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INFORMATION PROCESSING OF BIOMEDICAL SENSOR SIGNATURES FOR ENSURING THE QUALITY OF LIFE

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Abstract: New intelligent and miniaturized sensors for physiological parameters, frequently increasing computer performance and an information exchange via wireless networks and Bluetooth modules are supporting remote patient monitoring concepts. Moreover, advanced signature analysis and adaptive decision algorithms make innovative diagnostic tools possible for physicians. These developments are useful for patients living at home during rehabilitation and for chronically ill or handicapped persons. The new systems are discussed on the basis of our experience in sleep laboratory remote patient monitoring. Advanced measurement concepts contribute to ensuring the quality of life.

Keywords: Medical sensor signatures, information processing, remote patient monitoring, quality of life.

1. QUALITY OF LIFE

In 1999 the XVth IMEKO World Congress was held under the headline "*Measurement to Improve the Quality of Life in the 21st Century*". With the term *Quality of Life* originally in the beginning of the previous century social-political conditions were characterized. The expression was mostly colloquially used, in order to describe feelings such as luck, satisfaction, desires, hope, in addition problems and fear. The definition is not straight forward and is shaped by individualistic aspects [1]. Beside these descriptive features *Quality of Life* is nowadays an area of interdisciplinary research and development that has over the last two decades attracted an increasing number of scientists, particularly in the areas of medicine, health, rehabilitation, social services, education and gerontology. In medicine usually the term is used as "*Health related Quality of Life*" to illustrate the influence of an acute or chronic disease on the patient's life style, the health during the rehabilitation and it also includes the evaluation of the employed therapy.

Why do we attach such significance to this term? On the one hand side humans in the high technology countries grow older and older: "generation 50 plus" they are called. On the other hand less and less children are born. Different to the situation in the United States and in France, where the courage to children still exists, in Germany there is a dramatic birth drop [2]. In 2050 more than 50 % of the people in Germany will be older than 51 (now 40) years. And in some areas more 70 years old persons are living than newborns.

So it is not surprising, that since years the health care and patient monitoring costs are exploding. This applies to highly industrialized but also for developing countries. There are expenses due to improved or new developed diagnostic systems, but there are also rising maintenance expenses for clinical instruments and facilities. Increasing bureaucratic regulations, clinician shortages and at the same time their demand for better working conditions and higher payment have to be harmonized. And last not least the increasing awareness of patients for medical questions and their increasing medical knowledge as well as a higher self responsibility have to be taken into account.

The question is discussed, whether fully digitized hospitals are more expensive than conventionally managed ones [3]. With new, innovative diagnostic systems patients could receive an up to date treatment. Numerous diseases could be recognized in a very early stage and the therapy could start faster and could be more effective. Furthermore, high-performing information technologies accelerate the course of events in the hospital from patients admission until leaving and making out the invoice. Routine tasks could be taken on by special software while physicians and personal are free for their actual tasks: the treatment of the patients.

One way to cope with this challenge is again based on the use of advanced measurement concepts. In many research centres new W-LAN based patient monitoring systems are being developed. In order to relieve physicians from routine tasks, ambulant or stationary applied methods of patient monitoring from intensive care units (ICU) or sleep laboratories form the basis for these investigations.

Fig. 1. Monitored child (2 years) in sleep laboratory

2. PATIENT MONITORING

During a physical examination a physician usually judges on the basis of the patients report on the disease (anamnesis), straightforward to perform measurements of physiological parameters like auscultation, blood pressure and temperature, in particular cases ECG and diagnostic imaging i.e. ultrasonic or X-ray tomography. The diagnosis provides, however, only a snapshot of the patient's health situation. Under severe conditions after operations the patients usually are treated in intensive care units (ICU) in the hospital. There, a comprehensive monitoring under a physicians observation exists, but due to the costs it can be maintained only for a limited time. The following rehabilitation phase requires the patients frequent visits at the doctors practice. Such visits are for the patient often arduous, time consuming and costly.

A similar effective patient monitoring exists in sleep laboratories, where patients have medical examinations because of respiration disturbances, snoring or obstructive sleep apnoeas. A comprehensive monitoring using up to 16 simultaneous measured values is routine, Fig. 1.

Health, *critical deterioration of conditions*, *remaining life time* or *ageing* are complex quantities, which cannot be measured at all or at least cannot be determined utilizing one single sensor. Multiple sensor arrangements with different physiological readings are required. Their output signatures are to be combined and related to each other in order to yield a diagnosis. This is the concern of a physician. In case of emergency the monitoring systems must identify critical health conditions and establish immediate contact between patients and physicians or nurse personal.

The question arises whether an effective home monitoring of at-risk cardiovascular, chronic or elderly patients is possible. The intention is an automatic responding to the physiological state and obvious degradations and in case of emergency the immediate raising of an alarm. In pilot projects this idea has been demonstrated to be practicable. Patients, physicians and nursing staff can profit from such systems.

Patient monitoring systems require adequate sensors for recording ECG, EEG, EMG, blood pressure, blood oxygen saturation, respiration patterns, body temperature and body sounds and noises. Optical, capacitive, inductive, electrochemical or strain gauge sensors either integrated into clothing or directly attached to the patient's body exist or are being developed to meet the special requirements of remote monitoring. Earphones and microphones can also be used for better communication.

One of the first wearable vital signs monitoring system has been developed by NASA Ames Astrobionics [4]. The system collects the following physiological data: 2 channel ECG, respiration, 3-axis body acceleration, skin or ambient temperature, heart rate, pulse oximetry SpO_2 and the diastolic and systolic blood pressure, measured with a cuff around the arm. The sensors are connected with wires to a central data logger. ECG and respiration signals are acquired using standard snap-on button electrodes. The pulse oximeter has its own signal conditioning unit providing readings at a rate of one sample per second. Systolic and diastolic blood pressures are measured with an auscultatory motion-tolerant device.

Similar Monitoring devices with the potential to be used in home health care applications have been developed by the Institute of Computer Engineering, Medical University of Lübeck [5], the Fraunhofer Institut für Integrierte Schaltungen IIS [6], the IBM Research Laboratory, Zürich [7], Welch Allyn Comp.[8] and Duke University [9]. A trend can be recognized towards easy to exchange sensors, which can be handled even by elderly persons, and towards wireless data transfer, avoiding cables around the body.

At the Institute of Electrical Measurement at the University of Paderborn we developed in cooperation with the Cardiologic Department and the Children's Sleep Laboratory of the Vestic Children's Hospital, Datteln (Prof. Dr. E. Trowitzsch) the **Pol**ysomnographic **Di**agnostic System **POLDI** [10,11,12,13,14,15,16,17], which was successfully applied to examine reasons for the sudden infant death syndrome (SIDS) and which serves as a prototype for remote monitoring.

Based on this experience in baby monitoring for SIDS prophylaxis we will discuss an alternative remote monitoring scheme for home care. Aim is a reduced number of sensors and an intelligent signal processing utilizing adaptive algorithms without loosing monitoring potential. Fig. 2 shows schematically the draft of such a system.

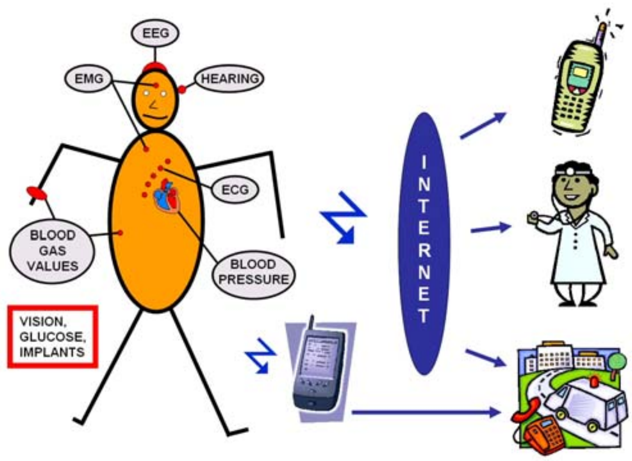


Fig. 2. Scheme of mobile Patient Monitoring System with W-Lan transmission of body sensor signatures
(EEG, EMG, ECG, blood pressure and blood gas values, wireless communication)

High-tech for elderly usually means the daily struggle with small keys, small displays and incomprehensible manuals. But there is a psychological barrier: Special solutions for "generation 50 plus" have a small acceptance, as mobile phone specially designed for older ones demonstrate. Special instruments for elderly are not acknowledged. Therefore, the answer could be sensors, easy to attach and to remove; patients, who have been instructed to do this themselves, even at home; internal wireless body-near data exchange, for example via Bluetooth modules; communication with medical experts in a hospital utilizing W-LAN solutions and Internet.

As raw data transfer between patient and hospital is not suitable an intelligent pre-processing, an artifact removal, a computation of diagnostic proposals and in emergency case an immediate notification of a doctor-on-call are necessary. An independent emergency call is also vital. False alarms must be avoided.

3. ANALYSIS OF SIGNAL SIGNATURES

For remote monitoring time dependent sensor signals are considered. Instead of processing the large bulk of data from ECG, EEG, oxygen saturation or blood pressure sensors a computation of features is necessary. A pre-processed diagnostic proposal must be derived before transmission. Signal processing, feature computation and decision algorithms for biomedical signals are required. Exceeding or falling below certain limits, i.e. for blood pressure or oxygen saturation, has to be recognized immediately. Insidious health condition deteriorations are to be recognized by intelligent pattern recognition algorithms and the information from several physiological sensor readings have to be summed up yielding a true picture of the patient's status. In the following proven algorithms applied from our sleep laboratory and sports medicine research are discussed and examples for applications are outlined.

Suitable features can be determined in the time or in the frequency domain. Classification is then the choice of one possibility out of a set of previously defined classes where the best agreement with the observed data set exists. In general, this is a similarity instead of an exact decision.

Often, a measured set of biomedical signals is disturbed by motion artifacts, cross-talk from other sources or insufficient signal-to-noise ratio. A-priory knowledge on the signal structure and the expected time history should therefore be used to reduce uncertainties and artifacts. In the following useful definitions for feature computation are reviewed. The signal examples originate from our own investigations at the University of Paderborn.

3.1 Signatures Time Domain

Time dependent signals are classified as deterministic or stochastic. Deterministic signals are periodic, non-periodic, transient or nearly periodic. Stochastic signals can be stationary or non-stationary. Generally, discrete time signals are processed where the analogue signal $s(t)$ is multiplied by the impulse function $\delta(t)$ yielding the sampled waveform

$$y(nT_A) = \sum_{n=-\infty}^{\infty} s(t) \cdot \delta(t - nT_A) \tag{1}$$

with the sampling time interval $T_A = 1/f_{sampl}$ and n the time index. The continuous time variable t is replaced by the discrete variable nT_A and for convenience the abbreviation $y(n)$ is used.

Average values like arithmetic or quadratic mean, the RMS value, the standard deviation and statistical moments help to characterize deterministic or stochastic time signals. The derived parameters asymmetric coefficient γ and kurtosis factor W

$$\gamma = \frac{M_3}{(M_2)^{3/2}} \quad \text{and} \quad W = \frac{M_4}{M_2^2} - 3 \tag{2}$$

with M_2, M_3 and M_4, the second, third and fourth central moment are characterizing the shape and the symmetry of a Gaussian distribution together with the mean value μ and the standard deviation σ.

A very effective parameter to describe short time variations of physiological signals is the so called *variability*, which is defined as

$$\text{variability} = \frac{\text{standard deviation}}{\text{mean value}} \tag{3}$$

This parameter is in biomedical signal processing used to characterize short time variations of the heart or the respiration frequency.

3.2 Signatures Frequency Domain

Spectral features are computed using the FFT algorithm for the Fourier transform DFT and the inverse transform IDFT yielding the complex spectral function $\underline{X}_d(k)$

$$\begin{aligned} \underline{X}_d(k) &= \sum_{n=0}^{N-1} x_d(n) \cdot e^{-j2\pi\frac{nk}{N}} && \text{DFT} \\ x_d(n) &= \frac{1}{N}\sum_{k=0}^{N-1} \underline{X}_d(k) \cdot e^{j2\pi\frac{nk}{N}} && \text{IDFT} \end{aligned} \tag{4}$$

The amplitude spectrum, the phase spectrum or the power spectrum

$$S_d(\omega_k) = \frac{1}{N^2} \cdot \left| X_d(k) \right|^2 \tag{5}$$

can be analyzed. The entire spectrum or single frequency lines or ranges are being used for characterization. $\underline{X}_d(k)$ or $S_d(\omega_k)$ define the spectrum of $x(t)$. Stationary signals are assumed. To analyze non-stationary signals the spectrogram, also called Short-Time Fourier Transform (STFT), can be used. It is obtained from the usual Fourier transform by multiplying the time signal with an appropriate sliding time window $w(t)$:

$$S(t,\omega) = \int_{-\infty}^{\infty} x(\tau) \cdot w(\tau - t) \cdot e^{-j\omega\tau} d\tau , \tag{6}$$

here again assuming stationary signal within the window.

For calculation of the spectrogram, the signal is subdivided into small records, which correspond to the use of a rectangular window. This is in general a poor window choice because of the potential discontinuities at the ends of the record. Calculation of the Fast Fourier Transform (FFT) causes the leakage effect. A better choice to reduce this effect is a Hanning window function, which is equal to zero at each end and whose amplitude varies smoothly. The problem is the selection of a suitable time window length for which the signal can be assumed as stationary. If the spectral content of the signal is changing rapidly then it is necessary to keep the length of the time window as short as possible.

This will reduce the frequency resolution. Therefore a compromise between the time and frequency resolution is unavoidable. The spectral resolution $\Delta\omega_k$ depends on the sampling time interval T_A and the number of data points N

$$\Delta\omega_k = \left(\omega(k+1) - \omega(k)\right) = \frac{2\pi}{N \cdot T_A} \cdot \left[(k+1) - k\right] = \frac{2\pi}{N \cdot T_A} \tag{7}$$

3.3 Autoregressive Filters

Autoregressive (AR) techniques are effective tools when short data records have to be regarded. A parametric model or a finite impulse response adaptive filter is employed assuming the signal comprises noise which has been spectrally shaped by a recursive digital filter. Three types are in use, the autoregressive (AR) model, the moving average (MA) model and the autoregressive moving average (ARMA) model. The power spectral density $S_{AR}(\omega)$ using the AR model can be estimated

$$S_{\mathrm{AR}}(\omega) = \frac{2\pi \cdot \hat{\sigma}_{\mathrm{N}} \cdot T_{\mathrm{A}}}{\left|1 + \sum_{k=1}^{K} a_k \cdot \exp\left(-j2\pi f n T_{\mathrm{A}}\right)\right|^2} \tag{8}$$

Here, a_k are the filter coefficients, K is the filter order and $\hat{\sigma}_N$ is an estimate of the noise variance.

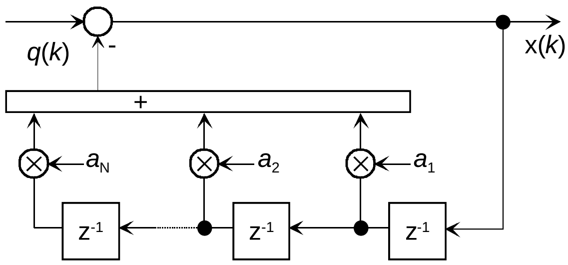


Fig. 3: Autoregressive model with white noise *q*(k) as input and *x*(k) as output signal

AR filters yield an estimate of the power spectrum with limited computational demands and can be used for online reduction of environmental noise in microphone signals.

3.4 Wavelets

The Wavelet Transform (WT) $W(t,a)$ of a time function provides information at a particular scale that is located in time domain. It is especially suited for analyzing non-stationary signals and is defined as:

$$W(t,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(\tau) \cdot g^*\left(\frac{\tau - t}{a}\right) \mathrm{d}\tau, \ (a > 0) \tag{9}$$

where $x(t)$ is the signal to be analyzed and $g(t)$ is the analyzing wavelet. The parameter a is a scaling factor that is inversely related to the frequency. The Wavelet transform can also be computed using the equation

$$W(t,a) = \sqrt{a} \int_{-\infty}^{\infty} X(\omega) \cdot G^*(a\omega) \cdot \mathrm{e}^{\mathrm{j}\omega t} \mathrm{d}\omega \tag{10}$$

where $X(\omega)$ and $G(\omega)$ are the Fourier Transforms of $x(t)$ and $g(t)$, respectively. This follows from the time convolution theorem. The function $g(t)$ should satisfy the limits

$$\int \left|g(t)\right|^2 \mathrm{d}t < \infty \quad \text{and} \quad \int \frac{\left|G(\omega)\right|^2}{|\omega|} \mathrm{d}\omega < \infty \,. \tag{11}$$

The last condition includes $G(\omega = 0) = 0$, which means $g(t)$ has no d.c. component. Often the additional assumption $G(\omega) = 0$ for $\omega < 0$ is used, which means, that the signal $g(t)$ is an analytic signal.

In contrast to the STFT, which uses a single analysis window, the WT uses short windows at high frequencies and long windows at low frequencies. The analyzing wavelet $g(t)$ has to be concentrated in time and frequency as much as possible to achieve suitable time and frequency resolutions. Several wavelets have been examined known as Haar-, Shannon-, Mexican-hat- and Morlet-wavelet, the latter being one of the most suitable ones (Gaussian function)

$$g(t) = e^{-t^2/2 + j\omega_0 t} \tag{12}$$

with $\omega_0 = 5.33$. This wavelet satisfies the mentioned conditions. Therefore the WT utilizing this wavelet can be interpreted as calculation of the envelope curve of $x(t)$ in several frequency channels. Considering the bandpass characteristics of the analyzing wavelet the magnitude of the Wavelet transform for a special scaling parameter a is the envelope curve of the bandpass filtered time signal $x(t)$. As an example the measured time function of a heart sound signal from a patient with aortic regurgitation (mitral insufficiency) is shown in Fig.4.

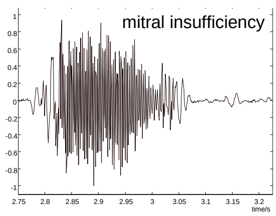


Fig. 4. Heart sound signal displaying mitral insufficiency (MI)

Fig. 5 shows the spectrogram of the MI and the corresponding Wavelet transform.

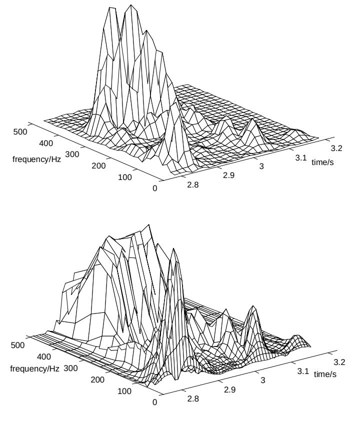


Fig. 5. Spectrogram of the MI, figure 4, above, and corresponding Wavelet Transform of the MI

Comparison of the two representations indicates the better resolution for low frequencies of the Wavelet transform than that of the short-time Fourier transform. Low frequency parts from closing valve and noise generated by blood flowing through the mitral valve during systole can easily be identified. In addition the time-frequency representation of the wavelet transform is more suitable for analyzing the time delay between the occurring sound phenomena. This applies especially for signals which are characterized by transients and fast changes in frequency. For a fast computation of the Wavelet transform only compactly defined wavelets are appropriate. The calculation using the FFT and the modulated Gaussian function as analyzing wavelet is time-consuming.

3.5 Wigner-Ville Transformation

Different from the spectrogram, the Wigner-Ville distribution (WD), which was introduced by Wigner in the area of quantum mechanics in 1932 and modified by Ville in signal analysis in 1948, is particularly suited for the analysis of non-stationary signals. The WD has achieved considerable attention and has been successfully applied in the analysis of biomedical signals. A recent survey is given in [18]. Considering a continuous-time signal $x(t)$, the WD is defined as:

$$W(t,\omega) = \int_{-\infty}^{\infty} x(t+\tau/2) \cdot x^{*}(t-\tau/2) \cdot e^{-j\omega\tau} d\tau \qquad (13)$$

The asterisk denotes complex conjugation. The WD depends on time t and circular frequency ω and presents the signal energy in both time and frequency. Assuming discrete signals $x(n) := f(n \cdot T_A)$, the discrete Wigner distribution (DWD) is then

$$W(n,\omega) = 2 \cdot \sum_{k=-\infty}^{\infty} s(n+k) \cdot s^{*}(n-k) \cdot e^{-j2k\omega T_A} \qquad (14)$$

Applying the WD optimizations are needed to reduce non-linear cross-terms and negative values. One possibility is the smoothing of the WD along the time axis, which can be carried out by employing appropriate weighted window functions. The smoothing effect is proportional to the window length and a combined time-frequency version of the original WD is called *Smoothed Pseudo-Wigner Distribution* SPWD.

Fig. 6 shows a respiration signal from a newborn measured with a thermistor sensor at the nose of the patient.

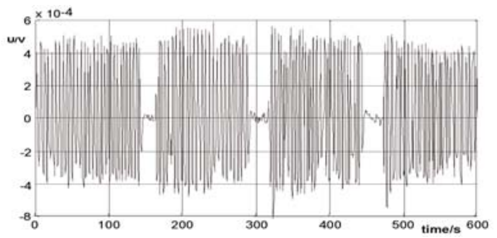


Fig. 6. Respiration signal (newborn) with three apnoeas, measured with a thermistor sensor.

Three respiration stops (apneas) can be seen in this registration. Measurements were carried out in a children sleep laboratory.

In the following Fig. 7 the SPWD is compared with the spectogram for this respiration signal. The SPWD appears more suitable than the spectrogram for describing this class of non-stationary signals. The apnoea induced respiration stops are clearly indicated in both represetations.

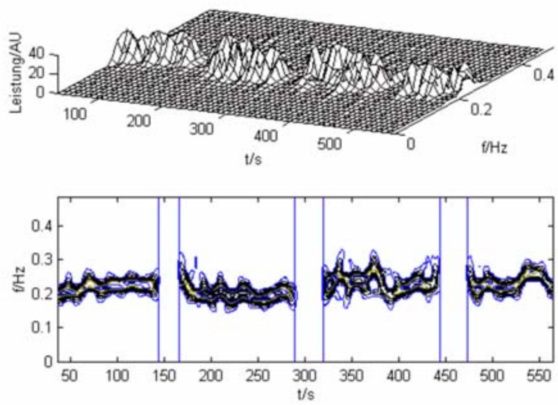


Fig. 7 Spectogram (upper) and Smoothed Pseudo Wigner Distribution SPWD (lower) computed from the respiration signal in Fig. 6.

Later we will demonstrate how a PPG-signal can be used to detect apnoeas.

3.6 Signal Artifacts

A measured set of data is from time to time corrupted by motion artifacts, noise, cross-talk, removed electrodes and disconnected or broken cables. Sudden motions of the patient lead to high signal amplitudes or overshooting causing flattened amplitudes. Hum, noise and cross-talk can usually be removed by filtering. Broken cables or disconnected electrodes lead to a signal drop-out or a constant dc signal and can easily be identified. Any a-priory knowledge on the signal structure and the expected time history should be used to reduce uncertainties and artifacts from the data.

4. ADAPTIVE FILTERING

A detailed analysis of sensor signals is only possible if the influence of disturbances can be removed. Effective concepts for noise suppression known from telecommunication and control techniques are spectral subtraction and adaptive filtering. The latter will be discussed because of its robust performance under time-variant conditions. Necessary are two sensors, for example two microphones. The first sensor measures the signal $\tilde{g}(t)$ containing the relevant information as well as a disturbing noise component $\tilde{s}_1(t)$. The second sensor measures the environment noise. After filtering and AD-conversion the summation signal is

$$d(n) = g(n) + s_1(n). \qquad (15)$$

An adaptive digital filter ATDF is used to estimate the noise component $s_1(n)$ from the second microphone output signal $s_2(n)$. The adaptive filter output $\hat{s}_1(n)$ is subtractted from $d(n)$. It is assumed that $\tilde{g}(t)$ and $\tilde{s}(t)$ are not correlated. Fig. 8 shows the principal arrangement for noise reduction during heart sound auscultation.

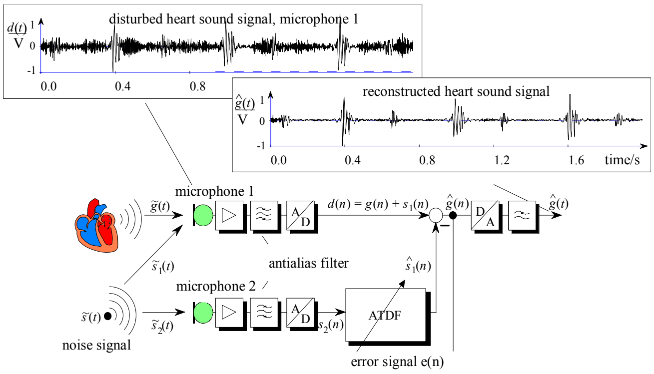


Fig. 8. Scheme of an adaptive filter for noise reduction during auscultation

Adaptation of the filter is achieved by changing the filter coefficients $a_j(n)$ of the digital transversal filter in correspondence with an error criterion. For this purpose the following signal is regarded

$$e(n) = d(n) - \hat{s}_1(n) \tag{16}$$

This scheme has been successfully applied in several biomedical and technical applications. The quadratic error or RMS signal is to be minimized

$$\varepsilon = E\left\{e^2(n)\right\} = \mathrm{E}\left\{\left(d(n) - \hat{s}_1(n)\right)^2\right\} \Rightarrow \min \tag{17}$$

With the filter output signal $\hat{s}_1(n)$ this yields

$$\hat{s}_1(n) = \sum_{k=1}^{K-1} a_k(n) \cdot s_2(n-k) = \vec{a}^{\mathrm{T}}(n) \cdot \vec{s}_2(n) \tag{18}$$

Here, $\vec{s}_2(n) = \left[s_2(n), s_2(n-1), ..., s_2(n-K-1)\right]^{\mathrm{T}}$ is the input vector with *K*, the order of the filter, $\vec{a}(n)$ is the filter coefficient vector, T denotes for transpose. The LMS algorithm allows for the change of the filter coefficients in order to reduce the noise. The result is an expected signal $e(n) = \hat{g}(n)$ where the disturbing components have been removed or at least damped. In the ideal case $\hat{s}_1(n) = s_1(n)$ the original signal is fully reconstructed.

The adaptation of the weight vector is achieved in real time, i.e. on a sample-by-sample basis using the LMS algorithm. Starting with the actual weight vector $\vec{a}(n)$, the update is computed from

$$\vec{a}(n+1) = \vec{a}(n) - \eta \cdot \vec{\nabla}(n) \tag{19}$$

where η denotes for the step size and $\vec{\nabla}(n)$ for the gradient at the corresponding iteration step

$$\vec{\nabla}(n) = \frac{\partial\left[e^2(n)\right]}{\partial \vec{a}(n)} = -2 \cdot e(n) \cdot \vec{s}_2(n-k) \tag{20}$$

In general the time constant for convergence of the filter weights a_k is inversely proportional to η.

4 AUTOMATIC DECISIONS

Decisions requiring immediate actions can be derived by pattern recognition algorithms or artificial neural networks.

4.1 Normalization

Feature normalization to a range of $0 < m_j < 1$ keeps the input feature vector of any algorithm within an appropriate range of acceptable values. The results can be compared with other applications.

$$m_{j,\mathrm{norm}} = \frac{m_{j,\mathrm{actual}} - m_{j,\min}}{m_{j,\max} - m_{j,\min}} \tag{21}$$

$m_{j,\max}$ and $m_{j,\min}$ are the maximum and minimum values of the *j*-th feature within the regarded measuring range.

Another normalization should be applied to the covariance matrix of a classifier by normalizing every element in the matrix to the diagonal elements after the following scheme.

$$\text{If } i = j \text{ then } c_{ij} = 1 \text{ else } c_{ij} = \frac{c_{ij}^2}{c_{ii} \cdot c_{jj}} \tag{22}$$

This normalization removes the contribution of the diagonal elements concerning the correlation between the elements of the matrix. The diagonal elements will then be equal to one and the other matrix elements will be in the range of $0 < r_{ij} < 1$. It may also be suitable in certain applications to normalize every matrix element to the largest element, indicating the degree of significance of the features.

4.2 Decision Algorithms

In computer based diagnostics a decision proposal supporting the physician's diagnosis is based on feature computation and decision algorithms. Diagnosis *just-by-the-look*, though still in use, is not up-to-date. An effective concept for computer based decision computation is the model of the Euclidean distance representing the distance d_k between two points in a multidimensional feature space,

$$d_k = \left(\vec{m} - \vec{r}_k\right)^{\mathrm{T}} \cdot \mathbf{G}_k \cdot \left(\vec{m} - \vec{r}_k\right). \tag{23}$$

$\vec{m}$ is the feature vector, $\vec{r}_k$ the class center of gravity vector and $\mathbf{G}_k$ is the weight matrix. This concept has been tested in numerous practical applications. Assuming normalized features in the range $0 < m_j < 1$ it yields very reliable results.

A scattering of the feature vectors can be taken into account by using an estimate of the sample variance $s_{jk} = \hat{\sigma}_{jk}$ yielding the weighted distance d_{w}

$$d_{\mathrm{w}} = \sum_{j=1}^{J} \frac{\left(m_j - r_{jk}\right)^2}{s_{jk}^{\;2}} \qquad k = 1,2,...,K \cdot \tag{24}$$

By using the inverse feature covariance matrix $\mathbf{C}_k^{-1}$ the *Mahalanobis* distance d_{Mah} between point $\vec{m}$ and the *k*-th cluster reference vector $\vec{r}_k$ is defined in the *K*-dimensional feature space by

$$d_{\mathrm{Mah}} = \left(\vec{m} - \vec{r}_k\right)^{\mathrm{T}} \cdot \mathbf{C}_k^{-1} \cdot \left(\vec{m} - \vec{r}_k\right) \qquad k = 1,2,...,K \tag{25}$$

This model takes oblique orientations of the main diagonal axis of cluster ellipsoids into account yielding reliable classification results.

During recent years, artificial neural networks (ANN) have proven as powerful tools in signal classification as well as in modeling of numerical data [19]. The most important advantage of ANNs consists in their adapting capability. Instead of applying time consuming methods for an analytical description of a problem, neural networks can adjust even to non-linear relations with good accuracy by learning from examples. This method safes design time especially when biomedical signals have to be classified. Nearly all physiological parameters, even if they refer to the same internal organ, for example ECG or blood pressure signatures, show different patterns from patient to patient due to individual differences. Learning from individual examples is therefore the crucial point to avoid misclassifications or false alarms. Fig. 9 shows schematically an example for an artificial neural network with several inputs and a coded output in correspondence to biological neurons.

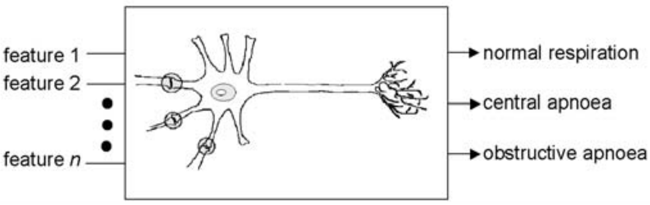


Fig. 9. Scheme of an artificial neural network for the classification of different types of apnoeas corresponding to biological neurons.

Different schemes for supervised and unsupervised learning have been developed. An effective network representation is the multilayer perceptron utilizing the back propagation training rule. It uses a least mean square error criterion in conjunction with a gradient descent technique. The algorithm does not necessarily converge, it can get stuck in local minima and the learning process may be time consuming. It also depends on randomly initialized weights. Another problem is the choice of the number of hidden elements for the actual problem. The best network structure has to be selected experimentally. Later an application for automatic detection of respiratory disorders like central and obstructive apnea from multi-channel signal recordings in a children sleep laboratory is described.

6. INNOVATIVE PATIENT MONITORING

The following examples from research projects of the Institute of Electrical Measurement at the University of Paderborn originate from remote patient monitoring in sleep laboratories with the purpose of investigating reasons for the sudden infant death syndrome (SIDS). Novel continuous blood pressure measurement techniques are also discussed, relevant for sleep disturbance identification, but also for long term 24h-monitoring of the human circulatory system. The assessment of cardio-vascular conditions in sport medicine and for stress induced changes is also relevant.

6.1 Patient Monitoring in a Sleep Laboratory

The reason for the sudden infant death syndrome is still not known. Probably, SIDS has more than one cause and so far it cannot be predicted. Because most cases occur during sleep SIDS is supposed as a sleep disorder. Respiration disorders are assumed as one of the main factors which can be examined in a sleep laboratory.

The physician identifies a patient's condition by examining the patient and noting symptoms like breathing break offs (apnoeas), sudden decreases of blood oxygen saturation values or fluctuations of the heart frequency and diagnoses sleep disturbances. Different sleep stages are to be considered. Both, breathing patterns and sleep stage analysis are influencing on the diagnosis.

The Polysomnographic Diagnostic System POLDI measures up to 20 analogous and 4 serial RS 232 channels. All signals can be recorded simultaneously with digitizing frequencies up to 100 Hz [20].

The POLDI system supported for the first time in polysomnography automatic decisions by adaptive learning algorithms like artificial neural networks. They are trained utilizing typical breathing pattern from coordinated breathing or central and obstructive apnoeas.

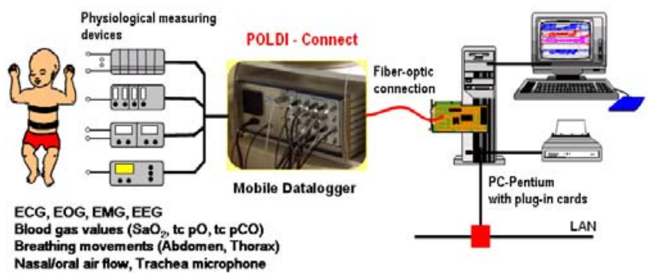


Fig.10. Polysomnographic Diagnostic System (POLDI): The output signals of several applications are gathered and sent via fibre-optic cable to a PC.

Characteristic training patterns of abdominal and thoracic breath movements like central, obstructive and mixed apnoeas, periodic and paradox respiration (swinging respiration), then oxygen saturation and typical distortions due to movements, coughing, sighs are chosen and verified by medical and computer experts. Artifacts, caused by loose or broken sensor cables and removed electrodes are also taken into account. The patterns are divided in a training and a verification set. The errors classifying both sets (re-classification, test-classification) must be determined. They are the basis for the accuracy of the monitoring.

After completing the training phase the neural network classifier is ready to process actual signal signatures. Fig. 11 shows schematically the data evaluation procedure.

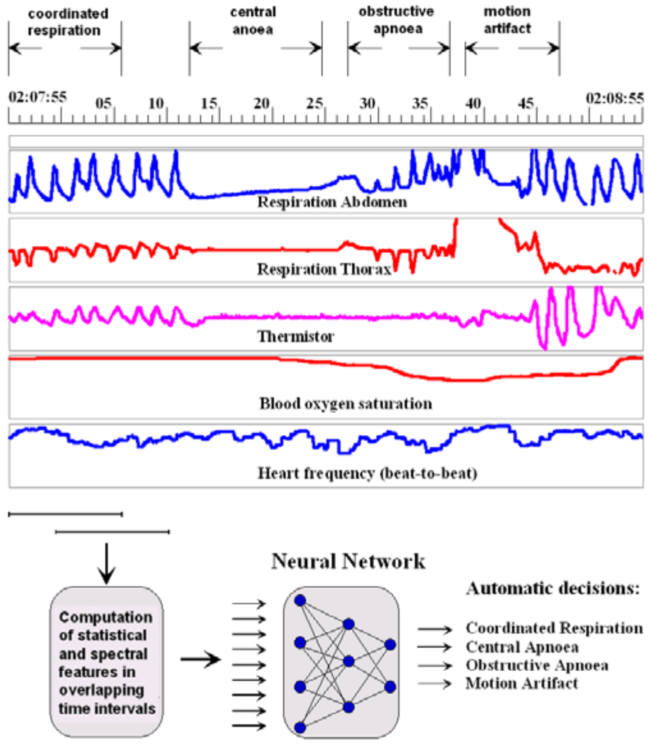


Fig. 11. Adaptive sensor signature evaluation using artificial neural networks (Characteristic signal sections are marked)

The computation is performed in time overlapping intervals and the respiration pattern decisions are displayed. A further training with new, relevant signatures is possible thus increasing the accuracy of an individual analysis.

The rate of false classifications is fairly low. Usually an automatic recognition rate of over 80% is achieved, compared with the results of an experienced medical expert. But the human expert needs about 200 times longer than the automatic system. Signal ranges with artifacts, which do not permit an evaluation, are recognized and marked for judgement by physicians.

Using three sensors a comprehensive analysis of the patients breathing patterns can be achieved. Fig. 12 shows an example, where central and obstructive apnoeas, signal distortion due to movement and the duration of paradox breathing is displayed (black and grey marks).

Apnoeas are most often observed at children, who had an *apparent life threatening event* (ALTE), when they were found blue, limb and not breathing. But they have survived. Among respiration disorders the obstructive sleep apnoea syndrome (OSAS) is a particularly serious symptom. However, the range of "normal" seems to be extremely wide in infancy and adults.

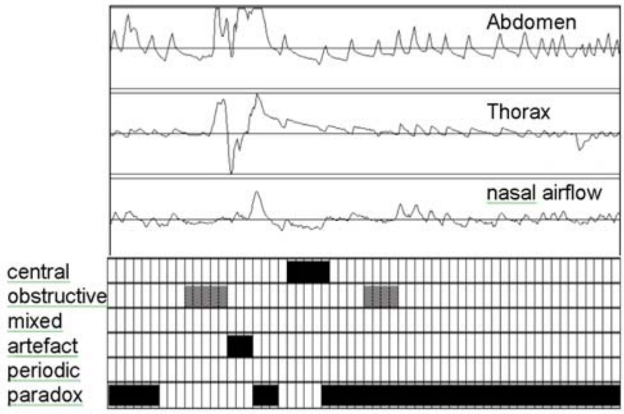


Fig. 12. Automatic respiration pattern display at a certain time interval, events are marked for easy identification

After sleep laboratory examinations a support of concerned children often in form of home monitoring is prescribed. Such instruments, analysing movements, breathing sounds or oxygen saturation can be regarded as predecessors of advanced patient monitoring systems. So far they only provide a local alarm signal in case of an emergency, warning the children's parents.

6.2 Respiration Monitoring with Trachea Microphone

Paediatricians use polysomnographic recordings of infants to evaluate disturbances of cardio-respiratory control mechanisms. Quantification and qualification of apnoea combined with blood gases and heart rate measurements are important tools for classifying their severity. Obstructive and mixed apnoeas are considered as pathologic and potentially dangerous. This applies also for adults. So far, apnoeas are only detectable by airflow measurement in combination with the signals of respiratory efforts. Oxygen saturation, decreasing during or shortly after en apnoea event must be regarded for definite identification.

It was the objective to develop a new microphone-based sensor for such measurement and improve accuracy and reliability for the recognition of obstructive and mixed apnoea [21]. To detect airflow a thermistor sensor was applied close to the nostrils and a microphone was attached additionally at the upper thorax aperture.

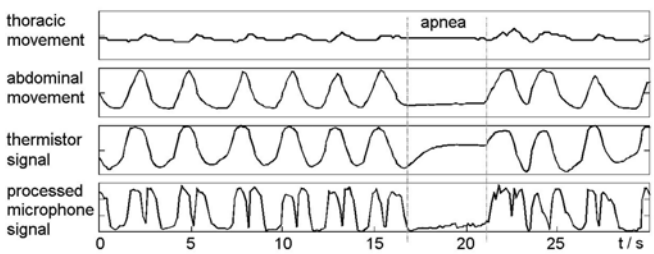


Fig. 13. Respiratory movements and signals of ventilatory airflow

The microphone signal was processed by a new developed monitoring device. The output signals of both systems were then used alternately in combination with other signals to detect apnoeas. For verification video recordings of the sleeping patients, acoustic recordings of breathing sounds and measurement protocols were taken.

The microphone signal was utilizable during 85.6% of the total recording time, compared to 78.0% of the thermistor signal. Apnoea quantification showed a recognition rate of 94.8% against 90.2% using the thermistor sensor. Using the duration of detected apnoea recognition rates were 91.0% against 81.3%. Additionally, characteristic curves of inspiration and expiration sounds could be qualified for different kinds of dyspnoea. It was concluded, that our new tracheal sound monitoring technique can add important information to improve the diagnosis process.

6.3 Optoelectronic Respiration Measurement

Optoelectronic sensors in the visible and near infrared region are used for pulse oximetry in standard clinical instrumentation. The outputs of the sensors are referred to as photoplethysmographic signals (PPG). Respiration influences on the human circulatory system in two ways. First, the arterial blood pressure varies with respiration, causing a slight decrease with inspiration and an increase with expiration. These rhythmic fluctuations associated with respiration are referred to as *second-order wave* of arterial blood pressure. Second, the heart period changes with respiration in a way that it shortens slightly with inspiration and lengthens with expiration. This effect is known as *respiratory arrhythmia* and causes a frequency modulation of the heart rhythm. Both effects influence on the PPG signal and can be extracted by signal processing techniques. In Fig. 14 absorption sensors for finger and ear-lobe utilizing two wavelength (red, 660 nm; infrared, 920 nm) are shown.

Fig. 14. IR PPG finger and ear-lobe sensors used for monitoring

The oxygen saturation is determined utilizing the two wavelengths absorption or reflection signals, influenced in different way by the haemoglobin carrying the O_2. It was the question whether in addition the information contained in the amplitude and frequency modulation of each signal can be extracted.

By analysing the signal of a thermistor at the nose of a patient, how it can be seen in Fig.1, we find in case of respiration pauses clear defined sections with very small amplitudes, Fig. 6. A comparison of spectrogram and Wigner-Ville transformation applied to this signal shows, that a contour plot obtained from the smoothed pseudo Wigner distribution clearly marks the signal sections with the missing respiratory efforts. Applying this technique to the red or infrared absorption signal of a PPG sensor, Fig. 14, the contour plot also displays the apnoea caused gaps, Fig. 15. This result was obtained by off-line signal analysis. It demonstrated the principal suitability method, but it was due to extensive computational time not suitable for online application and monitoring.

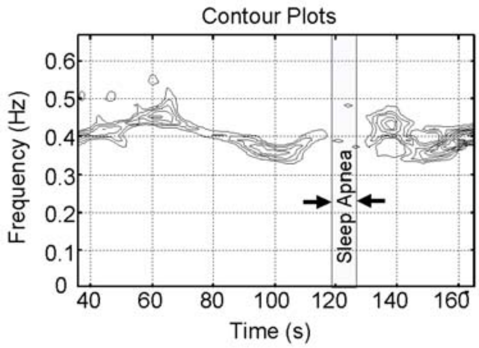


Fig. 15. Respiration monitoring with PPG sensor. Sleeping child, (2 years) sleep obstructive apnoea 8 sec duration.

The photoplethysmographic signal, however, does not follow the pressure pulse but the volume pulse. For a real time extraction of respiration the second order wave of arterial blood pressure can be used. Assuming that the peripheral arteries have similar characteristics like the aorta, there is also a respiratory depending volume wave, which results in a base line fluctuation of the photoplethysmographic signal. A new algorithm analyses the PPG superposed respiration components. To obtain the respiration the PPG data have to be filtered using a low pass filter with an edge frequency of 1 Hz for infants to extract the base line fluctuations. This is achieved using a recursive digital infinite impulse response (IIR) filter technique, implemented in the on-line data analysis algorithm [22]. For adults the edge frequency has to be adapted. Fig. 16 shows a result from the sleep laboratory application of the new technique (middle). As reference a thermistor signal is also shown (lower part).

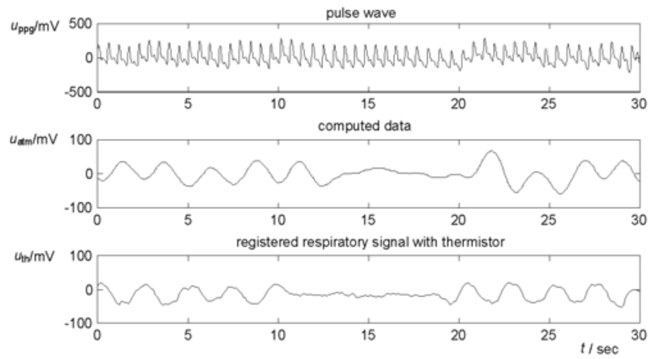


Fig. 16. PPG signature with respiration pause (apnoea) determined with IIR filter technique.

The IR PPG-sensor should be worn at the ear-lobe in order to minimize motion caused signal artifacts. During night time a measuring position at a finger is suitable, Fig. 14.

6.3 Continuous Blood Pressure Measurement

The systolic and the diastolic blood pressures are important parameters to characterize the circulatory system of a person. Limiting values for normal or high blood pressure are well defined and should be regarded. As hypertension causes no pain, often it is not noticed by concerned persons. A single measurement, even at the doctor's practise, gives only a snap-shot, not an indication on risks due to lasting high pressure values. Therefore often a 24-h blood pressure measurement is prescribed. A portable motion-tolerant measuring device with an inflatable cuff must be worn, which measures and stores readings all 15 minutes.

Manual blood pressure measurements in stress situations so far are only possible utilizing the procedure of Riva-Rocci, i.e. using an inflatable cuff and a stethoscope for listening to Korotkoff-sounds. The pressure is read from a manometer scale. Even if an experienced person executes the measurement, in- and deflating the cuff last about 20 seconds. The whole procedure is often uncertain and inaccurate. The time resolution is rather poor. In addition, due to the in- and deflating of the cuff around the upper arm and the associated pump noise, the blood pressure measurement highly influences on the person's attention, which itself again causes blood pressure changes. Moreover, a time interval of about one minute should exist between two measurements, all this again preventing the registration of fast blood pressure variations. Dynamic cardiovascular changes can not be detected.

As "gold standard" the direct invasive measurement using an intra-arterial catheter is regarded. This technique measures the blood pressure continuously but it is associated with a high instrumental expenditure and significant risks for the patient. Thus it is applied in the intensive medicine care but can not be used under laboratory conditions or in real life situations.

For continuous measurements there exists a non-invasive operating blood pressure measuring systems Finapres, using two switched finger cuffs [23]. An electronic servo mechanism raises and lowers the internal cuff pressure in correspondence with the heart beat. Thus systolic and diastolic blood pressures can be determined online after an individual adaptation to the patient. Disadvantage of this system is, that readings are sensitive to motions of the person. There is a poor applicability at patients with reduced blood circulation in the fingers and the correlation between the blood pressure in the finger and the pressure in the central circulatory system is not always ensured. Beyond that, squeezing of the fingers by the cuffs can lead to pain and deafness.

Finally, the systolic beat-to-beat blood pressure can be computed utilizing the heart frequency and the pulse transit time as physiological input parameters for a mathematical model. Our former investigations in this context were based on assuming a linear dependency between blood pressure and pulse wave velocity [24] and artificial neural networks trained with a great variety of patient data [25]. We finally found, that a high accuracy and long term stability of the model based blood pressure determination can only be achieved using the non-linear dependency of the systolic blood pressure on the pulse transit time PTT with personalized individual models. Fig. 17 shows schematically the determination of the pulse transit time via QRS-complex of the ECG and the pulse arrival time at the ear-lobe.

PTT is inverse proportional to the systolic pressure. The model based method is, however, not an absolute measurement, but needs a calibration. An invasive measurement using a catheter would give the most reliable values, but cannot be performed due to medical causes for concern. For calibration therefore cuff based instruments (Omron and Boso, accuracy ± 3 mmHg) were used and the calibration measurements were only performed, when the test persons were at rest.

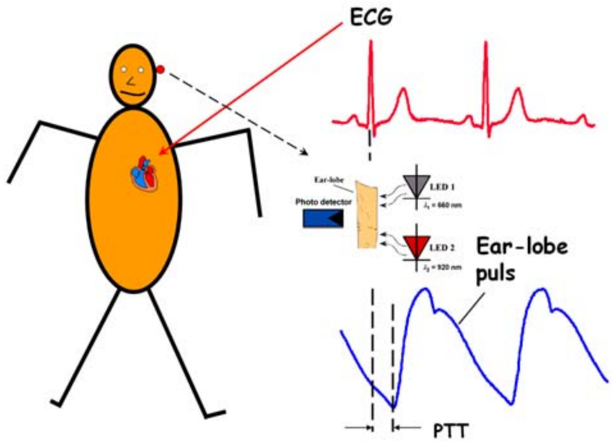


Fig. 17 Measurement of the pulse transit time for continuous systolic pressure determination.

In Fig. 18 results from a continuous blood pressure measurement are given, where a test person first climbs up and down stairs to the seventh floor of a building and after a short rest made a bicycle excursion riding over a moderate hill. In the final resting phase the test person recovered while drinking two glasses of wine.

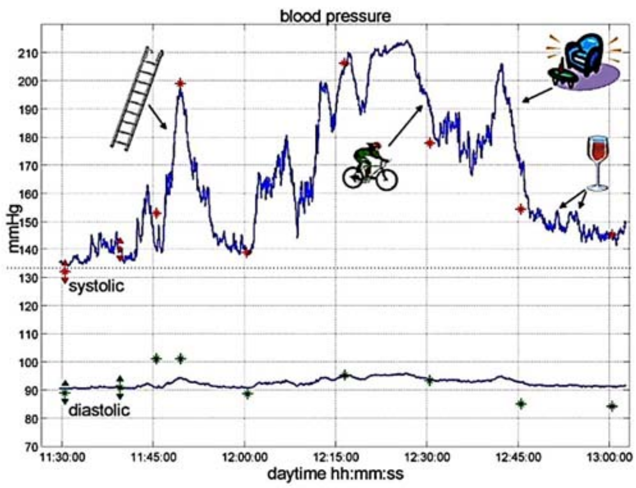


Fig. 18. Continuous blood pressure measurement during stair climbing up and down to 7th floor and a bike excursion; control measurements with Boso TM-2430

During this test discrete control measurements in 15 min intervals using a portable Boso TM-2430 PC 24 h instrument were performed (* in Fig. 18). At 11:49 h an extra measurement was made documenting the maximum pressure at reaching the 7th floor. Always when the cuff pumping automatically was initiated, the test person had to interrupt the activities and remained without motions in order to obtain valid readings of the Boso instrument. The activities and movements did not influence on the continuous model based measurement. It can easily be seen, that without the continuous measurement all details, especially the blood pressure peaks would not have been detected. For data evaluation in this case a neural network trained with personal, individualized values of the test person was used.

A potentially stressful everyday life situation is driving a motor vehicle. It was to be examined, which factors at all lead to stress in driving a car. It is known, that backing-up, driving through building construction sites and parking lead to stress, which correlates with measurable changes of the blood pressure, even when measured with cuff instruments.

In our investigation for the first time continuous blood pressure determinations during car driving could be performed [26, 27]. The motoring itself, without external influences, was considered. For the investigation the night driving simulator "*Nightdriver*" was used, which is located in the L-LAB, Paderborn. A "Smart" motor vehicle is placed within the interactive system, in which the test participants can drive comparably to a normal passenger car. A landscape-street model is projected with three beamers on canvases in front of the car. The next figure, Fig. 19, shows heart frequency, pulse transit time and systolic blood pressure of a driver, to whom the test track was known from previous drives.

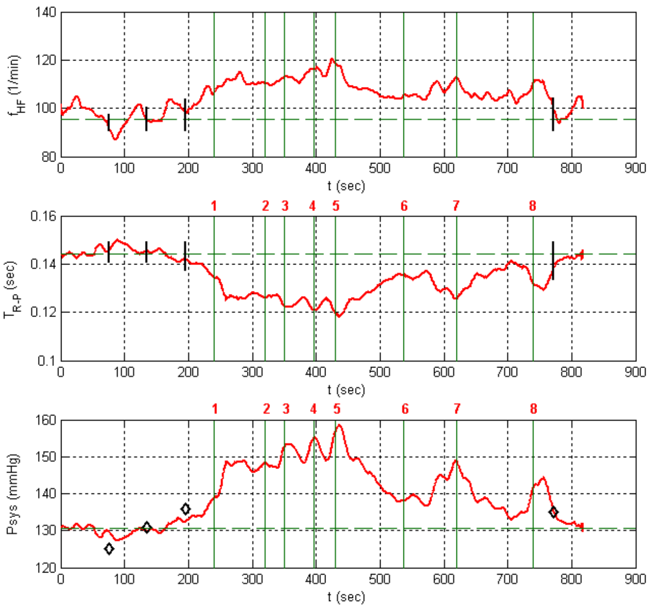


Fig. 19. Heart frequency (upper part), pulse transit time (middle) and systolic blood pressure (lower part) at driving the simulator track (Numbers refer to passing a village, narrow streets etc.)

There is an excellent agreement between specific driving situations on the track like small villages, narrow streets as well as a short highway passage and the measured systolic blood pressure.

These investigations using the driving simulator "*Nightdriver*" demonstrate the first continuous blood pressure measurements in stress situations. Due to the sensor technique the beat-to-beat measurement method is not at all influencing on the persons attention. The method therefore proves as valuable additional indicator for psychological conditions and stress levels.

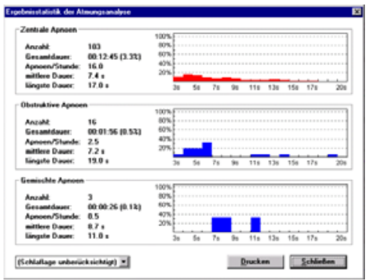
7. CONCLUSIONS

Hospitals and health care facilities get more and more tangled up in severe cost-saving programs. Though expenses permanently are increasing, somehow the health care of patients has to be secured. Not only has the patient's welfare during the length of a stay in the hospital to be guaranteed. Also the postoperative surveillance is vital. Help for handicapped persons and elderly people living at home must be provided.

In the hospitals a regular examination of a patient and the recordings of the physiological parameters is, of course, a routine in intensive care units and in sleep laboratories. They are examples for advanced monitoring, based however on conventional technology. Monitoring systems currently in use are becoming more and more out-of-date.

Innovative new concepts for mobile monitoring technologies based on embedded systems, miniaturized sensors, intelligent computing and wireless communication via Bluetooth modules and local area networks (W-LANs) are now state-of-the-art.

Patient monitoring of the future is where elderly persons can receive checkups while staying at home. A doctor will be able to turn on his mobile phone to check the status of his patient while analysing the transmitted report on sleep apnoeas during the last night, similar to the reports automatically provided by the POLDI system. A mother at work would receive e-mail messages with her sick child's present temperature.



For an acceptance of innovative remote monitoring systems by elderly patients the number of sensors must be as small as even possible. The minimum requirement would be a thorax belt for ECG-based heart frequency measurement, a two-wave-length ear-lobe sensor measuring oxygen saturation and the respiration frequency, simultaneously detecting apnoeas. This sensor is also part of the continuous blood pressure determination. A trachea microphone sensor, measuring respiration frequency, duration of apnoeas as well as coughing or snoring sounds and finally a cuff based blood pressure measuring device for obtaining calibration values two or three times a day are completing the list. A certain redundancy is given because some sensors are sensitive to several physiological signatures. False alarm can reliably be avoided by a supervised system adaptation for defining the patient's physiological status-quo at the beginning of the monitoring. Patients must be actively involved in the monitoring process. They must be able to exchange sensors and operate the patient's part of the monitoring devices independently. Not yet solved is the lasting power supply for wireless communicating sensors.

The principal feasibility of remote monitoring concepts including the automatic preparing of summarized results has been demonstrated. Further research can lead to user-friendly systems even accepted by elderly patients, if they are included in the development process.

8. ACKNOWLEDGEMENT

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