (HR is LOW) And (AI is ACTIVE)	Then (SL is MEDIUM)
If (LF/HF Ratio is LOW) And (HR is LOW) And (AI is MODERATE)	Then (SL is MEDIUM)
If (LF/HF Ratio is LOW) And (HR is LOW) And (AI is SEDENTARY)	Then (SL is MEDIUM)

In order to obtain the stress level in the range (0–1), the defuzzification step was performed by the average (arithmetic mean), according to the weights 0.2, 0.4, 0.6, 0.8 for the LOW, MEDIUM, MODERATE, HIGH outputs respectively. Blind expert clinicians analysed the input data of the model and autonomously evaluated the stress levels. The model correctly identifies the stress levels reported by clinicians with percentages of correct classifications of 90.5%, which is a considerable accuracy even if, due to the limited number of subjects, it should be considered as a preliminary encouraging result.

## 7. Conclusions

In this work a flexible automatic mobile pervasive architecture for the evaluation of individual momentary stress levels was described. The architecture is suitable for prolonged stress monitoring during daily activities and it is able to empower the user to take a more proactive role in stress prevention. Particular attention was paid to the description of the pervasive architecture and to the processing methodology. Main features of the architecture are the wearable sensors for the transduction of heterogeneous physiological and behavioral data, the mobile devices and the decision support system for the detection of momentary stress levels. The decision process is based on autoregressive modeling, artificial neural networks and fuzzy-logic rule-based algorithms. High performances in terms of classification of stress conditions were obtained, even if with a limited number of subjects. This simple and cost-effective architecture could play a key role in fostering a care model, yet unapplied in clinical care, where each individual participates to his/her own disease management. This approach will help to promote prevention, early diagnosis and continuity of care while reducing workload and costs.

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